Where are public transit needed – Examining potential demand for public transit for commuting trips

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Where are public transit needed – Examining potential demand for public transit for commuting trips

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Abstract

This study investigates the potential demand for public transit for commuting trips – a rarely explored perspective for the study of public transit systems. Potential demand for public transit refers to the kind of demand that is not explicitly expressed or realized but will be present if condition permits (i.e. when public transit facility is accessible). In this study, potential demand is surrogated by the proportion of people who may potentially use public transit as primary transportation mode, once public the transit facility becomes available and accessible to these people. A Need Index is introduced to measure the relative magnitude of potential demand. Multiple regression is employed to identify predictive variables for the share of public transportation for work trips. Given the predictive variables, two independent methods are developed to examine potential demands across the space. One method is the abovementioned Need Index method and the other is a data mining approach. The Need Index is mathematically modeled which computes a numeric measure for each spatial unit. The second method uses self-organizing maps (SOM) to find clusters in the high-dimensional vector space of the predictive variables. The study then presents a cross-examination analysis between the results from two methods. An empirical study of Atlanta, Georgia is carried out. In the case study, The United States Census Transportation Planning Package 2000 data at the traffic analysis zones (TAZ) level are used. Existing transit network data are prepared and preprocessed in GIS for spatial analysis. The results of both methods are compared and displayed in GIS for visual examination of spatial distribution of the potential demands. A critique on the comparison of advantages and shortcomings between both methods is provided. It shows that the need index is superior due to its simplicity and its higher level of measurement of potential demands.

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1. Introduction

After a long-term decline of public transit ridership since its peak time in the 1940s, the United States has recently witnessed remarkable increase of its public transit usage since the 1970s (Pucher, 2002). According to statistics by the American Public Transportation Association (APTA), unlinked trips by public transportation now have reached its highest level in the past 40 some years. The increase is particularly steady and dramatic in the past decade, with the total unlinked passenger trips jumping from the 7.8 billion in 1995 to 9.6 billion in 2004 (APTA, 2006). This means the average growth rate of public transportation ridership nationwide is over four percent per year since 1995.

As discussed in the literature, the surge of public transportation popularity is attributed to several factors. From a commuter's perspective, the escalated gas prices might be a major incentive to choose or shift to public transit. Meanwhile, economic growth could also contribute because it brings along more job-related trips. From planning and administration perspective, the social, economic, and environmental benefits of public transportation make it an attractive transportation option to advocate for. For instance, facilitating public transportation is considered one of the most effective policy options to moderate traffic congestion problems in many metropolises. More importantly, the concern of environment sustainability has been increasingly emphasized in the study of transportation alternatives. Private car driving becomes more and more costly to not only the individual drivers but also to the society in general. Public transit system is a competitive alternative due to reduced emission as a result of much higher passenger-ride ratio. Prior studies have pointed out that increasing transit use is indeed associated with overall environment sustainability (Sinha, 2003).

In spite of all the incentives to sustain the trend of increasing public transit usage, a fundamental issue is whether public transportation infrastructure is available and accessible to potential riders. Two underlying questions of the issue exist: Where are the potential riders? What is the current coverage of public transportation network? In this paper, potential demand refers to the proportion of people who are likely to use public transit as primary transportation mode, provided that accessible public transit network become available. If a planning authority knows the answers to both questions, it can compare the spatial distribution of potential demand and the coverage of current transit network. The areas which possess great potential demand but are not yet sufficiently covered by current network could be prioritized for the expansion of public transportation network. Although it is relatively easy to answer the question of where existing coverage by examining and analyzing current transportation network in geographic information systems (GIS), the question of potential riders are much more complicated to answer. A measurement of potential demand is important as public transit coverage does not seem to be sufficient in most American cities. Atlanta, the major commercial and transportation hub of the southeast United States, for example, had public transit system coverage in only three counties out of its ten-county metropolitan region by the year of 2000. The insufficient coverage has been a major barrier to many potential riders. Indeed many metropolises are either undergoing or planning extensions of public transit networks. Atlanta has extended its coverage from three counties to seven counties between 2000 and 2005. This study looks closely at the question of where potential riders are and presents an approach to measuring potential demand. An empirical study of Atlanta, Georgia in the United States is carried out to illustrate and verify the approach.

The rest of the article is organized as follows. The next section discusses prior studies of public transit and how this study relates to the prior theoretical framework. Section 3 presents an integrative analysis approach to investigating potential demand for public transit. Section 4 details an empirical study of public transit system in Atlanta using the proposed approach. The article concludes with a summary and critique in Section 5.

2. Demand for public transport

Research on public transport came from a variety of perspectives. According to the pertinence to the focus of this study, four lines of research are briefly discussed here. Firstly, many prior studies concern social, economic, spatial, and environmental factors that affect, or are affected by, public transport (Bento, Cropper, Mobarak, & Vinha, 2005; Brownstone & Small, 2005; Harford, 2006; Kennedy, 2002; Polzin, 1999). For example, Bento et al. (2005) investigated the relationships between public transit ridership and urban spatial structural characteristics including land use, socioeconomic attributes, job-housing balance, population centrality, and more. These studies have typically applied regression analysis, GIS-based models (Azar & Ferreira, 1994), and the multinomial logit modal split model (Ben-Akiva & Leman, 1985). The second thread of research looks at spatial coverage of public transit systems. A critical factor in this type of studies is the cost, such as time or distance, that takes to reach a transit service stop (Murray, 2001, 2005). GIS has been the primary modeling environment for the coverage study focusing on cost (e.g. Wu & Murray, 2005). Another side of the coverage issue is people's accessibility to public transit services. Miller (1999) provides a review of three major theoretical approaches to measuring accessibility. The first focuses on space-time constraints (Hagerstrand, 1975; Kwan, 1998). The second is the attraction-based approach that usually takes the spatial interaction form of measurements. The third is the benefits-driven approach based on the maximization of either the user's or the location's benefit. A noteworthy variation is the measure of geometric accessibility that measures relative nearness of location (Jiang, Claramunt, & Batty, 1999). There are also studies that address the accessibility issue to special groups of people (Blumenberg & Shiki, 2003). The third type of research deals with network analysis and spatial design for specific transit system or a single route. Examples include scheduling optimization and spatial design of a network (Matisziw, Murray, & Kim, 2006; Teodorovic & Lucic, 2005). Last but not least, there is the line of research concerning governments' role in public transport. Examples are studies of policy and planning issues of public transport (de Palma, Lindsey, & Niskanen, 2006; Pucher, 2002) and social equity of public transport service provision (Murray & Davis, 2001).

While this study draws on all of the aforementioned lines of research, it studies public transport from an under-explored perspective – the potential demand for public transit. While accessibility studies shed lights on the spatial distribution of availability and reachability of opportunities, it does not tell us where public transport is needed. In this sense the perspective of potential demands complements the line of research on accessibility. Similarly, the perspective also complements the research on spatial coverage of public transit system as the latter focuses more on the question of "where is covered" than the questions of "where *should* be covered". Furthermore, some earlier studies focus on who have higher need for public transport (Morris, 1981; Starrs & Perrins, 1989) instead of where the higher demands are located.

Few studies are seen that discuss approaches to spatial structural analysis of potential demands for public transit. Murray and Davis (2001) present a method to measure the potential need with a linearly weighted function of characteristic indicators of spatial units at issue. The indicators are pre-defined variables that affect the need for public transit, namely the household income, unemployment rates, and average family size. In order to make meaningful measurement of the potential need, these variables need to be appropriately transformed and standardized. Murray and Davis (2001)'s method transforms each variable into ordinal ranks from the least needy (for public transport) to most needy. The transformation of each variable is performed in light of the histogram of the variable and educated decisions by the researcher. This method is very useful as it produces an index of the need for public transit in a geographic area. However, the method also has a few limitations. First of all, the method involves significant amount of subjective choices to which the resulting indices could be very sensitive. The number of ranks (classes) for each variable is arbitrarily chosen. This number will heavily affect the results of the derived index. Furthermore, the class intervals for the transformation into ranks are subjectively defined and require expert knowledge which may not be available to all users. Secondly, because the resulting index takes the form of ordinal ranks, it only captures the differences between the potential needs at a coarse level (i.e. ordinal level). Thus it cannot tell, for example, the differences among needs in geographical areas with the same rank index. The coarse measurement of index, in combination with subjective choices, limits the interpretation and application of the results. In the following section, the study proposes a method to evaluate the potential need for public transport with numeric measures. Thus the potential need is measured individually without grouping. Because there is no embedded restriction on the precision of the numeric measures, the relative differences among individual indices (thus individual geographic areas) can be easily compared. In addition, this method does not require subjective choices of parameters so that it can be easily applied by all users.

3. Methodology

With this method, measuring the potential demand for public transit involves two steps. The first step is to identify contributing factors related to public transit ridership. Based on information of the contributing factors, the next step aims to examine the magnitude and spatial distribution of the potential demands. Methodologies proposed in this study for the two steps take advantages of the spatial analysis and visualization capability of GIS, the data modeling capability of mathematical and statistical analysis, and machine learning capability of data mining techniques.

Ideally, the potential demand should be measured in spatial units which are homogenous within each spatial unit and heterogeneous between the units in regards to travel choices and factors. For this reason, we need to choose spatial divisions at a fine level of spatial granularity. The finest census unit is census block, while traffic analysis zone (TAZ) is generally comparable to or slightly coarser than the block level. However, the TAZs are partitioned according to variables that are most pertinent to travel choices. Thus in the following discussion, we use data at TAZ level, although the methodology itself is equally applicable to other aggregate levels.

3.1. Identify predictive factors

The first and the most fundamental question is which factors contribute to the share of public transit ridership for commuting trips in a geographic area. Prior studies have primarily suggested land-use characteristics and socioeconomic characteristics of the potential riders (Ortuzar & Willumsen, 2001). Meanwhile some studies also find other contributing variables such as the spacing between stops, centrality, interline transferability (Kuby, Barranda, & Upchurch, 2004) and level of service of the transit system. While these variables present relevance in various case studies, the significance of such relevance varies from case to case. Thus the proposed approach first employs a multiple regression to identify the significant variables and relative contribution of each variable in specific study areas. The result of the regression is presented in a general form as in the following equation

$$R = \sum_{i=1}^{k} \beta_i v_i \tag{1}$$

where R is the proportion of workers taking public transit as the primary mode, v_i's are the identified independent variables, and k is the total number of these variables.

3.2. Measure and visualize potential demand

Based on the identified contributing variables, the study designs a so-called Need Index to measure the relative magnitude of potential demand. For reasons explained in more details in Section 3.3, another independent method is also employed to identify clusters in the high-dimension variable space of the contributing factors. Results from both methods are to be visualized and compared.

To introduce the mathematic formulation of the Need Index, let's first divide the right side of Eq. (1) into two parts, one for the transit system related factors, and the other for the remaining factors. This will take us to the following equation

$$R = \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{m} \alpha_i y_i \tag{2}$$

where y_i's are variables accounting for the transit network structure and level of service of transit systems, and x_i's are the land use and socioeconomic variables or any other contributing variables that are not related to the transit systems. The first part on the right side of Eq. (2) is defined as NI. The last part on the right of Eq. (2) is about the transit network characteristics. Let us use a variable Net to denote it, as shown in the following equations.

$$\mathrm{NI} = \sum_{i=1}^{n} \beta_i x_i \tag{3}$$

$$\mathrm{Net} = \sum_{i=1}^{m} \alpha_i y_i \tag{4}$$

Therefore Eq. (2) becomes

$$\begin{aligned} R &= \mathrm{NI} + \mathrm{Net} \\ &\text{or} \\ \mathrm{NI} &= R - \mathrm{Net} \end{aligned} \tag{5}$$

The composition of the Need Index (NI), as in Eq. (3), tells that it can be used to measure the relative potential demand for public transit in a spatial unit. The NI brings the composite effects of all other contributing variables that are innate to the spatial unit itself but nothing from the transit network. It means that NI will not change with the change of transit network. Provided the same network condition (i.e. Net part is fixed), Eq. (5) suggests that the NI and R (proportion of public transit ridership) will increase or decrease in the same direction. Higher value of NI implies greater potential of public transit ridership for work trips. Given two spatial units of the same NI value while the network accessibility (reflected in the Net part) is different, we will see a higher R for the spatial unit with higher Net. But once equal transit accessibility is made to the other spatial unit, the same public transit share can be expected due to the same potential need. Therefore, from a planner's perspective, the areas of high NI but poor public transit coverage are the target areas for improved service.

The second method uses self-organizing map (SOM), a data mining algorithm, to identify clusters of the spatial units in the high-dimensional variable space. For each zone, we have a vector of the identified contributing variables, denoted as $\langle x_1, x_2, \ldots, x_n \rangle$. The x_i's are the same variables as those in Eq. (3), namely all the other contributing variables except those about the transit systems. Although all these predicting variables are taken as numeric data the scales of data vary greatly among different variables. To avoid dominance of a few variables in the SOM algorithm, we need to standardize all variables. The standardized variables are denoted $Stx_1, Stx_2, \ldots, Stx_n$, respectively. As a result, the variable space to be input to the SOM algorithm is as follows:

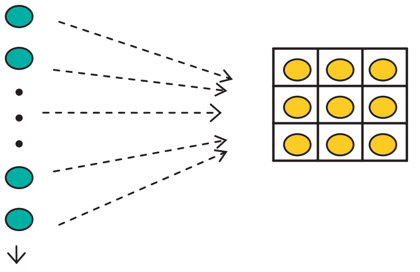
$$\langle Stx_1, Stx_2, \ldots Stx_n \rangle \tag{6}$$

SOM (Kohonon, 1995) is both a dimension–reduction and a clustering machine learning method through unsupervised learning. The SOM algorithm maps high-dimensional data into two-dimensional (2D) space, and at the same time similar data samples are mapped to the same or nearby output nodes (Kohonon, 2000). In the SOM algorithm, inputs are high-dimensional vectors such as that expressed in (6). Each output node is also a vector of the same dimensions as that of the inputs. The output nodes are organized into an m by n 2D output map as illustrated in Fig. 1. The size of the 2D output space (m by n matrix) is user-defined. The vector associated with each output node is called "weight" of that node.

Initially, the weights of the output nodes are randomly generated. The SOM algorithm presents each input vector to search for the closest output node, in which the distance between an input and an output node is defined by

$$d_j = \sqrt{\sum_{j=1}^{N} (x_i(t) - w_{ij}(t))^2} \tag{7}$$

where $x_i(t)$ is the value of ith dimension of the input vector at time t, $w_{ij}(t)$ is the value of the ith dimension of the weight of the output node j at time t.



$<x_1, x_2, \ldots. x_n>$

Fig. 1. The input and output of the SOM algorithm.

Each time an input vector is presented, the closest output (also termed the winning node) and its neighboring nodes will updates their weights (or vectors) so that the weights are even closer to the input vector. Thus this process is named the ‘‘training’’ process. Let’s denote the winning node j^*. The weight to nodes j^* and the weights to the neighboring nodes are updated using

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)(x_i(t+1) - w_{ij}(t)) \tag{8}$$

where $\eta(t)$ is an error-adjusting coefficient ($0 < \eta(t) < 1$) that decreases over time. In both of Eqs. (7) and (8), time (t) refers to the count of iterations. An iteration is completed when all input vectors have been presented once and only once to train the output nodes. Usually multiple iterations are necessary until certain matching criteria are met (for example, no significant update can be made to the output nodes).

Once the training process is completed, a SOM model is represented by the output map. The $m \times n$ nodes in the output map form clusters because the nearby nodes are more likely similar in the high-dimensional attribute space than the distant ones. A classification method can be applied to finally identify the clusters. Fig. 3b shows such as output map and clusters of output nodes for the case study of Atlanta. Because each input case has a corresponding winning node in the output map, it can be then assigned to the cluster which the winning node belongs to. All input cases (spatial units) are assigned to respective clusters using the established SOM model.

3.3. Compare the two methods

The study cross-examines the results from the two stand-alone methods, Need Index and SOM respectively, for two purposes. First, through a qualitative comparison between the two methods, I argue that Need Index is superior to SOM in regards to usefulness of the results. Here SOM is used as an example of many other data mining techniques for multi-dimensional scaling and clustering. The advantages and shortcomings of the SOM method are just the opposite of that of the Need Index method. The SOM method does not apply any assumption on the form of the relationship between the factors and the final output (i.e. categories). However, the shortcoming of SOM method lies in that it only generates and visualizes clusters of the potential demands. Thus it is not possible to have a quantitative measure of the potential demand in a spatial unit, neither is it possible to quantify the differences between the demands in different spatial units. On the other hand, the need index (NI) method calculates a simple numeric index for each spatial unit as a relative indication of its potential demand. It is easy to calculate and interpret the measures, and it is also possible to rank them or to quantify the differences among them. Therefore, in this regard, the Need Index approach is superior to the data mining approach as the result contains higher level of information.

The second purpose of comparing the two methods is to cross-examine the agreement or disagreement between the results of the two methods. Although the Need Index can provide higher level of information, its validity is based on the linear relationship assumption. As the spatial data mining method is free of assumptions, the spatial distribution yielded from this method is generally reliable. The comparison can therefore shed lights on the validity of the Need Index method. This study is about "potential demand" – something of which the validity is hard to be tested. For the lack of optimal testing approach due to the nature of the topic in study, a couple of practical alternatives are discussed here. One alternative is to compare the NI potential demand predictions with empirical aftertime transit expansion. This is done in the case study in the following section. The Need Index is calculated based on year 2000 data. The distribution of the Need Index is then compared with the transit expansion between year 2000 and 2005. Despite of the usefulness of this comparison, it is acknowledged that transit expansion could result from combinations of a variety of reasons including potential demand. Many reasons other than the demand itself may influence the decision of transit expansion. Another alternative is to compare the Need Index method with another independent method. I chose an inductive machine learning algorithm, SOM, as the other independent method to be compared with, because the unproven assumption of linear relationship is not necessary in the machine learning method. SOM is such a good independent data mining method for this purpose. The following case study uses both practical alternatives to test the validity of the NI method.

4. Case study

The case study area is the metropolitan Atlanta in Georgia, a major employment center in southeast United States. This study concerns the ten-county urban area in which regional planning and intergovernmental coordination are managed by the Atlanta Regional Commission (ARC). In the past decades, Atlanta has experienced rapid population growth and the associated problem of traffic congestion. According to the Urban Mobility Report (Schrank & Lomax, 2005), Atlanta ranked the 4th most congested urban areas in the US in terms of annual traffic delay per traveler in 2003. In response to this problem, the ARC has released the new long-range regional transportation plan, named "Mobility 2030", in which the regional transit aims to play a major role in alleviating congestion and improving air quality.

The ten counties and the public transit systems in the year of 2000 and 2005 are displayed in Fig. 2. The transit lines in orange in Fig. 2b are new expansions. It is clear that the expansion of the transit system is quite noticeable over the past five years. This study will examine the relationship of public transit ridership for commuting trips, and aim to predict potential demand for public transit. Employing the proposed methods, I will predict potential demands on public transit based on the 2000 data in the case study area. The prediction will be compared with the expansions between 2000 and 2005. The hope is that the measures and the visualization of them could provide useful information for planning future transit system expansions.

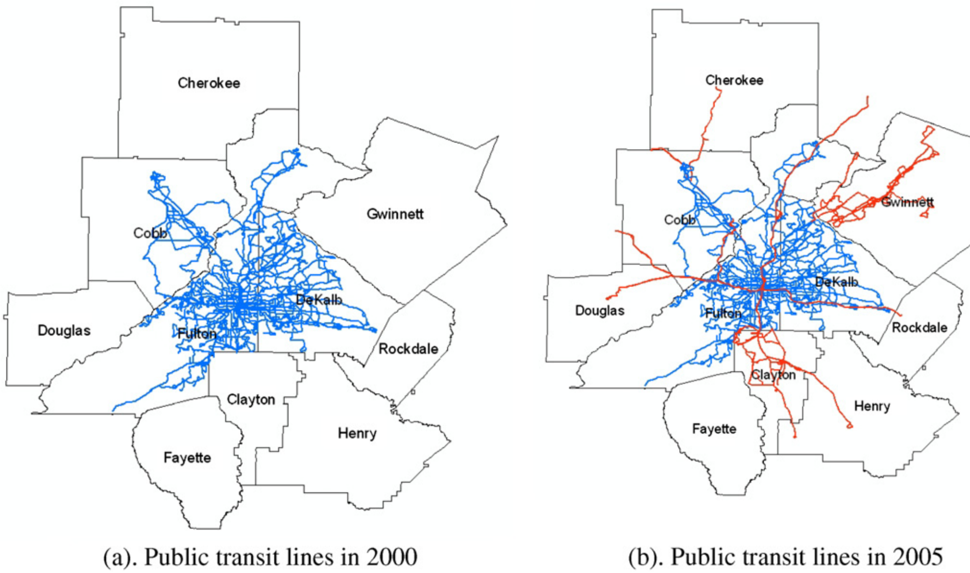


Fig. 2. The ten-county ARC region and the public transit lines.

4.1. Data and preliminary data processing

The following two types of data sources are used for the empirical study. Both datasets are examined and pre-processed in ArcGIS.

1. The United States Census for Transportation Planning Package (CTPP) 2000 data.
2. The GIS datasets of transit lines and transit stops provided by the Atlanta Regional Commission.

The CTPP 2000 census data provides population, socioeconomic, and transportation related attribute data aggregated at county, block group, traffic analysis zone (TAZ) and some other spatial aggregate levels. *I* use the data at TAZ level because this level has fine granularity. More importantly, the spatial partition of TAZs is based on criteria related to travel behavior and choices. There are totally 1593 TAZs in the 10-county study area. About 180 of them are excluded during data pre-processing due to empty data or inconsistent data in those TAZs. As a result, 1417 TAZs are included for the study. For each TAZ, *I* extracted variables from CTPP 2000 to be used in the following spatial analysis and modeling processes.

4.2. Statistical analysis

A multiple regression is conducted to identify the predictive factors for public transit ridership for commuting trips in Atlanta. The dependent variable is the percentage of workers using public transit as their primary transportation mode for work trips. Listed below are three groups of independent variables which are entered in the regression analysis.

1. Land-use characteristics:
   - Population density.
   - Employment rate (percentage of people who have jobs).
   - Job density (total jobs in the TAZ divided by the area of the TAZ).
   - Average number of jobholders per household.
   - Percentage of home workers.

2. Socioeconomic characteristics:
   - Income: Percentages of jobholders in each of the three income status (below poverty line, between 100–150% of the poverty line income, above 150% of the poverty line income).
   - Car ownership: Percentages of jobholders whose households have 0, 1, or 2+ vehicles, respectively.

3. Network structure:
   - Density of public transit stops in the TAZ.

To adjust for the size variation of the TAZs, all variables are converted into rate, percentages, and density. Particularly, the stop-density is proposed to describe the characteristics for network structure as relevant to the ridership of public transit. In ArcGIS, the number of transit stops/stations within each TAZ is calculated. This measure is further divided by the area of the TAZ, which converts the measure into stop-density.

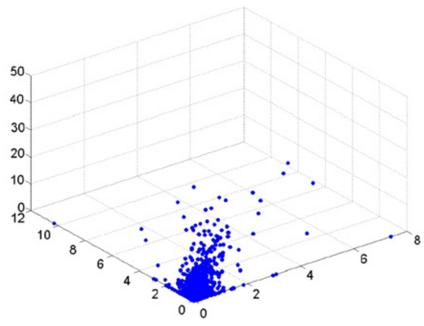
Table 1
Regression Results for the prediction of share of public transit for work trips

Predictive variables	(Unstandardized) Coefficients		Significant	Collinearity statistics	
	B	Standard error		Tolerance	VIF
(Constant)	2.113	0.862	0.014		
Percentage of home workers	0.023	0.036	0.532	0.869	1.151
Percentage of workers below poverty line (x_1)	0.085	0.020	0.000	0.634	1.578
Percentage of workers with income from 100% to 150% of poverty line (x_2)	0.087	0.027	0.001	0.683	1.464
Percentage of worker with 0 vehicle in the household (x_3)	0.465	0.018	0.000	0.536	1.865
Percentage of worker with 1 vehicle in the household (x_4)	0.038	0.010	0.000	0.557	1.797
Employment rate (x_5)	−0.066	0.015	0.000	0.553	1.809
Average # of workers per household	0.027	0.537	0.960	0.551	1.814
Population density (x_6)	0.046	0.007	0.000	0.642	1.558
Public transit stop-density	0.024	0.004	0.000	0.728	1.374

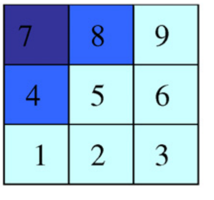
A correlation analysis among these independent variables is performed to diagnose potential collinearity problem. Two variables (the 150% income category and the 2+ vehicles in a household) are excluded in the regression due to identified significant correlation between each of the two variables and other dependent variables. In addition, it is also found that the job density has high correlation (correlation coefficient 0.731) with transit stop-density. Thus the variable of job density is also excluded from the final regression. During the regression analysis, the collinearity testing is also performed and the statistics are shown in Table 1. No collinearity is found with any of the entered variables in the regression.

Table 1 shows that all variables except the two that are grayed-out in the table turn out to be predictive variables at the significance level of 99%. The R square of the regression model is 0.668, which tells us that about 70% of the variation in public transit shares for work trips can be explained by the model.

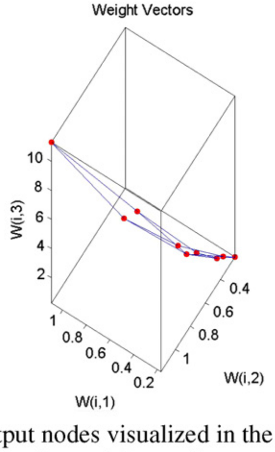
A close look at the two grayed-out (insignificant) predictors offers a few observations. Despite of the increase of telecommuting jobs, the share of home workforce in Atlanta was not significant enough to impact the public transit ridership for commuting trips,



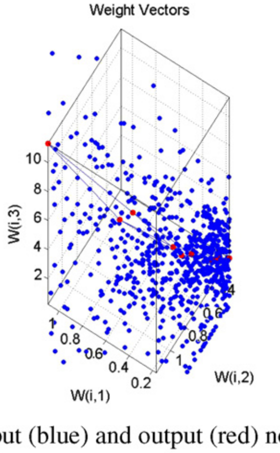
(a) The input cases visualized in the first three dimensions of the attribute space



(b) spatial configuration of the nine output nodes



(c) The output nodes visualized in the first three dimensions of the attribute space



(d) input (blue) and output (red) nodes

Fig. 3. Input and Output nodes with the SOM method.

according to the census 2000 data. Another observation is that the number of jobholders in a household does not influence the jobholders' choice of public transit in Atlanta.

4.3. Potential demand analysis and visualization

Two types of demand analysis are carried out and compared in this case study. The first is the Need Index method. The index measure for each TAZ in Atlanta is calculated following Eq. (3) using coefficients from Table 1.

$$NI(i) = 0.085x_1 + 0.087x_2 + 0.465x_3 + 0.038x_4 - 0.066x_5 + 0.046x_6$$

where x_1 through x_6 are the variables as defined in Table 1, the $NI(i)$ is the Need Index measure for the ith TAZ in Atlanta. It is noted that the last independent variable in Table 1, the public transit stop-density, is not included in the equation. It is because the Need Index is by definition a measure of the potential, but not the actual demand that is heavily influenced by the actual transit system itself.

The SOM method in this study aims to put each TAZ, represented as an instance in the high-dimensional attribute space, into different categories. Because the machine learning method does not subscribe to any assumption on the form of the relationship, the coefficients associated with the variables obtained in the regression analysis are therefore not used. As reasoned in the methodology section, the variables are standardized when they are used in SOM. Fig. 3a displays the distribution of input cases in the first three-dimensions of the 6D attribute vector space, constrained by the number of dimensions that can be visually depicted directly. The size of the output map is arbitrarily defined as 3 by 3.

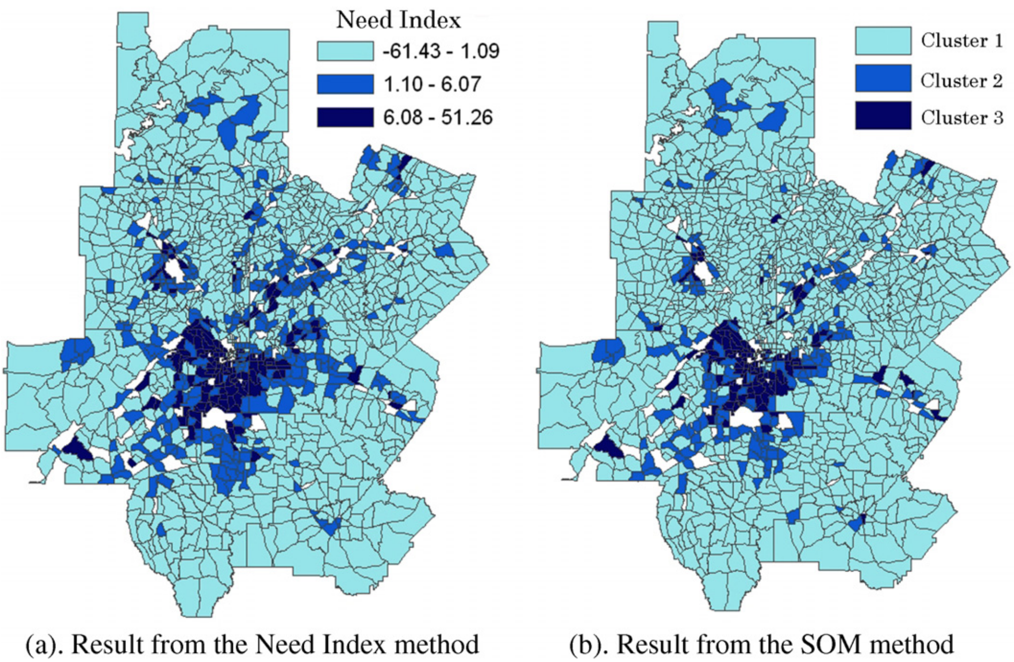
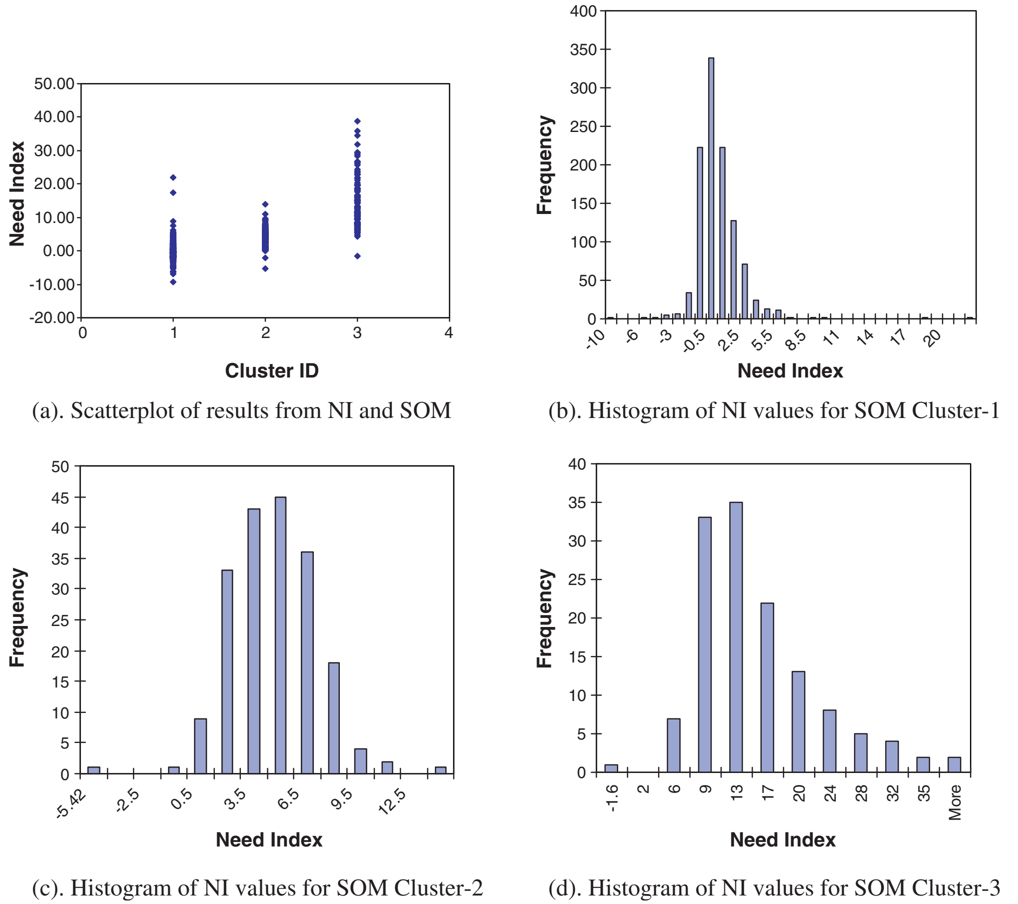


Fig. 4. Spatial Distribution of potential demand for public transit for commuting trips.

Fig. 3b is the spatial configuration of the output map. During the training period with the 1417 input vectors, the output nodes are updated according to Eqs. (7) and (8). At the end of the training, the attribute vector of the nine output nodes are visualized as red dots in Fig. 3c. These nine nodes are put into three clusters using *K*-mean clustering method. The respective nodes in each cluster are displayed using the same shade in Fig. 2b. For comparative examination, Fig. 3d plots both output nodes (red) and the input nodes (blue) in the same space.

The results from both methods are transformed into a visual form in Fig. 4 for comparison. In Fig. 4a, the Need Index values are classified into three categories using Jenk's Natural Break classification method. This classification is only necessary for visualization and comparison purpose. Fig. 4b displays the results of the data mining approach, the three clusters. In both of Fig. 4a and Fig. 4b, the white TAZs are those excluded in the analysis due to lack of data. Although both figures are choropleth maps using the color value as the visual variable, the data in Fig. 4a tell quantitative differences among TAZs while that in Fig. 4b can only tell qualitative differences.



(a). Scatterplot of results from NI and SOM

(b). Histogram of NI values for SOM Cluster-1

(c). Histogram of NI values for SOM Cluster-2

(d). Histogram of NI values for SOM Cluster-3

Fig. 5. Scatterplot of the Need Index and the SOM method results.

A scatterplot of the two sets of results is provided in Fig. 5. Fig. 5a shows each of the three clusters (horizontal axis) corresponding to a range of Need Index values (vertical axis) – a necessary condition for the agreement between the two sets of results. The three ranges of NI values do overlap. However, according to Fig. 5b–d, the histograms of the three ranges of NI values, the overlapping areas are marginal with low frequencies. Furthermore, the modes of the three ranges are very distinctive from each other. In summary, the scatterplot and histograms in Fig. 5 speak highly for the consistency between the results of the two methods. As discussed in Section 3.3, the consistency is a practical alternative to prove the validity of the Need Index method.

To further test the validity of the Need Index method, we can compare the NI results with the real transit expansions. To do that, we can examine the spatial pattern of potential demand revealed in Fig. 4a against the transit expansion as displayed in Fig. 2b. To make the examination easier, Fig. 6 visualizes all the necessary information in a layered 3D perspective view. The figure displays the potential demand distribution in 2000 (bottom layer), the 2000 transit system (middle layer), and the transit expansion between 2000 and 2005 (top layer). It is obvious that the expansion of transit systems in Atlanta from 2000 to 2005 have addressed the issue of under-served high potential demand in many areas. However, there are still patches that have high potential demand are identified as still not being served in current system. For examples, such patches are seen in the northern most TAZs and some in the south and southwest regions. These areas could be the priority zones for future transit expansion in the ARC region.

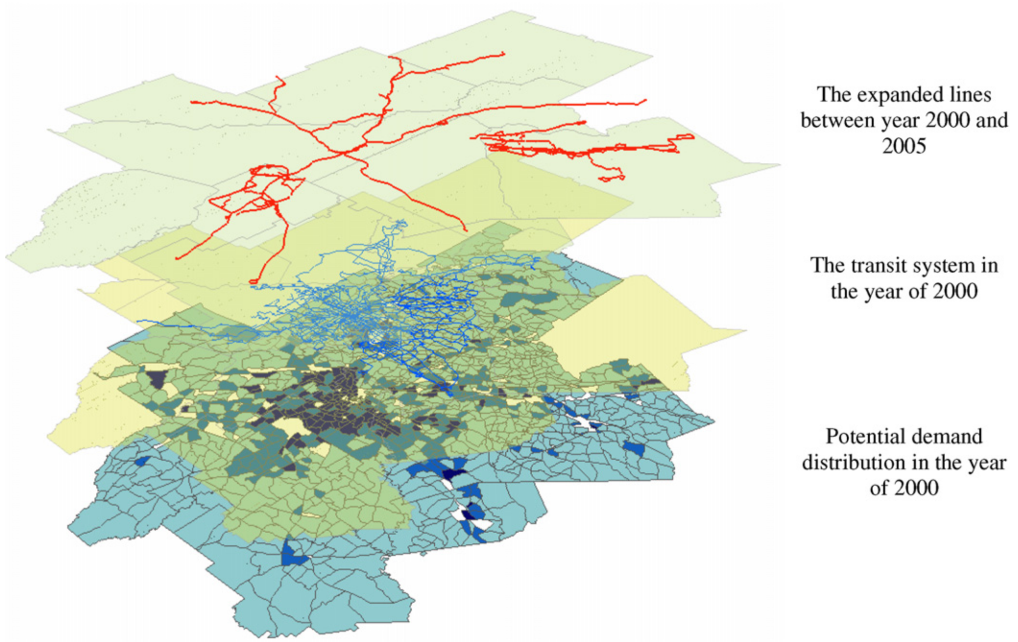


Fig. 6. A layered 3D perspective view for the potential demands, coverage, and expansion of public transit system in Atlanta.

5. Conclusions

Public transit ridership in the United States has been experiencing remarkable increase for decades. Today, many social, economic, and environmental benefits of public transportation support that it is an excellent transportation option for the society. It is found the public transit coverage is insufficient in many American cities. To explore the spatial distribution of the insufficient coverage, this study investigates the potential demand for public transit. If public transit facility is available in an area of high potential demand and low existing transit coverage, it is an important signal for transit expansion. In this study, potential demand is represented by the proportion of people who may potentially use public transit as primary transportation mode. A Need Index method is proposed to measure the relative magnitude of potential demands of public transit service. The study also uses a data mining approach to be compared with the performance of the Need Index in a case study.

Two steps are involved in examining the potential demand. The first step is to identify the contributing variables using multiple regression. The second step models potential demand based on the contributing variables. The Need Index is mathematically modeled using findings from the multiple regression. It is an adaptive construct that is subject to data analysis findings specific to the study area. The advantage of need index relates to its numeric measure for each spatial unit and thus comparison and quantification are possible. However, the possible criticism lies in its assumption of the linear relationships. Therefore, I use two types of practices to indirectly confirm the validity of the Need Index method. The first is to compare the NI findings with real transit expansion pattern. The second is to compare the NI result with the result from the self-organizing maps approach as the latter is free of any prior assumption on the form of the relationship among the variables. In the case study, the results of both methods agree to each other to a great extend. Both types of practices confirm the validity of Need Index method in the case study. A critique on the advantages and shortcomings between both methods is provided. Particularly, because the data mining approach only tells qualitative differences among spatial units, it is not able to give an overall ranking of the spatial units in terms of potential demand. The study shows that the Need Index method is superior due to its simplicity and its higher level of measurement of potential demands. It is concluded that Need Index is a simple yet more powerful method to model the potential demand for public transit.

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