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Understanding crime and demographic influence on non-motorized trips: Macro-level analysis

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ABSTRACT

Interest and emphasis on non-motorized modes of transportation have been increasing in the recent years. A better understanding of factors affecting non-motorized commuting trips would enable stakeholders in non-motorized transportation to come up with relevant and cost-effective strategies to promote it. This study aims to improve the understanding on the association between non-motorized commuting trips, crime, and related demographics. Moreover, this study demonstrates an innovative approach for using yearly crime dataset (Chicago) in conjunction with the American Community Survey (ACS) dataset. ACS dataset contains data pertaining to non-motorized commuting trips and important socioeconomic characteristics. An unsupervised data mining technique called Self-Organizing Map (SOM) was used to find association between different factors as it does not require any prior assumptions. The findings show that areas with lower income households are associated with high pedestrian and bicycle commuting. A negative association between crime and non-motorized commuting was also identified. The results also show that areas with larger youth populations are likely to have high non-motorized commuting trips. This study provides insights into the ongoing state-of-the-art study designs and analysis methods associated with non-motorized travel mode.

KEYWORDS

Non-motorized commuting; crime; demographics; self-organizing map

Introduction

The American Community Survey (ACS) demonstrated that the population of U.S. bicycle commuters has increased from about 488,000 in 2000 to nearly 786,000 between 2008 and 2012 (around 60% increase), a larger percentage increase than any other commuting mode (McKenzie, 2014). Government agencies are supporting this modal shift by evaluating existing facilities (Shawn Turner et al., 2017) and improving them to facilitate non-motorized traffic. This shift toward non-motorized modes is crucial in dealing with many traffic and health-related problems in the USA. Walking and biking can help reduce congestion and improve the quality of air. According to 2012 Urban Mobility Report, congestion cost was about 121 billion dollars in wasted time and fuel cost (Schrank, Eisele, & Lomax, 2012). Moreover, physical activity helps to reduce the risk of obesity. A recent Center for Disease Control (CDC) report shows that over 78 million adults and about 12.5 million children and adolescents in U.S. are obese (Ogden, Carroll, Kit, & Flegal, 2012). Incorporating physical activity in daily life such as walking or biking to work or

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nearby places can help alleviate the obesity problem. Therefore, it is important to study the factors that impact the pedestrian and bicycle trips.

Few studies have attempted to find an association between crime and safe walkability in the urban roadways. For example, Foster and Giles-Corti (2008) compared and evaluated 41 studies from a database including PsycINFO, Medline, Web of Science, Science Direct, ProQuest Social Science Journals and Pubmed on the correlation between crime rate and physical activity. Some studies found a negative correlation between crime and physical activity, but others show no correlation (Foster & Giles-Corti, 2008). It is important to note that bike commuting can be encouraged if safety is ensured throughout an area or a region. Study on the metropolitan cities with higher crime rates (for example, Chicago, and Houston) may reveal a significant impact of crime rates on the non-motorized activity (Friedman, Grawert, & Cullen). This study uses Chicago as a focus city due to the availability of crime data.

Researchers have looked at the correlation between build environments such as sidewalk condition, availability of bike lanes, socioeconomic characteristics, crime, safety, and physical activity. As the U.S. Department of Transportation (USDOT) has been supporting the development of integrated transportation systems that include pedestrian and bicycle infrastructure, a closer look at population dynamics, crime, and pedestrian and bicycle trips would be beneficial. This study aims to fill this gap by using Self-Organizing Map (SOM) to perform knowledge extraction from a data set fused with non-motorized trips, crime, and population dynamics.

Earlier work and research context

The literature review covers three broad areas: 1) macro-level analysis on pedestrian and bicycle trips; 2) association between crime and physical activity; 3) application of SOM in transportation research.

Macro-level analysis on non-motorized trips

A common measure of non-motorized travel, at the macro level, is the total number of trips made in large spatial zones, such as cities, states, or countries, allowing for comparisons between jurisdictions (Greene-Roesel, Diogenes, & Ragland, 2007). Table 1 shows a list of studies conducted at a macro level that used trips as their unit of measurement for non-motorized activity. While all the studies were conducted at an aggregate level, the study area scale, or geographic size, varied greatly. Some studies focused on a state and national level, while others performed their analysis for specific regions or communities (e.g., city, county, and metropolitan statistical area). At these macro scales, a household travel survey is a common method for enumerating the number of trips per geographic unit. In areas where household travel survey data is not available, Census data products, such as Journey to Work and American Community Survey, are employed to estimate the total number of trips made.

Assessing walkability

There are different approaches to evaluate the walkability of an area. Transportation planners generally use socioeconomic characteristics of people in a neighborhood to estimate the number of walk or bike trips for a particular traffic analysis zone. Walk

Table 1. Macro-level analysis associated with non-motorized trips.

Scale	Data Sources	Unit of Measurement	Study
State	National Highway Traffic Safety Administration (NHTSA)	Population, number of walk trips	(Alluri, Haleem, Gan, Lavasani, & Saha, 2015)
County	Regional and national household travel surveys	Number of trips, distance traveled, time spent traveling	(Blaizot, Papon, Haddak, & Amoros, 2013)
County	Regional household travel surveys	Total time traveled in million hours, total number of trips in millions	(Guler & Grembek, 2016)
City, county, country	Survey data and U.S. Census Journey to Work data	Kilometers walked/bike, portion journey to work trips for walk and bike	(Jacobsen, 2003)
Metropolitan statistical area, community	NHTS, ACS, annual count data for pedestrians and bicyclists	Number of trips per mode, mode share, VMT	(Rasmussen, Rousseau, & Lyons, 2013); (Lyons, Rasmussen, Daddio, Fijalkowski, & Simmons, 2014)

Score uses a walking distance of a location from nine different types of amenities to calculate the walkability of an area (Walk Score, 2014). The count and distance to the amenities are weighted to calculate walk score. Moreover, an area's walkability can also be identified by using metrics such as residential density, intersection density, and land use mix (Terzano & Gross, 2016). Terzano and Gross (2016) argued in their paper that crime rate should also be incorporated in walkability calculation to get a more accurate assessment. The authors conjectured that areas with favorable built environment for walking such as low-income neighborhoods could have lower or same walkability as high-income neighborhood due to high crime rate. This study presented a theoretical understanding of how crime rate can impact walkability. Foster, Knuiman, Hooper, Christian, and Giles-Corti (2014) used a data-oriented approach to understand the relationship between perceived safety and physical activity. The findings demonstrated that one level increase in fear of crime (Likert scale) could reduce the walking time by 22 minutes per week. Kerr, Evenson, Moore, Block, and Roux (2015) identified actual crime rate along with the perceived crime rate to understand their impacts on physical activity. The authors could not find an association between crime rate or perceived safety and physical activity. Mason, Kearns, and Livingston (2013) indicated a positive correlation between objective crime rates and physical activity in one of their models which did not consider the socio-economic information.

Use of SOM in transportation engineering

The availability of large-scale data set has enabled researchers to employ machine learning techniques in traffic safety. Machine learning techniques have been used in applications such as analyzing the severity of crashes (Sohn & Lee, 2003), estimating accident index (Mussone, Ferrari, & Oneta, 1999), and developing incident detection models (Dia & Rose, 1997). This study used SOMs for analyzing the data. SOM, also known as Kohonen Map, is an unsupervised learning approach which is not guided by a predefined target output (Kohonen, 1998). The approach is frequently used as a data mining and visualization tool to investigate large and complex dataset (Asan & Ercan, 2012). Several fields including robotics, telecommunication, and product management have been extensively using this approach. SOMs preserves topology while projecting high-dimension input signal pattern into simpler low-dimensional discrete output map (Asan & Ercan, 2012). It is particularly useful when data has a nonlinear relationship. SOMs are flexible thus have a low bias, allowing the researchers to make no assumptions about the data.

A number of studies have utilized SOM to investigate pattern and create clusters for traffic engineering data. Sirvio and Hollmen (2007) used SOMs to reveal the natural clustering structure of a large crash data set in Southern Finland to identify the crash contributing factors. Egilmez, Park, and McAvoy (2015) applied SOMs to cluster the states in the United States into different categories based on their road safety performance. This classification can then be used to identify unique safety improvements for states in different categories. Taking advantage of SOMs, Uno, Kageyama, Yamaguchi, and Okabe (2013) explored patterns in fatal motor vehicle crashes and developed unique safety treatments for the identified clusters, concerning their characteristics. For instance, one cluster included the majority of interstate crashes with the single drivers speeding. Based on this observation, the authors suggested using advanced warning systems such as forward collision warning or lane departure warning. Moura, Beer, Patelli, Lewis, and Knoll (2017) used SOMs to discover patterns within accidents in high-risk places such as nuclear power plants. There are several other studies (Alikhani, Nedaie, & Ahmadvand, 2013; Mussone & Kim, 2010; Pham, Faouzi, & Dumont, 2011; Shirota et al., 2012) that have employed SOMs to identify and describe patterns in various roadway safety/crash data set.

Data

This study used two data sets to perform the analysis: 1) 2010–2014 Chicago crime data, and 2) Five-year (2010–2014) ACS estimate data.

Chicago crime data

Chicago maintains a publicly available crime dataset starting from 2001. To match with five-year (2010–2014) ACS estimate years, crime data between 2010 and 2014 was used to conduct the analysis. The research team selected three variables from crime data: 1) type of crime; 2) location of the incident; and 3) crime year to identify roadway-related crimes that are associated with pedestrian and bicycle trips. It should be noted that the total number of crime incidents steadily decrease from 2010 to 2014. This study includes crime data based on location (i.e., alley, streets, sidewalks, bus stops, and driveways) and crime type (e.g., stalking, homicide, narcotics, theft, and assault), which are relevant to non-motorized trips. During 2010 to 2014, driveways had the lowest number of crimes (5 crimes), and streets had the highest number of crimes (306,314 crimes). Notably, 23 crime types such as stalking and homicide were selected for further analysis. It was observed that there were more than 100,000 narcotics- and theft-related crimes. The number of assault, robbery, criminal damage, and battery-related crimes were more than 30,000.

American Community Survey (ACS)

The ACS is a common source of commute travel information in areas where more detailed household travel survey data is not available. Since the 2007–2008 household travel survey is the most recent data for Chicago, this study uses the ACS 5-year estimate for 2010–2014 to assesst the number of non-motorized trips at the Census block group level. The 5-year estimates benefit from a larger sample size than 1-year estimates, which improves its statistical reliability for spatial units with smaller populations, such as block groups. Figure 1 depicts the commonly used Census geographies relative to each other. Block groups offer enough area to capture a sufficiently large sample but are small enough to provide a relatively fine geographic resolution for a zonal analysis of a city or county.

Data preparation

Figure 2 presents a flowchart describing the final data preparation for SOM analysis. The initial data has 531,867 rows, including the total number of crimes between 2010 and 2014. The crime data is transformed into a wide format after subsetting the relevant rows and

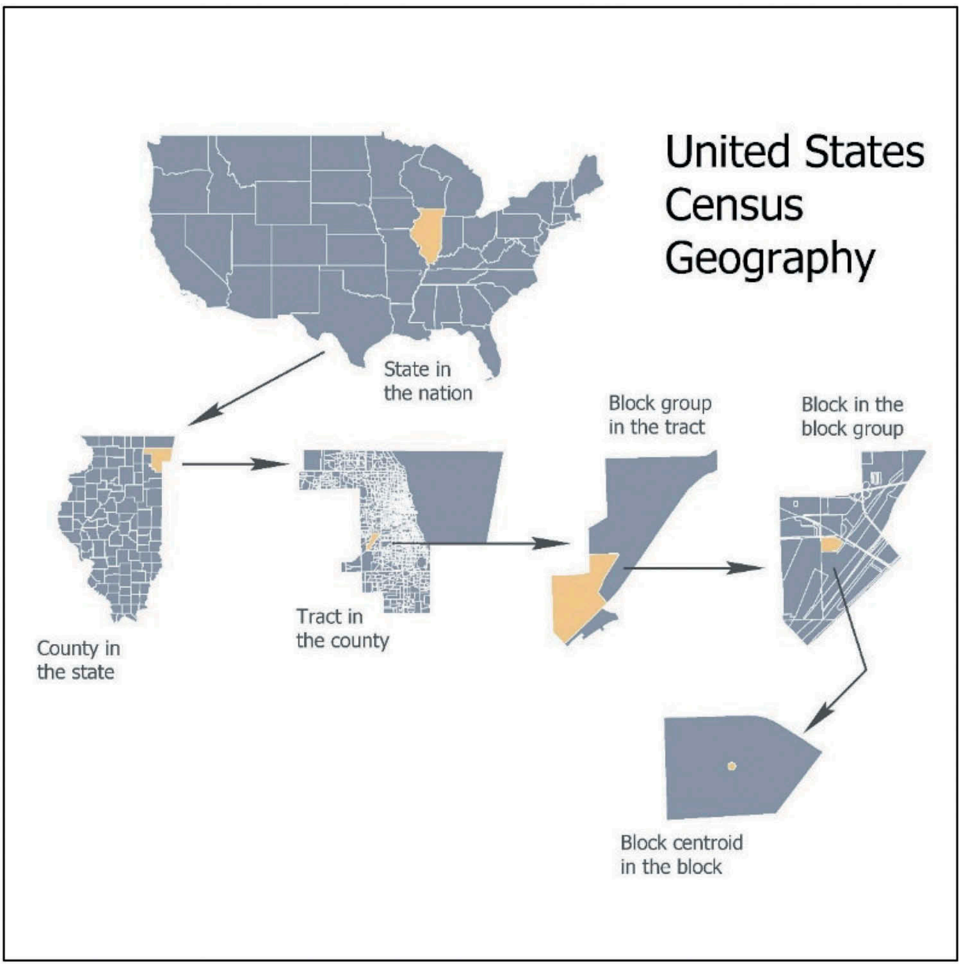


Figure 1. Various spatial units in U.S. Census.

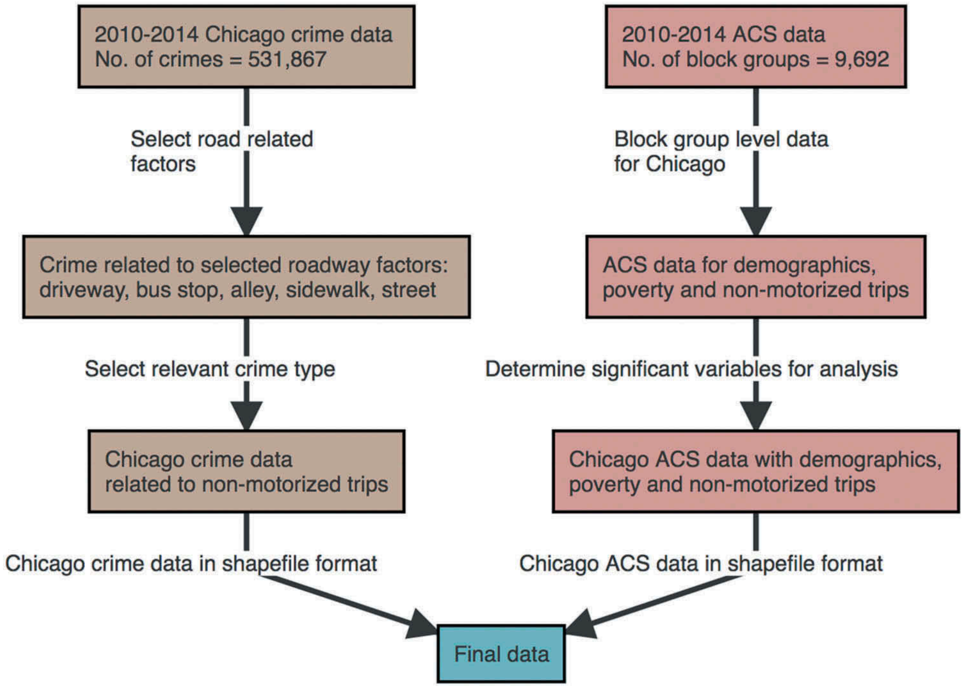


Figure 2. Data preparation method.

columns for pedestrians and bicyclists. The wide data set contains crime count by block group ID for each year, primary crime type, and location description columns. Therefore, each row contains information for a block group with the total number of crimes for each year between 2010 and 2014, five location types, and 23 crime types. The total number of crimes in a block group can be computed by aggregating the total number of crimes over a year, location type or primary crime type. Finally, crime data in the wide format is compiled with the ACS data containing socioeconomic characteristics, pedestrian and bicycle trips by block group identification number. The ACS data had 2,171 block groups common with the crime data thus the final data set has crimes by year, location and crime type, socioeconomic characteristics and non-motorized trips for 2,171 block groups.

This study identified four significant variables that are associated with the crime rate and pedestrian and bicycle trips per block group. Table 2 lists descriptive statistics of the selected variables.

Self-organizing map (SOM)

Much of this study has focused on the effects of crime and demographic factors that influence the frequencies of non-motorized trips. This section provides a short theoretical description of SOM. A detailed description of SOM can be found in an earlier work (Kohonen, 1990); however, it was considered important to include the basic theoretical concept here as well, so that the reader can have a general concept of the algorithmic framework.

Table 2. Selected variables for analysis.

Variable	Description	Size	Minimum	Maximum	Mean
CrimePY	Crime per year per block group	2,171	0	323	41
NonMoto	Pedestrian and bicycle commute trips per block group per year	2,171	0	1,940	47
Male_PopuPer	Male population percentage per block group	2,171	0	88	48
Female_PopuPer	Female population percentage per block group	2,171	12	100	52
PL_LT1Per	Percentage of population living under poverty level per block group	2,171	0	86	23
Popu_LT22Per	Percentage of younger population (age less than 22) per block group	2,171	0	87	27

SOM evolved from Hebbian learning (Yin, 2008). According to Hebbian learning, the neurons adjust their weights according to the input. The weights are eventually tuned to particular inputs thus allowing them to carry out unsupervised learning. SOM is a type of neural network that reduces the dimension of a high dimensional data into two dimensions and creates visualization and clusters which help in discerning patterns in the data (Moura et al., 2017).

SOMs consist of two layers: input and output layers that include nodes. The number of input nodes is equal to the number of rows in the data. The user determines the number of output nodes and how they would be arranged. There is a weight vector associated with the output node that has the same dimension as the input nodes. Let $\mathrm{x} \in \mathbb{R}^n$ be the input then $w_i(t) \in \mathbb{R}^n$will be the weight vector for each output node i at iteration t. The weight vectors are initialized by drawing a random number between 0 and 1 from a uniform distribution. At each iteration of SOM algorithm, a row from the dataset is used to compute the Euclidean distance between the input (n elements) and the output nodes using the weights associated with the output node (Kohonen, 1998). At each iteration, an output node with the minimum Euclidean distance from the input is determined as the winner. Following equation is used to determine the winner node $c(t)$ at iteration t (Kohonen, 1998), (Yin, 2008):

$$c(t) = argmin_{i\in I} \parallel \mathrm{x(t)} - w_i(t) \parallel \tag{1}$$

where I is the set of all output nodes.

A neighborhood function is then used to find the neighboring output nodes, and their weight is updated based on the distance between these output nodes and the winner node for the next iteration. A wide neighborhood is selected at the first iteration, and it is then monotonically decreased. The influence of a winner node on the weight of other output node decreases as the Euclidean distance between two node increases. Also, the winner node does not impact the weight of other output nodes after a certain distance. A learning rate factor is used to subsequently reduce the influence of a winner node on the nearby output nodes as the number of iterations increases. Following equation is used to update the weights for the next iteration (Kohonen, 1990):

$$w_i(t+1) = w_i(t) + \alpha(t)(x(t) - w_i(t))\ if\ i \in N_c(t) \tag{2}$$

$$w_i(t+1) = w_i(t)\ if\ i \notin N_c(t) \tag{3}$$

where $\alpha(t) \in (0,1)$ is the learning-rate factor (Kohonen, 1998) and $N_c(t)$ is the set of neighborhood nodes around $c(t)$.

Results and findings

The current study aims to use an unsupervised learning approach to determine the overall association between non-motorized trip and other socio-economic and demographic variables. Additionally, the study attempts to investigate the role of the fused dataset prepared from various sources to develop this relationship. This study used open source R software packages '*kohonen*' and '*som*' to perform the analysis. These two packages offer adequate flexibilities to conduct the analysis. The final output of SOM is a map that can represent the topographical properties of the data. The algorithm is based on an iterative process that forms several small groups (known as 'nodes') based on the similar properties of the variables. The groups are arranged on the surface such that groups with similar characteristics are closer and groups with different characteristics distant. The primary construction of the map builds an empty grid of nodes, each with a random vector in n-dimensional space (where n is the number of input variables). The data set is converted into n-dimensional vectors, and a vector created from a data point is placed in the node it best matches.

Figure 3 illustrates three SOM maps: 1) node counts, 2) neighbor distances, and 3) node quality/distance. The left bar Figure 3a,b shows the frequency count by different color codes. The color 'blue' indicates lower frequency, 'green' indicates medium frequency, 'yellow-orange' indicates high frequency, and 'red' indicates the highest frequency. The node count plot allows the visualization of the count of samples that are mapped to each node on the map. This metric can be used as a measure of map quality. In this analysis, each data point is a block group, so each node in the SOMs represents a small/large group of block groups. The 'blue' color nodes represent nodes with a small number of block groups, and it goes up to the node with the larger number of block groups (for example, red indicates node with 12 block groups). The neighbor distance, known as the '$U - matrix$,' is the distance between each node and its neighbors. Areas with large distances indicate the nodes are dissimilar in nature and indicate natural boundaries between the clusters. The $U - matrix$ is used for identifying clusters within the SOM map. The node distance maps show that the nodes are not far away from each other except for few nodes.

A SOM heatmap allows the visualization of the distribution of a single variable across the map. Generally, SOM concept involves the creation of multiple plots for comparison purpose to identify important areas on the map. It is important to note that the individual sample positions do not move from one visualization to another, the map is colored by

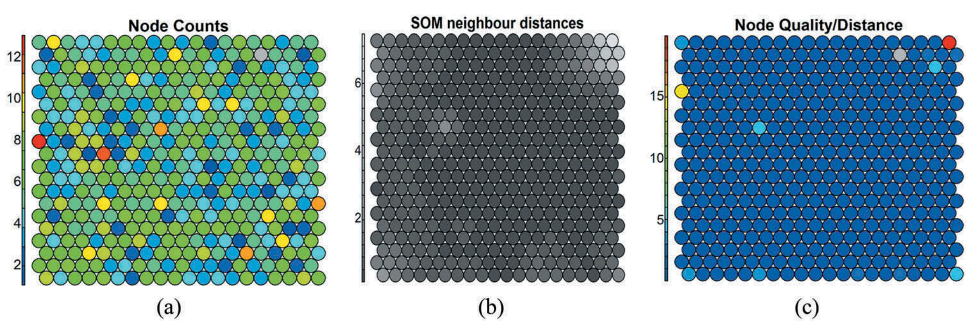


Figure 3. SOM parameters.

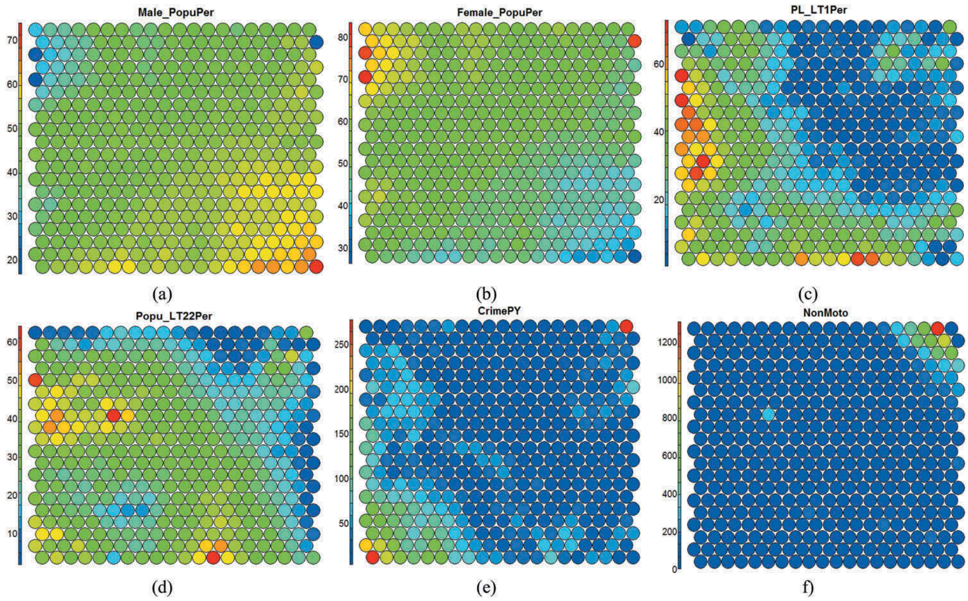
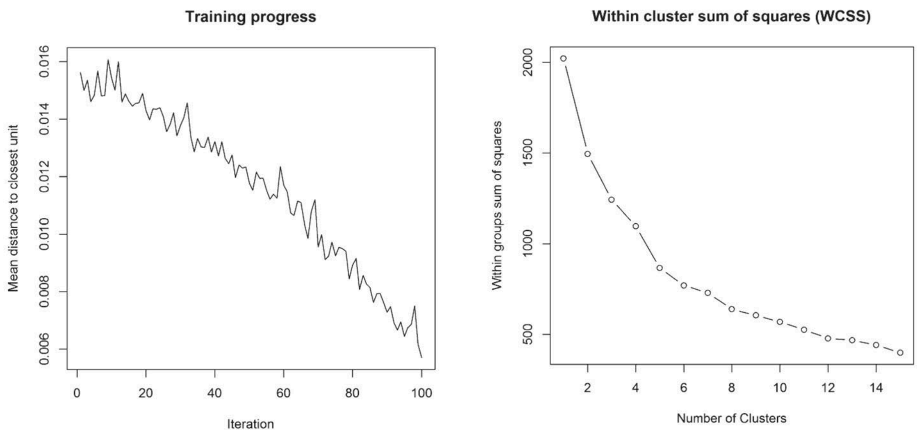


Figure 4. SOM for selected variables.

different variables. This would be beneficial in segregating the data properties. The findings from Figure 4 are given below:

- Both male and female populations are considered in the final model to see whether gender role can be directly associated with the non-motorized trip. Although it is arguable that high male association will infer low female association for certain nodes (see . Figure 4a,b).
- Poverty SOM plot shows (Figure 4c) clear association with three other variables: 1) younger population, 2) crime intensity, and 3) non-motorized trips. Nodes with block groups having higher poverty are associated with nodes with block groups containing a large proportion of younger populations. Poverty level also shows a positive association with crime rates. Nodes with larger non-motorized trip property also have a positive association with poverty level.
- Younger popular has somewhat association with crime rates. It also shows that non-motorized trips are more likely to be associated with younger populations.
- Figure 4e shows SOM for the crime rate. Around 35% of the nodes show somewhat higher crime rate associated with block groups. The crime rate is inversely associated with non-motorized trip generations for few of the nodes. One distinct node (also distinct in node distance plot) shows a clear negative association.
- Figure 4f shows SOM for non-motorized trips. Around 16% of the nodes show a higher number of non-motorized trips. Nodes with lower crime rates are associated with a higher number of non-motorized trips.

Figure 5a shows the number of iteration requires for the model development. The plot shows a decreasing trend with some sudden peaks. Figure 5b illustrates the number of



(a) Training Process (b) WCSS

Figure 5. SOM modeling.(a) Training process. (b) WCSS.

clusters against within group sum of squares. With the increase of clusters, the group sum of squares decreases without showing any discontinuity.

The clustering was performed by using hierarchical clustering Figure 6 shows 10 clusters. An estimate of the number of clusters that would be suitable can be ascertained using a K-means algorithm and examining for an elbow-point in the plot of within cluster sum of squares. In this map, color distinguishes different variables, and the size of the wedge represents the magnitude of each variable. The wedges in each node represent the cluster membership for the students in that node. The findings associated with non-motorized trips are stated below:

- Poverty and younger population are likely to be associated with a higher number of non-motorized trips. In general, non-motorized trips are lower in numbers for most of the nodes. Around 16% of the nodes show higher non-motorized trips. Those nodes show a positive association between poverty, younger population, and non-motorized trips.
- The crime rate is negatively associated with non-motorized trip generation. For the clusters on top right corner, the wedges show a clear positive association with poverty, younger population, and gender-based population. Figure 4e,f show that crime rate is completely inversely related with non-motorized trip generation.

Conclusions

One of the most useful characteristics of SOM is its versatile applicability. Kohonen SOMs are unsupervised learning methods that answer the requirements of treating large numbers of variables, assessing their importance to refine the analysis, and obtaining correlation patterns without any predefined assumption. In summary, this analysis contributes to the general knowledge about non-motorized trip patterns in urban areas and provides new

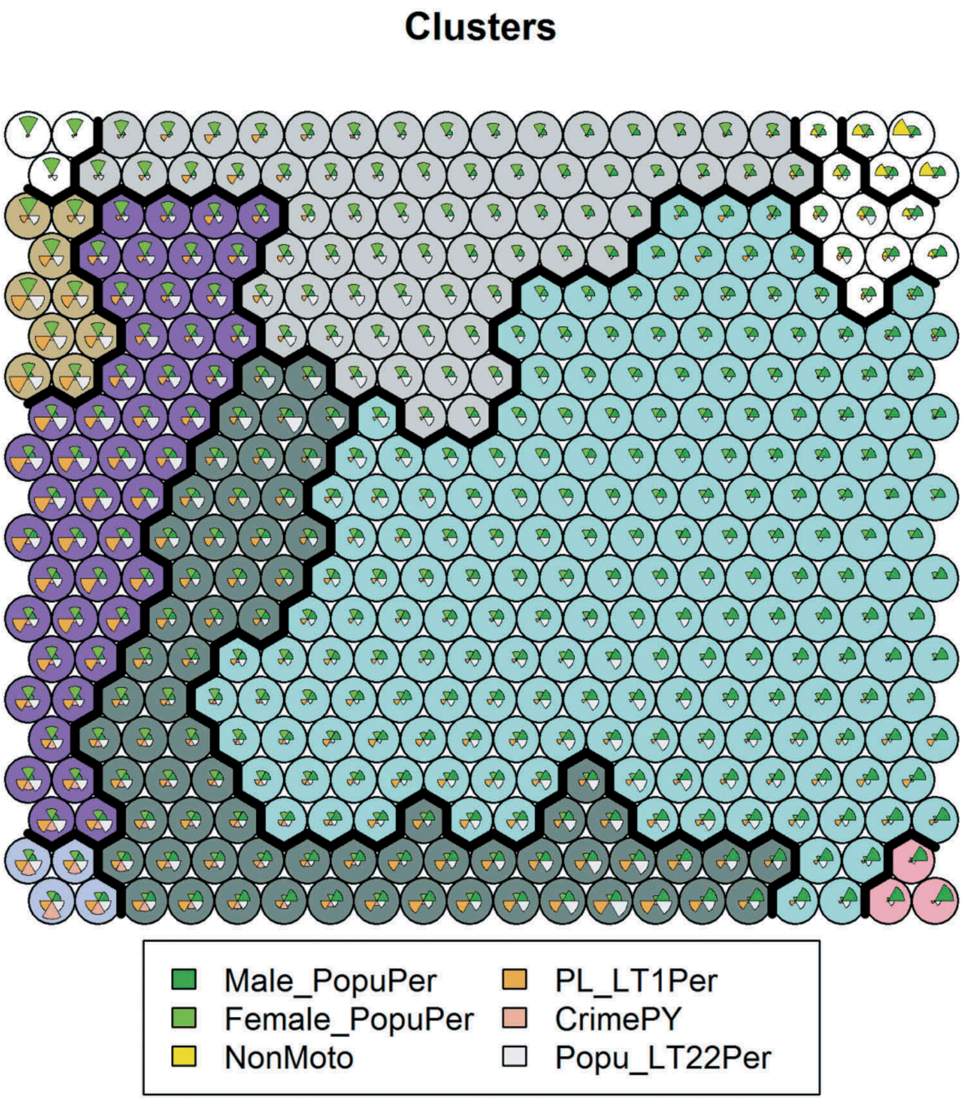


Figure 6. SOM clustering.

insight into the association between these trips with crime, poverty, and other relevant demographic properties.

This study finds some evidence to suggest that there is a negative association between crime and non-motorized commuting trips. Additionally, there is evidence that areas with higher poverty and the younger generation are more like to have higher pedestrian and bicycle trips than other areas. An important caveat about results pertaining to the relationship between crime and non-motorized trips is that only a few output nodes showed an association between the two. Most of the output nodes did not provide much information about the nature of their relationship. One possible reason is that the fused data might require additional factors for a robust association. A planned continuation of this work involves the consideration of additional urban spatial zones with crime and demographic information. Future work also includes examining the current efforts with additional significant variables from other data sources. Moreover, the analysis of smaller spatial units like Census blocks can be performed. Data from Longitudinal Employer-Household Dynamics (LEHD) could be used instead of ACS for the block level analysis. As shown in this study, there is a need to determine factors affecting non-motorized commuting. SOM can be used as an effective tool for investigating non-motorized trips at U.S. census block level (smaller unit than block group).

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