2019

The Spatial Dynamics of Amazon Lockers in Los Angeles County

Project Number 5.4c Final Report | October 2019

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. MF-5.4c	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle The Spatial Dynamics of Amazon Lockers in Los Angeles County		**5. Report Date** October 1, 2019 **6. Performing Organization Code** N/A
7. Author(s) Jiawen Fang, USC https://orcid.org/0000-0002-6339-134X Genevieve Giuliano, USC https://orcid.org/0000-0002-9257-826 An-Min Wu, USC		**8. Performing Organization Report No.** MF-5.4c
9. Performing Organization Name and Address University of Southern California 650 Childs Way, RGL 216 Los Angeles, CA 90089		**10. Work Unit No.** N/A **11. Contract or Grant No.** USDOT Grant 69A3551747109
12. Sponsoring Agency Name and Address Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE Washington, DC 20590		**13. Type of Report and Period Covered** Final report (Feb. 2019–Oct. 2019) **14. Sponsoring Agency Code** USDOT OST-R
15. Supplementary Notes Report URL: https://www.metrans.org/research/the-spatial-dynamics-of-amazon-lockers-in-los-angeles-county		

16. Abstract

The rise of e-commerce has imposed increasing pressures on urban freight distribution systems with a significant demand for dedicated delivery services to the end consumers. Last-mile delivery, which usually happens in residential areas conducted by small vans or trucks with low speeds, raises concerns for environmental and safety issues. One of the strategies to address these problems is to set up Pick-up Point (PPs) networks or Automated Parcel (APs) systems. This research will focus on the spatial dynamics and the associated potential GHG emission reductions of Amazon Lockers, one of the most popular APs, in Los Angeles County. The location data of Amazon Lockers will be obtained by Google Map API and Python. Specifically, the questions to be answered include: (1) Describing the spatial distribution of lockers using spatial pattern analysis tool (Kernel density and Moran's I statistics); (2) Analyzing the socio-economic and built environmental factors that might affect the spatial distribution of Amazon Lockers using spatial regression models (Geographically Weight Regression); and (3) Predict and estimate the potential GHG emission reduction based on the spatial regression models. The results indicate that (1) There is a "three-tier-clustering" pattern based on the level of density; (2) There is a significant positive spatial autocorrelation at 99% confidence level; (3) Geographic Weighted Regression with independent variables *population/internet use, income, education, walkability, transit and parking* can explain 41% of the variations in dependent variables; (4) Business cooperation and spillover effects also greatly affect the locker distribution.

17. Key Words E-commerce; urban freight; last mile delivery; sustainability; safety		**18. Distribution Statement** No restrictions.	
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 30	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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0 ACKNOWLEDGEMENTS

This research was supported by the Volvo Research and Educational Foundation through the MetroFreight Center of Excellence.

The report is also affiliated with the Pacific Southwest Region University Transportation Center (PSR UTC). The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

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THE SPATIAL DYNAMICS OF AMAZON LOCKERS IN L.A. COUNTY

By Jiawen Fang

1 INTRODUCTION

The rise of e-commerce has imposed increasing pressures on urban freight distribution systems with a significant demand for dedicated delivery services to the end consumers. Last-mile delivery, which usually happens in residential areas conducted by small vans or trucks with low speeds, raises concerns for environmental and safety issues. Trucks with low speeds would consume more energy and emit more pollution. Residents, especially in dense neighborhoods, are concerned that delivery trucks impose great threats on their safety. One of the strategies to address these problems is to set up Pick-up Point (PPs) networks and Automated Parcel (APs) systems (Nolmark, Browne, Giuliano, & Holguin-Veras, 2016). Pick-up Points (PPs) typically operate through local shops such as dry cleaners, florists, gas stations, bars, etc. where consumers can receive and return deliveries. This model provides more flexibility to both consumers and carriers. Consumers have more time and location options to pick up their goods, and carriers can also consolidate their deliveries to save money, energy and time. PPs have already been very popular in European countries. For instance, in France, the PP networks have replaced 20 percent of the home deliveries and covered 90 percent of the French population within walking distances. Another alternative is Automated Parcel systems (APs), or locker banks, which can be found in shopping centers, gas stations, and train stations or on the streets. APs are not as common as PPs due to technical issues, with few pilot lockers in dense urban areas. However, APs are becoming more popular both in European and US cities, mainly driven by several big online retailers like Amazon and Walmart. In London, grocery retailers and locker bank providers offer online shopping collection services in transportation stations and parking lots (Nolmark, Browne, Giuliano, & Holguin-Veras, 2016).

The PPs and APs could provide clean and efficient means of delivery, but their success relies on many key factors like location, population density, people's acceptance, accessibility, and operational efficiency (Nolmark, Browne, Giuliano, & Holguin-Veras, 2016). More importantly, there is no solid evidence to show whether PPs and APs can really reduce the environmental impacts of last-mile home delivery. The location of those PPs and APs is an important perspective from which spatial indications can be revealed combining factors like population density, neighborhood characteristics and accessibility. Specifically, the questions to be answered include: (1) Describing the spatial distribution of lockers using spatial pattern analysis tools; (2) Analyzing the socio-economic factors (population density, income, education, ethnics, age, internet penetration) and built environmental factors (retail density, walkability and parking density) that affect the spatial distribution of Amazon Lockers using spatial regression models; and (3) Predicting the potential GHG emission reduction based on the spatial regression models and people's travel behaviors regarding self-picking-ups. In this research, I will mainly focus on the first two questions. Further studies will focus on the potential environmental benefits of Amazon Lockers, building upon the results of this research.

2 LITERATURE REVIEW

2.1 THE ENVIRONMENTAL BENEFITS OF PP NETWORKS

Studies on the environmental benefits of PPs are mostly done in European countries. One study evaluated the environmental impacts of e-commerce and found that introducing e-commerce (B2C) may lead to more traffic in urban areas and make negative impacts on the environment, but strategies like designating time windows and PPs could effectively reduce the total cost, time and NOx emissions Eiichi Taniguchi & Kakimoto (2003). A case study in Thailand used an analytic hierarchy process (AHP) and a criteria framework to determine the location of last mile delivery center (LMDC) to optimize the delivery efficiency. The outcomes showed that LMDC could improve last mile delivery efficiency to destination amides conditions of GHG emissions, traffic congestion, and pollution problems (Amchang & Song, 2018).

Durand & Gonzalez-Feliu (2012) compared the vehicle trips incurred by three picking up methods -- (1) warehouse picking (2) store picking and (3) depot picking -- using simulations. They revealed that store-picking, though more popular, generated more trips because the use of freight vehicles had not been optimized. Proximity picking-up points, where most trips could be made on foot, would significantly reduce vehicle trips. What should be noted here is that the passenger transport mode for store purchase or pick-up points will greatly affect the energy consumption. If the trip to the store substituted by e-commerce was made by bike, foot or public transport, the effects on energy consumption would be minor. However, most current studies reported that most trips were made by car or a mix of car, train and bus (Pålsson, Pettersson, & Hiselius, 2017).

2.2 THE FACTORS THAT AFFECT THE DESIGN OF PP NETWORKS

Following this track, the key to tap the environmental potential of PP network is to increase its efficiency and accessibility with good design. Weltevreden (2008) studies the collection-ad-delivery points (CDPs) in Netherlands and revealed that both shoppers and PPs benefit from vicinity -- online shoppers would be more willing to use CDPs when they have many CDPs near their home, and CDPs with many consumers in their immediate surroundings could also perform efficiently. Morganti, Dablanc, & Fortin (2014) found a significant positive correlation between PP distribution and population density. Another research on PP system operated by Polish InPost Company showed that the most important factor of efficiency was the proper location of the machines used for deliveries. Users reported that the most significant expectations should be “close location from home”, “on the way to work” and “availability of parking spaces”. Deutsch & Golany (2017) took one step further trying to optimize the design of parcel locker networks using a simulation model that included factors of locker facilities and customer benefits. More recently, Lachapelle, Burke, Brotherton, & Leung (2018) explored the development, site and location characteristics of parcel lockers in five South East Queensland (SEQ) car-oriented cities, Australia. The findings suggested that though site locations were constrained by commercial decisions, proximity to highways, to public transport, population density, a balance of jobs and population, and higher rates of households Internet access was associated with the distribution of parcel locker network.

People's attitudes and behaviors are also important to the success of pick-up point networks. Moroz & Polkowski (2016) discovered that Generation Y respondents in Poland did not perceive parcel machines as an environmentally friendly method. However, they would be willing to pay a bit more for environment-saving measures. Oliveira et al. (2017) analyzed the potential demand of automated delivery stations (lockers) in the city of Belo Horizonte, Brazil and found that though home delivery was the preferred option, automatic delivery stations scored high potential demand for online shoppers. Vakulenko, Hellström, & Hjort (2018) followed a focus group design and built on grounded theory to provide insights into customer value in relation to parcel lockers. Liu, Wang, & Susilo (2017) used a panel cross-nested logit model to explore how people's travel behaviors (mode choice and trip chaining decisions) might change with the use of CDPs, based on the "picking up/leaving goods" trips selected from the Swedish National Travel Survey. Compared to previous research with general conclusions for average population, this research revealed some heterogeneities among populations -- young adults living with partners/spouses or children were more likely to use cars in CDP trips. A calibrated model in this research also indicated that the VKT of CDP trips would reduce 22.5 percent if relocating CDPs from urban area to suburban and rural areas.

2.3 Building up Sustainable Networked Delivery System

A further step making full use of PPs is to create a sustainable networked delivery (SND) system, which combines e-commerce and centralized PPs together (Kim, Xu, Kahhat, Allenby, & Williams, 2008, 2009). Kim and his research team compared the GHG emissions and energy consumptions of the "sustainable networked delivery" (SND) system, "traditional networked delivery" (TND) system, and "e-commerce networked delivery" (END) system in delivering books to customers. The outcomes showed that both energy consumption and GHG emissions of the TND and END systems were over 5 times more than those of the SND system. The SND system has a lot of possibilities to save local transportation energy consumption and reduce environmental emissions in delivery system. Xue and colleagues found similar outcomes after exploring the dynamics of e-commerce market and the associated environmental impacts using an agent-based model simulation for book market in the US (Xu, Allenby, Kim, & Kahhat, 2009; Xu, Kim, Kahhat, & Allenby, 2008). The results showed that the book retail market would reach to an equilibrium state where the market shares of conventional bookstore, e-commerce and self-pick-up system were about 50 percent, 10 percent and 40 percent respectively. Correspondingly, the energy consumption and GHG emissions would decrease dramatically by the rapid growth of the e-commerce and self-pick-up system. The concept of SND/END system has also been used by Chinese scholars who presented a comparative study of the energy consumption and GHG emissions of books from the END and SND systems. In their research, the SND system had less environmental impacts than the END system thanks to the reduced round trips by couriers in the SND system (Zhang & Zhang, 2013).

2.4 Research Gaps

Overall, most studies focus on relatively small areas and seldom talk about the spatial distribution patterns of PP or AP locations. And currently there are no studies that investigate the spatial distribution of Amazon lockers in US cities since its new development. Los Angeles is a mix of walkable and non-walkable places where the spatial pattern of lockers should be different from European cities. The aim of this research is to fill this gap by describing the spatial pattern and analyzing the socio-economic and built environmental factors of Amazon lockers in the US.

Los Angeles County will be used a case in this study, after which further studies will be focusing on other major cities in the US.

3 THEORETICAL MODEL

As discussed above, this research will be conducted in three steps – (1) Describing the spatial patterns of Amazon Lockers; (2) Analyzing the demographic and built environmental factors; and (3) Predicting the potential GHG emission reduction. Figure 1 shows the conceptual relationships between these three steps. In Step 1 – Description, various spatial analysis tools will be used to identify whether there is a clustered pattern with strong spatial interaction between neighboring places. In Step 2 – Explanation, spatial regression models will be developed to analyze how demographic and built environmental factors affect the spatial distribution of Amazon Lockers. In Step 3 – Prediction, travel behavior survey and spatial regression model specified in Step 2 will be used together to estimate the potential GHG emission reduction relative to locker use compared to door side home delivery. This paper will only focus on the first two steps.

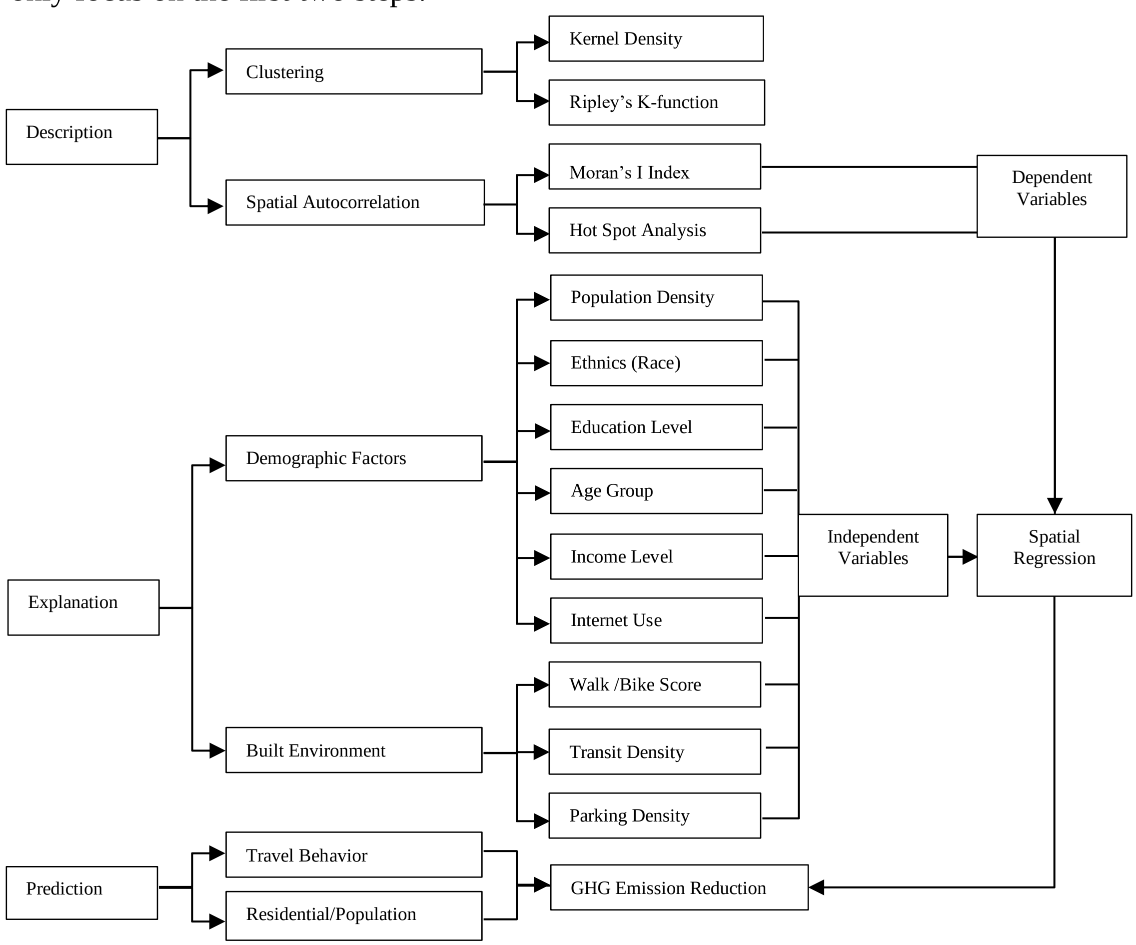


Figure 1 Theoretical Model

4 DATA COLLECTION

In this research, three sets of data will be used. The first dataset includes the locations of all the Amazon lockers in Los Angeles County, which has already been obtained. The dataset includes the name, and the coordinates of each locker. The data was obtained using Google Map API (Text Search Request) and Python. Considering the limit of results that I can get from each API call (20 maximum per query), I divided the LA County into several sub-regions using "Generate Tessellation" tool in ArcGIS Desktop 10.6. Since the "Google Map API-Text Search" can only be conducted in the form of circles, the tessellation I created in ArcGIS was in form of hexagons to minimize the overlapped areas in circular search. The radius of the hexagon, which was also the radius for the circular search, was 2 miles, resulting in 502 units that could cover the whole area of LA County. I calculated the coordinates of each hexagon center and imported them into Python to conduct the search for 502 times (See Python Script in Appendix). After removing all the duplications, I finally got the names and coordinates of 339 lockers located within LA County boundary. Figure 2 shows the tessellation grid (yellow shades with orange lines) and the locations of Amazon Lockers (red dots). The map was made by Google My Map online tools, which was also useful for geocoding. Then I downloaded the map in KML format and converted it into shapefile in ArcGIS.

The second dataset includes the demographic data regarding population density, income,

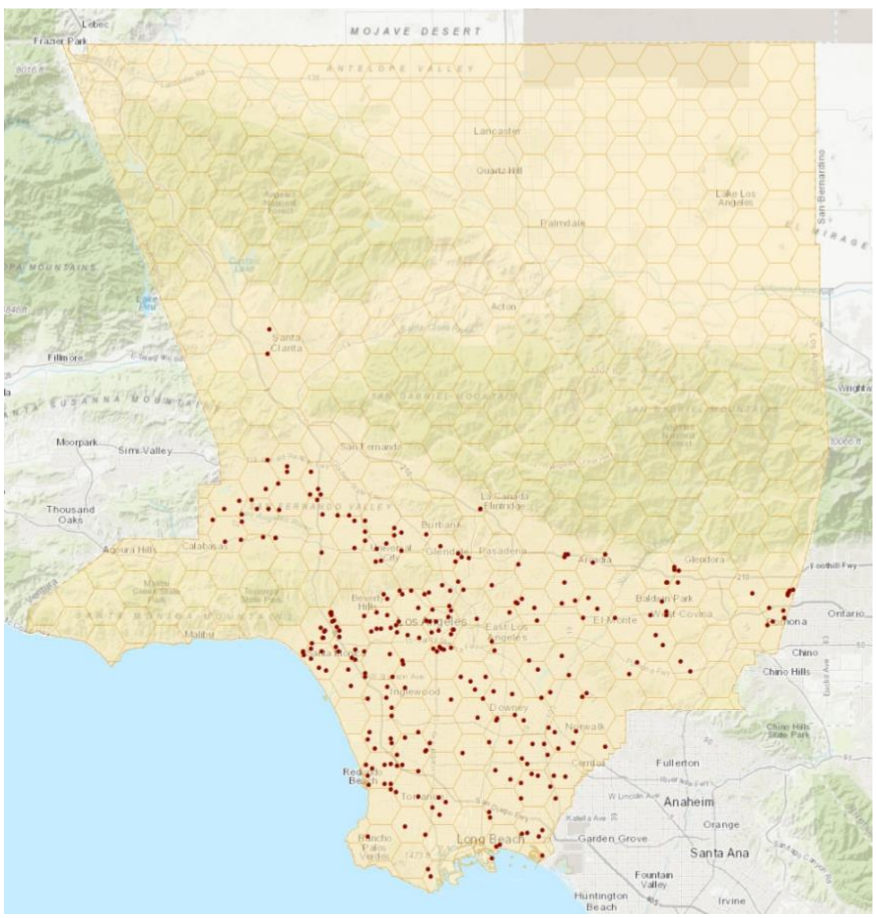


Figure 2 Tessellation Grid and Amazon Lockers in LA County

education, age, ethics and internet penetration by census tract in Los Angeles County. These data were used to measure the explanatory (independent) variables and then explore how the spatial distribution was affected by socio-economic factors. The existing literature indicated that PPs/APs were located near people who were more likely to do online shopping. So I selected six variables that might have the highest influencing power. The data was the latest updated version - 2017, ACS 5-year estimates, obtained from US Census Bureau[1]. Some data were missing across variables in some census tracts (about 20) where there were also no Amazon Lockers, so they were excluded from the regression model. The geographic boundary data was obtained from U.S. Census Bureau, Geography Division, TIGER/Line Shapefile, 2010, Los Angeles County, CA[2]. The tract numbered 06037599100, Santa Catalina Island, was excluded from the analysis because there were neither urban life nor Amazon Lockers.

The third dataset includes the factors that reflect the built environment like walkability, transit density, and parking density. These data were obtained via API call using the same fishnet and Python script as the first dataset, with some changes regarding API parameters. The measurement of walkability and bikeability – walk score and bike score – will be requested from Walkscore.com. The transit station/stop data was obtained from LA Metro Bus and Rail GIS Data[3]. The parking location data can also be obtained from "Google Map API – Nearby Search", where the "type" will be defined as "parking". Table 1 shows the detailed information of the demographic and built environmental data for each variable and how they were used in the research.

Table 1 Independent Variables

Variable	Data (unit of analysis – census tract)	How to use it in research
Population	The number of people	The number of people / Tract Area
Age 15-39	The number of persons aged 15-39	The number of persons aged 15-39 / Tract Area
Education	The number of people with bachelor's degree or higher	The number of people with bachelor's degree or higher / Tract Area
White	The number of white people	The number of white people / Tract Area
Internet	The number of households with internet use	The number of households with internet subscriptions / Tract Area
Income	The median household income ($)	The median household income ($)
Walkability	Walk score at the centroid of each census tract	Walkscore at the centroid of each census tract
Bikeability	Bike score at the centroid of each census tract	Bike score at the centroid of each census tract
Transit	The number of transit stops	The number of transit stops / Tract Area
Parking	The number of parking lots	The number of parking lots/ Tract Area

[1] https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml
[2] https://egis3.lacounty.gov/eGIS/2011/01/04/release-of-2010-census-tigerline-shapefiles-for-california/
[3] https://developer.metro.net/docs/gis-data/overview/

5 METHODS

Different spatial techniques were used for spatial pattern description and explanation. To begin with, I geocoded the locker location data as the base map in the format of shapefile, and then used ArcGIS Desktop 10.6 for all the following analysis. Parameters will also be specified in this section.

5.1 SPATIAL POINT PATTERN ANALYSIS - KERNEL DENSITY AND RIPLEY'S K FUNCTION

The first step was to detect spatial point pattern of the lockers' location. The locker location data is point data originally, which is suitable to use Kernel density and K-function to determine if the lockers are dispersed, clustered or randomly distributed throughout the study area. The Kernel density assumes that the spatial distribution is independent but has a varying intensity. The Input Feature Class was the point data that showed the locations of all the Amazon Lockers. The analysis used default settings, with the Output Cell Size as "1045.50 SQUARE_MILES", the Output Values as "DENSITIES", and the Method as "PLANAR".

The K-function, however, assumes that individual distributions of points are spatially dependent. In this analysis, the input feature class was also the point data that showed the locations of all the Amazon Lockers. I used default settings as well, with Number of Distance Bands as 10, Compute Confidence Envelope as "99_PERMUTATIONS" and Study Area Method as "MINIMUM_ENCLOSING_RECTANGLE". The envelope analysis was included in the K-function to allow for sampling variations. If the observation line is above the envelope area, clustering can be detected in this area. Since there was no evidence showing whether lockers were spatially dependent or not, it would be better to use both methods, compare the results and then determine which one would be the best.

5.2 SPATIAL AUTOCORRELATION – MORAN'S I STATISTICS AND HOT SPOT ANALYSIS

The next step was to look at the spatial interaction between different census tracts regarding the *availability* of Amazon lockers. The *availability* was measured by the number of one-mile locker buffers intersecting each census tract as one of the attributes for each polygon. Global Moran's I statistics were first used to assess the overall pattern whether a positive or negative autocorrelation existed. The Input Feature Class was the polygon data of all the census tracts in LA County, with the Input Field as the number of one-mile locker buffers intersecting each census tract. The Conceptualization of Spatial Relationships was primarily "INVERSE_DISTANCE", because the input data was a continuous polygon data, so the closer two features were in space, the more likely they were to interact with or influence each other. However, considering that the variation in polygon size did exist, I also conducted the analysis using "FIXED_DISTANCE" as the conceptualization of spatial relationship to see if the results would get changed[4]. The Distance Method is "EUCLIDEAN_DISTANCE", and the Standardization was set as "NONE".

In order to examine the spatial autocorrelation at the local level, Hot Spot Analysis (Getis-Ord Gi*) tool was then used to assess each census tract within the context of neighboring features and

[4] See how to select a conceptualization of spatial relationships here: https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/modeling-spatial-relationships.htm#GUID-729B3B01-6911-41E9-AA99-8A4CF74EEE27

compared the local situation to the global situation. The Input Feature Class was also the polygon data of all the census tracts in LA County, with the Input Field as the number of one-mile locker buffers intersecting each census tract. Both "INVERSE_DISTANCE" and "FIXED_DISTANCE" were used as the Conceptualization of Spatial Relationships. The Distance Method is "EUCLIDEAN_DISTANCE". The default neighborhood search threshold was 51486 US feet.

5.3 SPATIAL REGRESSION - OLS AND GWR

The final step was to explore the relationships between demographic factors and locker locations. The analysis was conducted in the unit of census tract. The dependent variable was the number of one-mile locker buffers intersecting each census tract. The independent variables were population density (*population*), age 15-39 density (*age*), white density (*white*), high-educated density (*education*), the density of households with internet (*internet*), and median household income (*income*), walkscore (*walk),* bikescore (*bike),* transit density (*transit*) and parking density (*parking)*. A correlation test was run first for variables filtering regarding multicollinearity issues. Then, Ordinary Least Squares (OLS) regression model was run without taking spatial interaction into consideration. Geographically Weighted Regression (GWR) model was next conducted incorporating all six independent variables to reveal the joint effect of all the demographic factors. The Kernel Type was "ADAPTIVE" to ensure that the number of neighbors used for local regression was the same for all the census tracts. The Bandwidth Method was set as AICc. And the Output Cell Size was set as default, 1571.97, which was the shortest of the width or height of the extent specified in the geoprocessing environment output coordinate system, divided by 250. The results of OLS and GWR were compared to see if spatial interaction did play an important role in determining the spatial distribution of Amazon Lockers.

6 FINDINGS

6.1 SPATIAL POINT PATTERN ANALYSIS

The results of Kernel Density and K-function analysis both indicate that clustering exists in the spatial distribution of Amazon Lockers within LA County. Figure 3 shows the results of kernel density. The black dots represent the real location of lockers and the color shades indicate the value of kernel density. The density is classified into nine levels by equal interval, with deeper color shades representing higher density. From this map, we can identify a three-tier-clustering pattern based on the level of density. Tier 1 includes two major clusters with the high level of density at their centers (around 0.9) - (1) Westside including Santa Monica and UCLA; (2) Downtown including USC and Korean Town; Tie 2 includes another two clusters with the medium level of density (around 0.6) at their centers– (3) North Redondo including Lawndale, Hermosa Beach, North Torrance and Gardena; and (4) Bellflower including Paramount, Lakewood and Artesia; Tie 3 includes eight small clusters with the low level of density (around 0.3) at their centers – (5) Winnetka, (6) North Hollywood, (7) Glendale, (8) Alhambra, (9) Covina, (10) Claremont, (11) Downey, and (12) Long Beach.

The results of K-function, shown Figure 4, provide additional evidence of the clustered spatial pattern of lockers. The left graph depicts the results from ArcGIS, where the L(d) represents the transformed K-value so that the y-axis can always match the x-axis. The red solid line represents the observed K value while the blue solid line represents the expected K value. The two grey dotted lines are the upper and lower limits of the confidence envelop constructed from random permutations (99% confidence levels, 99 permutations). The graph basically depicts how the spatial clustering of lockers changes when the neighborhood size changes. In the graph, the observed K value (red line) is always higher than expected K value (blue line) and the upper envelop limit (upper gray line) whatever the neighborhood sizes. Therefore, we can conclude that, at 99% confidence level, the pattern of lockers is significantly clustered in LA County. However, one thing worth noticing in this graph is that when the distance exceeds 15000 US feet on the x-axis, the expected line (blue) jumps out of the confidence interval (grey dotted lines). That might indicate that when we use L(d) transformation, large-sized census tracts may cause some errors. For a further check, I conducted K-function in R, and the results are shown as the right graph in Figure 3. The issues encountered in ArcGIS did not happen in R, and more importantly, we got the same spatial pattern detected as ArcGIS – the observed line is way above the theoretical line. Therefore, we can still conclude that, at 99% confidence level, the pattern of lockers is significantly clustered in LA County. The R scripts can be seen in Appendix.

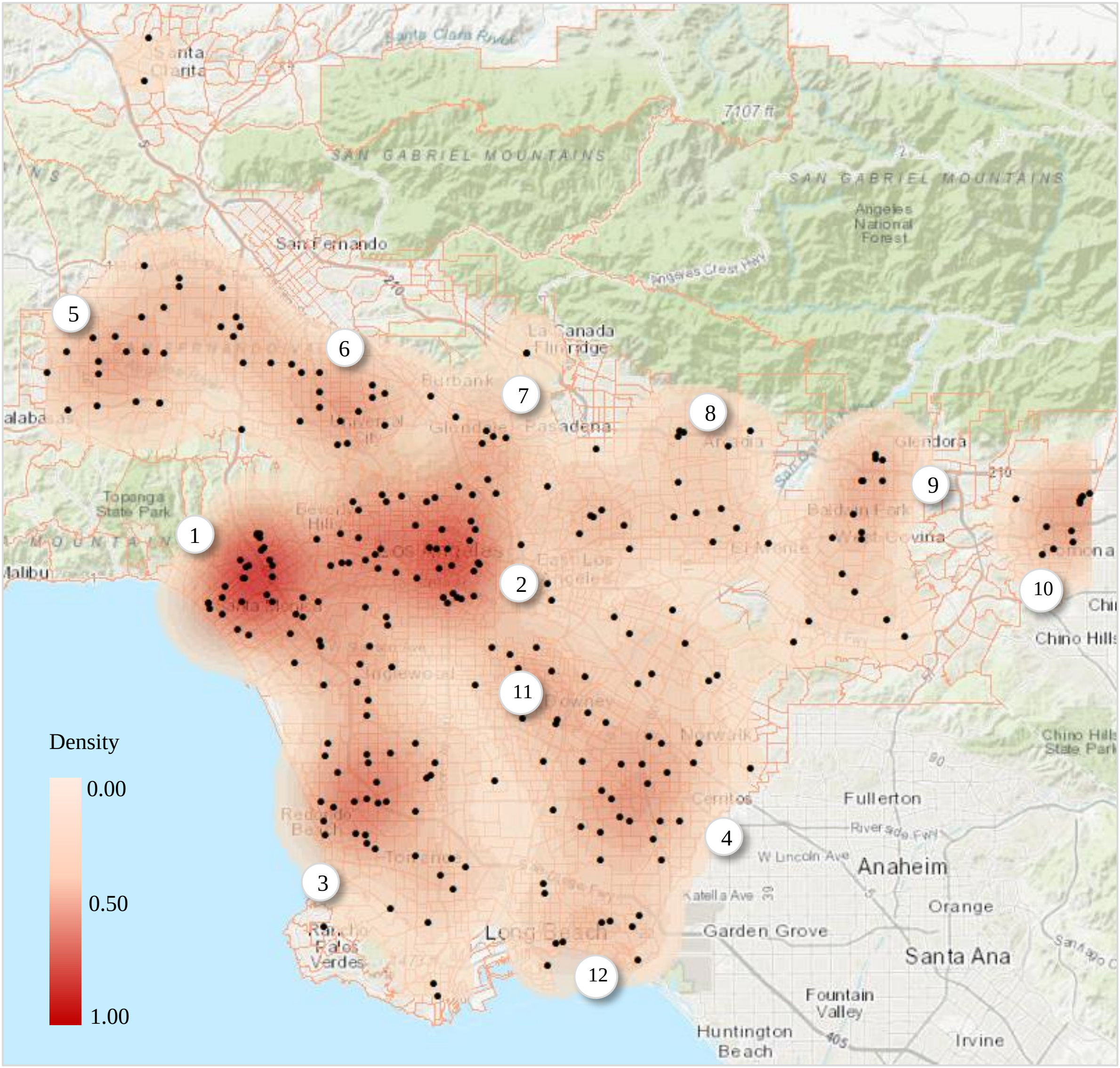


Figure 3 Kernel Density

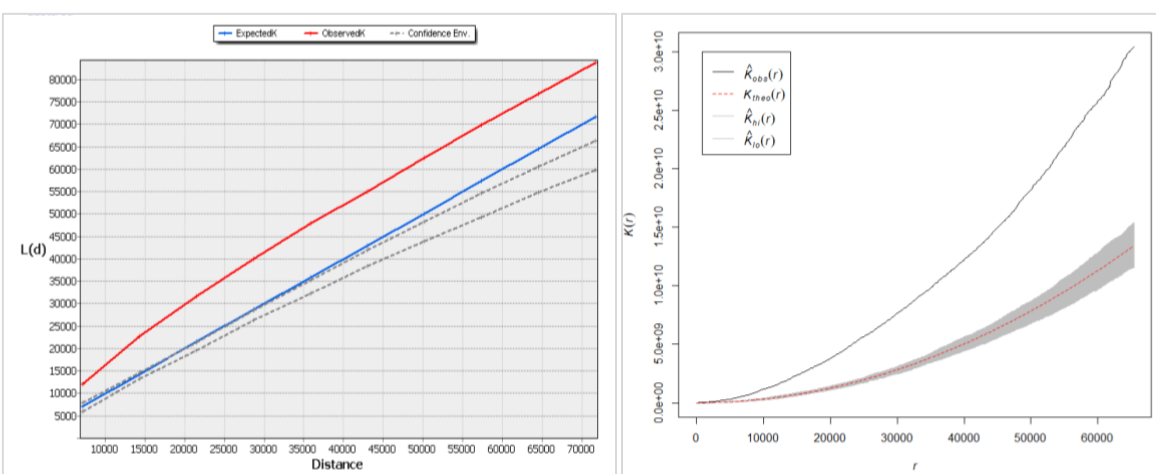
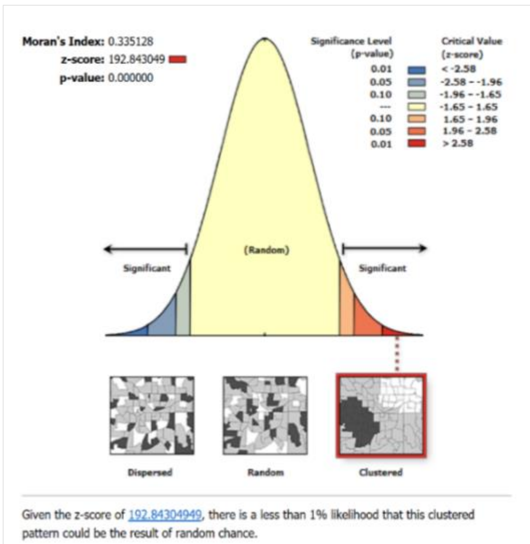


Figure 4 K-function Results from ArcGIS (left) and R (right)

6.2 Spatial Autocorrelation

The clustered pattern of Amazon lockers indicate that spatial interaction might also exist between census tracts that have access to lockers, given Tobler's first law of geography– near things are more related with each other. That leads to the detection of spatial autocorrelation. Figure 5 shows the inputs and outputs of Global Moran's I analysis. Different Conceptualization of Spatial Relationships did not result in much difference. Although Moran's I index was different, the p-value was the same, which was 0.000000, suggesting a significant positive spatial autocorrelation at 99% confidence level (falling within the red zone in the left graph).

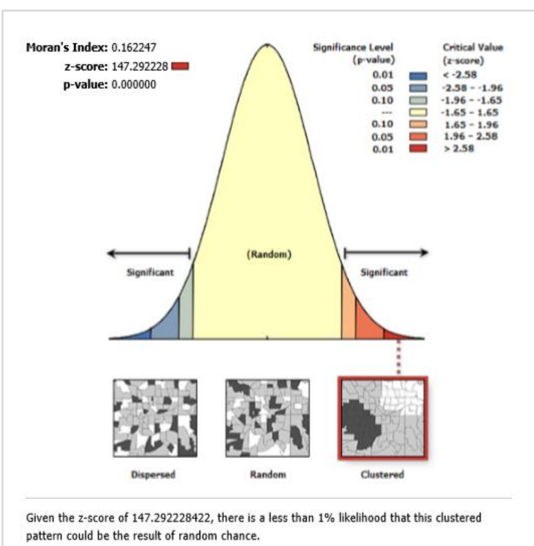


Global Moran's I Summary

Moran's Index:	0.335128
Expected Index:	-0.000427
Variance:	0.000003
z-score:	192.843049
p-value:	0.000000

Dataset Information

Input Feature Class:	LockerBufCT
Input Field:	JOIN_OUTPUT_2.COUNT_
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	51485.9851 US_Feet
Weights Matrix File:	None
Selection Set:	False



Global Moran's I Summary

Moran's Index:	0.162247
Expected Index:	-0.000427
Variance:	0.000001
z-score:	147.292228
p-value:	0.000000

Dataset Information

Input Feature Class:	LockerBufCT
Input Field:	JOIN_OUTPUT_2.COUNT_
Conceptualization:	FIXED_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	51485.9851 US_Feet
Weights Matrix File:	None
Selection Set:	False

Figure 5 Global Moran's I Report

The results of Hot Spot Analysis (Getis-Ord Gi*) provide additional evidence of spatial autocorrelation at the local level. Again, different Conceptualization of Spatial Relationships did not result in much difference. Figure 6 depicts the spatial distribution of hot spots and cold spots with different levels of confidence. The hot/cold spots represent the census tracts both with a high/low value itself and surrounded by other tracts with high/low values as well. The deeper the color shade is, the higher the confidence level would be. From the map, we can identify five clusters of hot spots whose centers reach 99% confidence level. These clusters correspond with the clusters we have identified in Kernel Density, but with some differences. Cluster #1 is broken up into two clusters, with Beverly Hills becoming another new center. The size of the Cluster #1 also seems larger in Hot Spot Analysis than that in Kernel Density Analysis. This might indicate that Cluster #1 has a trend of expansion.

Another interesting phenomenon is that there are some cold spots near Long Beach, where Tie 3 – Cluster #12 is located (marked with a blue solid circle in Figure 6). That means tracts with low values are more likely to cluster there than anywhere else. The combination of "cold spots" and "kernel density clustering" near Long Beach reveals a very special spatial pattern – "sparsely distributed mini-clusters". Some tiny clusters have formed in this area, but located far from each other, with some "gaps" in between (marked with several blue dotted circles in Figure 6). This might be resulted from the distribution of commuter hubs in this area.

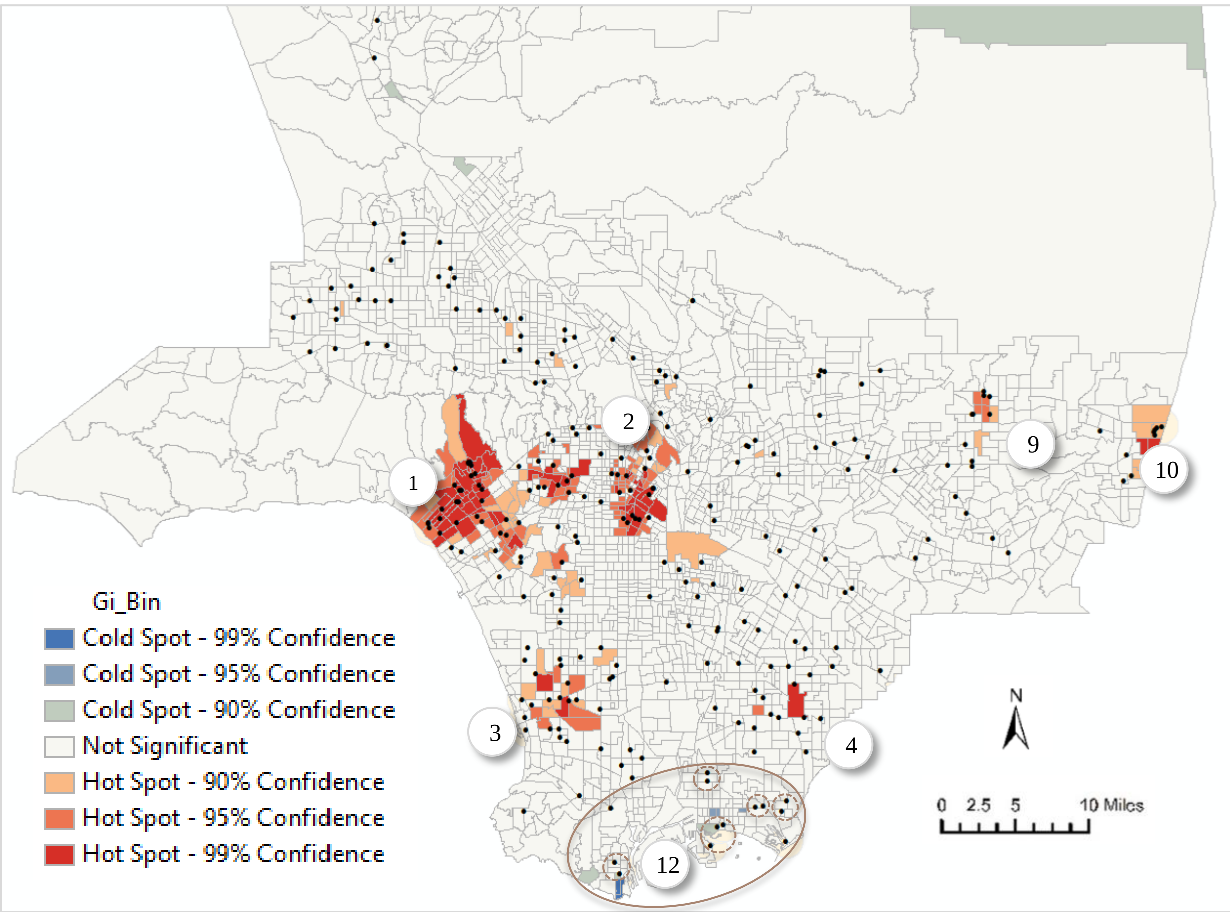


Figure 6 Hot Spot Analysis

6.3 Spatial Regression

6.3.1 Comparative Results of OLS and GWR

The above analysis indicates that although all the census tracts have been included, there are 13 census tracts whose results keep insignificant. These tracts are generally non-urbanized, located in mountain areas, and do not have any Amazon Lockers. Considering that the spatial regression models are very sensitive to such noise, this research narrowed the geographic boundary down to urbanized census tracts in LA County, which contains 2329 census tracts (see Figure 7). Among them, 1718 tracts have at least one locker buffers accessed while the rest 611 tracts have no locker buffers accessed.

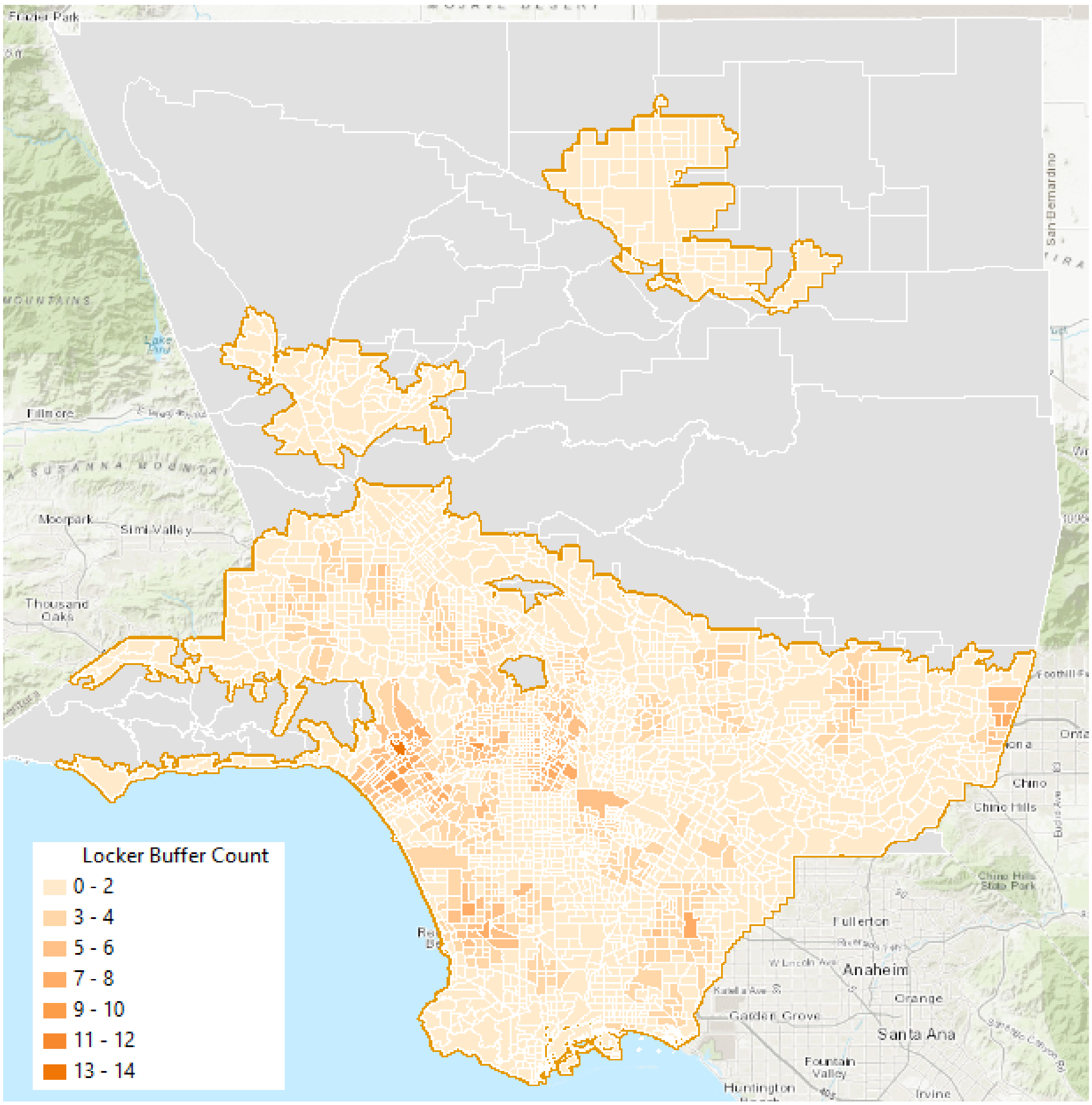


Figure 7 Geographic Boundary for Spatial Regression Models (urbanized areas)

To begin with, I grouped the census tracts by the number of locker buffers they have access to and calculated the average values of independent variables for each group, trying to see if there were potential correlation patterns between independent variable and dependent variables. The results shown in Table 2 suggest that except for Average Household Income, generally there is a positive correlation between dependent and independent variables – tracts with higher values of independent variables tend to have higher values of dependent variables.

Table 2 Dependent and Independent Variables

Locker Buffer Count	0	1	2	3	4	5	6	7	>7
Tract Count	611	546	457	306	222	96	44	27	20
Ave Pop. Density	9180	12528	13754	16005	17871	21981	20039	20936	14827
Ave White Density	4518	5953	6863	7453	8440	9433	9729	9909	8659
Ave Bach. Density	1283	1834	2481	3573	4985	5678	5242	5946	7006
Ave Int. HH Density	1991	2784	3536	4446	5384	6179	5630	5910	5508
Ave Age1539 Density	3433	4755	5331	6581	7498	9680	9174	12109	8496
Ave HH Income	70235	64684	62455	59328	65845	61406	65698	61903	68976
Ave Walkscore	42	56	62	68	69	76	73	75	78
Ave Bike Score	44	53	57	60	59	66	62	69	71
Ave Transit Density	46	66	73	117	131	207	185	154	100
Ave Parking Density	8	12	15	23	28	35	43	53	38

Next, I did a correlation test including all the dependent and independent variables, in order to avoid including independent variables that are highly correlate. Table 3 shows the results of the correlation test, in which the deeper the color shades are, the higher correlation would be. The variables selection was based the criteria as: (1) the correlation coefficients with dependent variable were higher than 3.0; (2) the correlation coefficients with other selected independent variables were no greater than 0.70; and (3) *Income* were tested for its significance and then decided whether to be included in.

Table 3 Correlation Test Results

	Locker	Walk	Bike	Parking	Transit	Income	Population	White	Education	Internet	Age
Locker	1.00										
Walk	0.38	1.00									
Bike	0.33	0.80	1.00								
Parking	0.35	0.47	0.35	1.00							
Transit	0.30	0.53	0.36	0.68	1.00						
Income	-0.06	-0.47	-0.47	-0.26	-0.39	1.00					
Population	0.28	0.60	0.47	0.68	0.75	-0.45	1.00				
White	0.26	0.55	0.43	0.59	0.52	-0.29	0.81	1.00			
Education	0.41	0.42	0.28	0.60	0.43	0.01	0.55	0.58	1.00		
Internet	0.37	0.55	0.40	0.70	0.61	-0.24	0.82	0.75	0.90	1.00	
Age	0.31	0.55	0.43	0.72	0.71	-0.43	0.95	0.79	0.60	0.83	1.00

An Ordinary Lease Squares (OLS) multivariate regression model was conducted to explain the relationships between independent variables and locker availability using STATA. Two models have been tested and the results are shown in Table 4. Overall, the OLS models can explain about 23% of the variations in locker distribution. Model (1) has a higher Adjusted R_2 than Model (2) but not all the variables are significant at least at 95% level. All else equal, *income* is significant when regressed with *population density* but not significant when regressed with *internet use.* The results of Spatial Autocorrelation on the regression residuals indicated a statistically significant autocorrelation of residuals. One or more key explanatory variables were missing from the model. Since the previous analysis has already suggested a significant spatial autocorrelation, a local model like Geographically Weighted Regression (GWR) could be used to improve the predictions by incorporating nonstationary variables associated with location.

Table 4 OLS Results

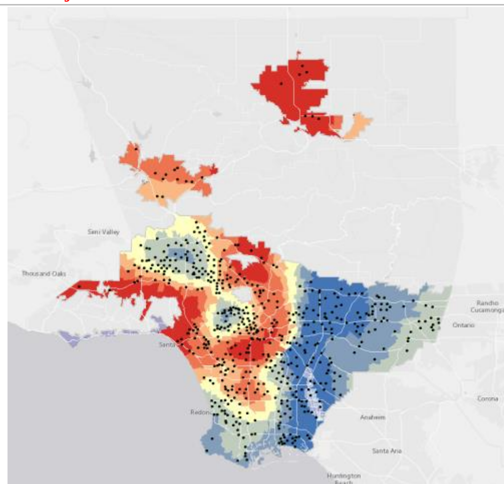
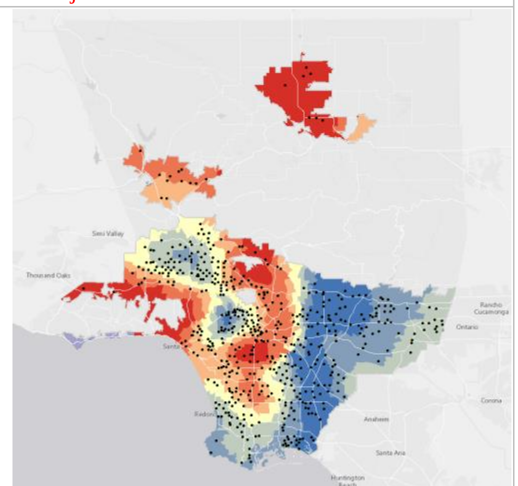
	(1) LockerNum		(2) LockerNum	
Walk	**0.0204*** **	(**12.12**)	**0.0204*** **	(**11.89**)
Parking	**0.00831*** **	(**4.25**)	**0.00798*** **	(**4.02**)
Transit	**0.00162*** **	(**3.99**)	**0.00165*** **	(**3.77**)
Income	**0.00000229**	(**1.82**)	**0.00000378** **	(**3.03**)
Education	**0.000282*** **	(**11.27**)	**0.000132*** **	(**9.97**)
Internet	**-0.000226*** **	(**-7.83**)		
Population			**-0.0000257*** **	(**-4.96**)
_cons	**0.297* **	(**2.01**)	**0.176**	(**1.18**)
N	**2329**		**2329**	
adj. R-sq	**0.249**		**0.238**	

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

With GWR, the Adjusted R_2 went up to 0.40, which means spatial autocorrelation did play an effective role in explaining the distribution of lockers. Table 5 shows the results of GWR models using ArcGIS 10.6. Similar with OLS, Model 1 has a higher adjusted R_2 (0.412) than Model 2 (0.401). In addition, AICc is another measure of model performance and is helpful for comparing different regression models. Taking into account model complexity, the model with the lower AICc value provides a better fit to the observed data. AICc is not an absolute measure of goodness of fit, but is useful for comparing models with different explanatory variables as long as they apply to the same dependent variable. If the AICc values for two models differ by more than 3, the model with the lower AICc is held to be better. The AICc value for Model 1 (8099) is much lower than Model 2 (8143), with a difference more than 3, so we can say that Model 1 provides a better fit than Model 2. The Local R_2 Maps illustrate how well the local regression model fits observed dependent values. Very low values indicate the local model is performing poorly. Generally, census tracts in central and western LA have higher local R_2 than eastern LA. This indicates that prediction results might be more reliable in western LA.

Table 5 GWR Results

	Model 1	**Model 2**

Dependent	Locker Buffer Count	Locker Buffer Count
Independent	Walk (Walk score) Transit (Density) Parking (Density) Income (Median HH) Education (Over Bachelor Density) Internet (HH Density)	Walk (Walk score) Transit (Density) Parking (Density) Income (Median HH) Education (Over Bachelor Density) Population (Density)
GWR Results	Neighbors : 590 Residual Squares : 4176.94197 Effective Number : 83.19679 Sigma : 1.36378 AICc : 8099.71943 R2 : 0.43308 R2Adjusted : 0.41234	Neighbors : 592 Residual Squares : 4259.38846 Effective Number : 82.20450 Sigma : 1.37687 AICc : 8143.70572 R2 : 0.42190 R2Adjusted : 0.40100
Local R2 Map LocalR2 0.02 - 0.05 0.06 - 0.09 0.10 - 0.12 0.13 - 0.16 0.17 - 0.21 0.22 - 0.26 0.27 - 0.37		

6.4 Other Potential Factors beyond the Model

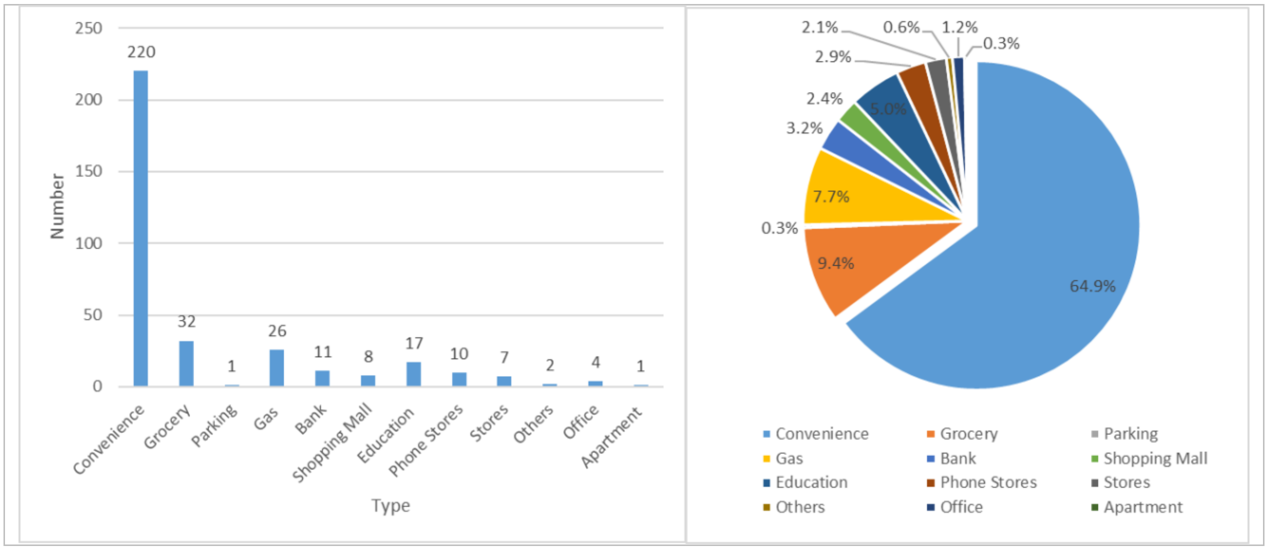
Although GWR models have a much better fit than OLS models, there are still half of the variations in dependent variables that cannot be explained. What are the other potential factors? Based on my observation, many Amazon Lockers are located together with Chase Banks, 7-Eleven, and Whole Foods Market. So, there might be some particular business cooperation between Amazon and these retailers, which disrupt the theoretical locker distribution predicted by GWR models. To test this hypothesis, I checked the specific retailer that each locker is installed with using Google Map. Table 6 shows the results of my search where the rows in light orange indicate the strong cooperation between Amazon and particular retailers regarding locker installation. Among them, 7-Eleven is the largest partner, taking up 65% of the lockers installed in LA county. Next comes Grocery stores like Whole Foods Market and Albertsons, accepting almost 10% of the lockers. Gas stations are the third largest category, taking 7.7% of the lockers, with Chevron, Mobil, 76 and G&M enrolled in. Chase is the only bank that takes Amazon Lockers, and so is Spring as a phone service store. In addition to retailers, higher educational institutions are another big target of locker distribution considering the popularity of Amazon among students.

The basic mechanism behind is a win-win cooperation patterns that both benefits Amazon and the retailers. From retailers' side, they can benefit from the spillover effects of lockers that bring more foot traffic to their stores. Such effects are especially attractive for small businesses who do not have much money for advertisement. When the lockers first came out, 7-Eleven was one of the early adopters, so that's why they take up the majority of locker locations. When a customer comes to pick up a package, they might also get drinks, snacks and other items that are not so expensive but would make your pick-up journey more pleasant. The same logics also go behind gas stations and coffee shops. Another group of retailers are not small business, like Whole Foods, Chase and Sprint. If you really look into them, you will find that they are actually not chosen randomly, since they are all in close business cooperation with Amazon. Whole Foods was bought by Amazon in August 2017, and it's now what supports Amazon Fresh online. Chase has two credit cards named after Amazon, with which Prime members can get 5% discount when purchasing on Amazon online and Whole Foods. Sprint has a discounted unlimited plan for Amazon Prime members at $12.99/month. Installing lockers at these retailers brings *double* foot traffic to Amazon and *single* foot traffic to retailers.

Amazon has lowered the bars of being a locker host for small business and they are also trying to reach out some large retailers. The application of being a host locker is very simple, with some basic questions to answer online showing you have enough space, circuit available and ADA compliance. Amazon reviews the submissions bi-weekly, so the process is quickly updated. However, things are not as rosy as it seems to be. There are also some disadvantages of being a locker host. Firstly, if the products of the stores overlap a lot with what people can get from Amazon at a lower price, foot traffic will definitely not be translated into sales. Secondly, very few stipends are paid to hosts, so if foot traffic does not work well, hosting a locker is not attractive at all.

Table 6 Amazon Locker and Retailers

Type	Count	Share	Notes
Convenience	220	64.9%	7-11
Grocery	32	9.4%	Whole Foods, Albertsons
Parking	1	0.3%	Structure
Gas	26	7.7%	Chevron, Mobil, 76, G&M
Bank	11	3.2%	Chase
Shopping Mall	8	2.4%	/
Education	17	5.0%	UCLA, USC, CSULB, CSUSA
Phone Stores	10	2.9%	Sprint
Stores	7	2.1%	Smoke, Shoe, Printing, Computer, etc.
Others	2	0.6%	/
Office	4	1.2%	/
Apartment	1	0.3%	/



7 CONCLUSIONS

This research described and explained the spatial dynamics of Amazon Lockers in LA County using several spatial analysis tools. As for description, two sets of spatial analysis tools were used. The first sets - Kernel Density and Ripley's K-function - analyzed point data. Kernel Density tool identified a "three-tier-clustering" pattern based on the level of density. The second sets - Global Moran's I Index and Hot Spot Analysis – dealt with polygon data and focused on the availability of lockers for each census tract. Global Moran's I Index detected a significant positive spatial autocorrelation at 99% confidence level. Hot Spot Analysis further proved spatial autocorrelation at the local level, and also indicated the expansion trend of Cluster #1 as well as the "sparsely distributed mini-clusters" pattern near Long Beach.

As for explanation, this research selected three demographic variables – *population/Internet use, income and education*, as well as three built environment variables – *walkability, transit density, and parking density* - as the independent variables that might affect the distribution of locker availability. Ordinary Lease Squares (OLS) multivariate regression model and Geographically Weighted Regression (GWR) was both run and compared to see which one has a better fit. The results showed that GWR model can explain 41% of the variation in dependent variables, while OLS model can only explain 24% of the variation in dependent variables. Beyond the spatial model, potential spillover effects and business cooperation are also important factors that affect the distribution of lockers.

8 LIMITATIONS AND FUTURE RESEARCH

The major limitation of this research is the misspecification of the GWR model. Although GWR model has higher explanatory power than OLS model, still half of the variation in dependent variables cannot be explained by the independent variables specified in the model. Besides, *smart phone penetration* might be a better factor than *internet use* since people need to use their smart phones for pick-ups. However, the data for smart phone penetration was not as complete as internet use, so future studies will also try to get better data on smart phone use and online shopping penetration.

Business cooperation seems to play an important role in locker distribution, but currently it is hard to quantify that as an independent variable and include it into the spatial regression model. Besides, the distribution of those stores are actually the results of demographic and built environment variables specified in the model, given the common logic of location decision a business would make. So future studies would focus on how to incorporate business cooperation without multicollinearity issues.

The estimation of GHG savings is still in theoretical stage, where people's travel behavior is only indicated from walk score. The reality is even more complicated, with many people combine their shopping/dinning with picking up by car, or by transit. Future studies will focus on collecting travel behavior data regarding order pick-ups and the factors that might affect their travel behaviors, in order to make estimation that can reflect better reality.

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10 DATA MANAGEMENT PLAN

10.1 PRODUCTS OF RESEARCH

Three sets of data are used in this research. The first dataset includes the locations of all the Amazon lockers in Los Angeles County, which was obtained through Google Map API - Text Search and Python. The dataset includes the name and the coordinates of each locker. The second dataset includes the demographic data regarding population density, income, education, age, ethics and internet penetration by census tract in Los Angeles County. The data was the latest updated version – 2017, ACS 5-year estimates, obtained from US Census Bureau. The geographic boundary data was obtained from U.S. Census Bureau, Geography Division, TIGER/Line Shapefile, 2010, Los Angeles County, CA. The third dataset includes the factors that reflect the built environment like walkability, transit density, and parking density. The measurement of walkability and bikeability – walk score and bike score – will be requested from Walkscore.com. The transit station/stop data was obtained from LA Metro Bus and Rail GIS Data. The parking location data can also be obtained from "Google Map API – Nearby Search", where the "type" will be defined as "parking".

10.2 DATA FORMAT AND CONTENT

All the data sets are stored as CSV files.

10.3 DATA ACCESS AND SHARING

Locker location data, walk/bike score data, and parking location data, which are extracted via API by the author can be accessed via Dataverse: https://doi.org/10.7910/DVN/QTUW3J

10.4 REUSE AND REDISTRIBUTION

Locker location data, walk/bike score data, and parking location data, which are extracted via API by the author are available in Dataverse for reuse. Demographics data and transit data are open to public.

11 APPENDIX

11.1 PYTHON SCRIPTS FOR COLLECTING AMAZON LOCKER LOCATION DATA

```
import requests
import pandas as pd
import json
import time

fishnet = pd.read_csv('C:\\Users\\janef\\Documents\\LAcountyFishnetHex.csv')

outputfile = open('C:\\Users\\janef\\Documents\\amzlocker.csv', 'w')
locker_list=list()

target = "Amazon+Locker"
# api_key = 'AIzaSyDTa6oDLJCak4XZ4WDmfq-TKT_ooaNh5tE'
api_key2 = 'AIzaSyBSDGJvv3Sd3yM5w2s8mb1OO4T4Ybf473Y'
radius = 3200

for i in range(0,502):
    coord = str(fishnet["Lat"][i]) + "," + str(fishnet["Long"][i])
    print(i)
    url =
        "https://maps.googleapis.com/maps/api/place/textsearch/json?query={}&location={}&radiu
        s={}&key={}".format(target,coord,radius,api_key2)

    locker = requests.get(url)
    data = locker.json()

    if 'results' in data:
        for r in data['results']:

            lat_val =r['geometry']['location']['lat']
            lng_val =r['geometry']['location']['lng']
            name_val = r['name']

            locker_list.append([name_val, lng_val, lat_val])
            outputfile.write(name_val +',' + str(lng_val) + ',' + str(lat_val) + '\n')

    time.sleep(4)

outputfile.close()
```

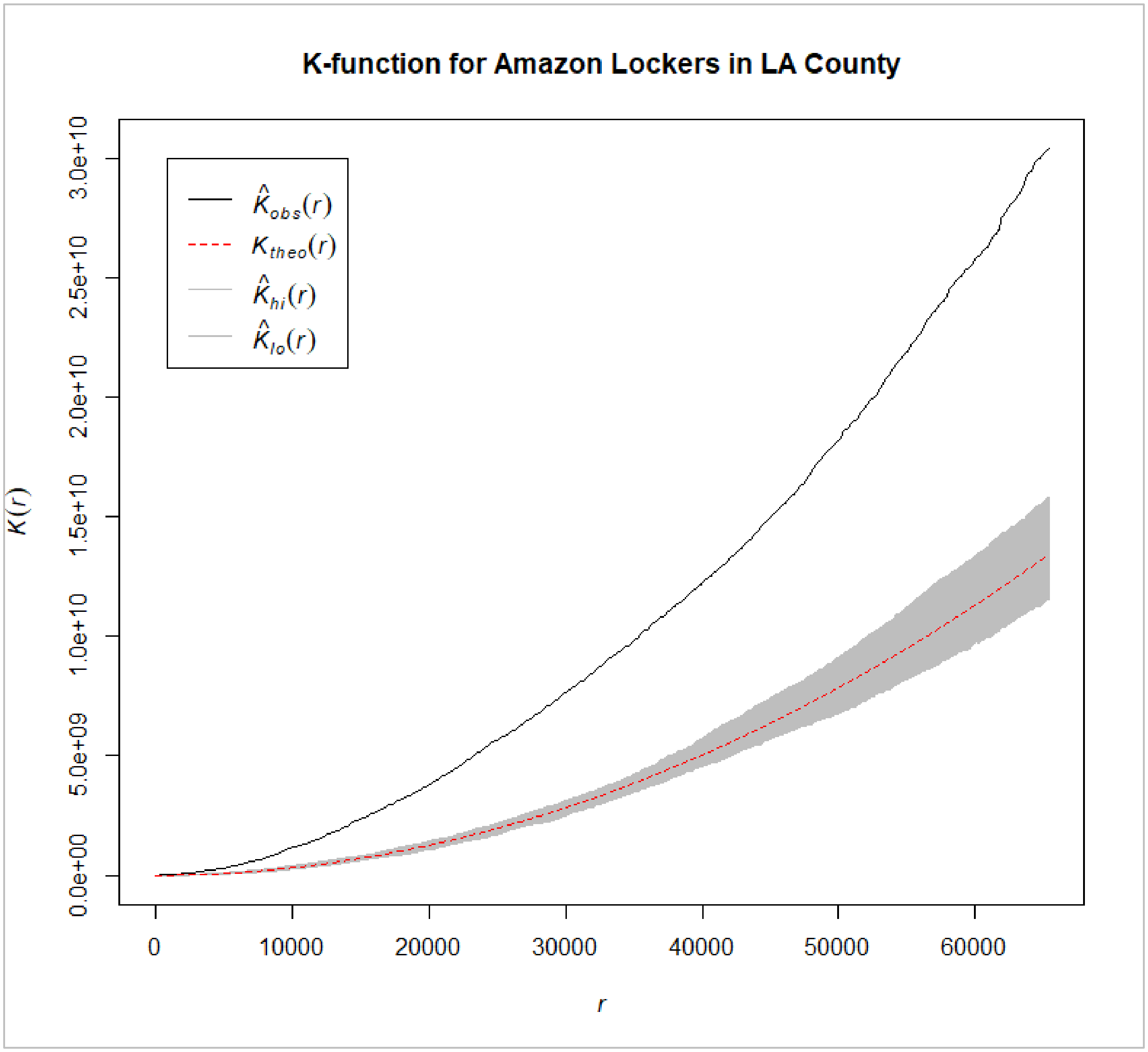
11.2 R SCRIPTS FOR K-FUNCTION

```
> Locker <- readOGR("C:\\Users\\janef\\Desktop\\LockerLA\\AmzLockerInLAclip.shp")

OGR data source with driver: ESRI Shapefile
Source: "C:\Users\janef\Desktop\LockerLA\AmzLockerInLAclip.shp", layer:
"AmzLockerInLAclip"
with 275 features
It has 10 fields
Integer64 fields read as strings:  FID_AmzLok OID_ FID_CENSUS OBJECTID
```

```
> names(Locker)

 [1] "FID_AmzLok" "OID_"        "Name"        "FID_CENSUS" "OBJECTID"    "GEOID10"
"CT10"
 [8] "LABEL"      "X_Center"    "Y_Center"

> plot(Locker, pch=20)
```

```
> class(Locker)

[1] "SpatialPointsDataFrame"
attr(,"package")
[1] "sp"

> summary(Locker)

Object of class SpatialPointsDataFrame
Coordinates:
              min      max
```

```
coords.x1 6367298 6651318
coords.x2 1723235 1984609
coords.x3       0       0

Is projected: TRUE
proj4string :
[+proj=lcc +lat_1=34.03333333333333 +lat_2=35.46666666666667 +lat_0=33.5 +lon_0=-118
+x_0=2000000 +y_0=500000.0000000001 +datum=NAD83 +units=us-ft +no_defs +ellps=GRS80
+towgs84=0,0,0]

Number of points: 275
Data attributes:
   FID_AmzLok  OID_                       Name       FID_CENSUS     OBJECTID
GEOID10
 0      :  1   0:275   Amazon Locker - Agides:  1   2339    :  5   2341    :  5
06037401901:  5
 1      :  1           Amazon Locker - Allie :  1   585     :  4   586     :  4
06037265301:  4
 10     :  1           Amazon Locker - Altair:  1   1001    :  2   1003    :  2
06037111301:  2
 100    :  1           Amazon Locker - Alva  :  1   110     :  2   111     :  2
06037139401:  2
 101    :  1           Amazon Locker - Andale:  1   1129    :  2   1131    :  2
06037191201:  2
 102    :  1           Amazon Locker - Andes :  1   1145    :  2   1147    :  2
06037207502:  2
 (Other):269           (Other)               :269   (Other):258   (Other):258
(Other)    :258
      CT10          LABEL        X_Center          Y_Center
 401901 :  5   4019.01:  5   Min.   :-118.6   Min.   :33.73
 265301 :  4   2653.01:  4   1st Qu.:-118.4   1st Qu.:33.93
 111301 :  2   1113.01:  2   Median :-118.3   Median :34.05
 139401 :  2   1394.01:  2   Mean   :-118.3   Mean   :34.03
 191201 :  2   1912.01:  2   3rd Qu.:-118.1   3rd Qu.:34.10
 207502 :  2   2075.02:  2   Max.   :-117.7   Max.   :34.44
 (Other):258   (Other):258

> Lockerpp <- as.ppp(Locker)

> class(Lockerpp)
[1] "ppp"



> kf.envelope <- envelope(Lockerpp, Kest, correction = "border")
Generating 99 simulations of CSR  ...
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23,
24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44,
45, 46, 47, 48, 49, 50, 51, 52,
53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73,
74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94,
95, 96, 97, 98,  99.
Done.

> plot(kf.envelope, main = "K-function for Amazon Lockers in LA County")
```


K-function for Amazon Lockers in LA County
$\hat{K}_{obs}(r)$
$K_{theo}(r)$
$\hat{K}_{hi}(r)$
$\hat{K}_{lo}(r)$
K(r)
0.0e+00
5.0e+09
1.0e+10
1.5e+10
2.0e+10
2.5e+10
3.0e+10
0
10000
20000
30000
40000
50000
60000
r