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DYNAMIC OPPORTUNITY-BASED MULTIPURPOSE ACCESSIBILITY INDICATORS IN CALIFORNIA

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Abstract

Accessibility, defined as the ease (or difficulty) with which activity opportunities can be reached from a given location, can be measured using the cumulative amount of opportunities from an origin within a given amount of travel time. These indicators can be used in regional planning and modeling efforts that aim to integrate land use with travel demand and an attempt should be made to compute at the smallest geographical area. The primary objective of this paper is to illustrate the creation of realistic space-sensitive and time-sensitive fine spatial level accessibility indicators that attempt to track availability of opportunities. These indicators support the development of the Southern California Association of Governments activity-based travel demand forecasting model that aims at a second-by-second and parcel-by-parcel modeling and simulation. They also provide the base information for mapping opportunities of access to fifteen different types of industries at different periods during a day. The indicators and their maps are defined for the entire region using largely available data to show the polycentric structure of the region and to illustrate the method as a generator of choice sets in discrete choice models.

Keywords: hierarchical spatial choice, spatial cluster analysis, multi-scale representation

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1. INTRODUCTION

Recent legislation in California aiming at stricter mobile source emissions control and planning for dramatic decreases in Greenhouse gas emissions emphasizes the need for integrated land use policies with transportation policies (see http://www.ca-ilg.org/SB375Basics). This is expected to happen with planning tools such as a Sustainable Communities Strategy (SCS), which among its many objectives also needs to understand residential location and relocation decisions and explain possible futures under different scenarios of policy to a variety of audiences including decision makers and professional planners and engineers. Similar to many European jurisdictions land use planning is in the local (e.g., the City) domain and transportation planning is at many higher levels. In the US transportation planning is a foundational activity of Metropolitan Planning Organizations (MPO) that were created in the 1960s to ensure coordinated planning among local jurisdictions. Two of the most important elements of this planning activity are the Long Range Regional Transportation Plan (LRTP), which every 4-5 years creates a vision and a path to reach goals that protect the environment, foster economic growth, and ensure equity and the second is the development of the regional Transportation Improvement Program, which is an multi-billion USD investment plan to satisfy LRTP goals. The recent legislation adds the land use and transportation goal with a SCS to the MPOs. In California the four largest MPOs (their region surrounds Los Angeles, Sacramento, San Diego, and San Francisco) are also required to build simulation models to assess scenarios for meeting specific targets of Greenhouse gas emissions by 2020 and 2035. At the heart of these urban simulation models are behavioral equations of residence, workplace, and school location choices by households and their members together with activity and travel behavior equations to represent the daily activities and movements of people in the region. All these models and simulation tools are currently developed and often face two major stumbling blocks: a) lack of understanding of the behavioral processes we try to change with the new policies; b) lack of suitable tools to explain spatio-temporal phenomena that emerge from complex interactions among people. The short statement below is indicative of the relationships we should disentangle, understand, and recreate in predictive urban simulation models.

"A household's decisions of residential location, workplace, activities and travel pattern are an inextricably entangled weave of mutual interdependencies and constraints. Each of these choices is connected to all the others,…" Page 138, Eliasson, 2010.

At the core of this we find spatial structure analysis and particularly the spatial structure analysis of urban environments, which is a key informant about location choices of people. This is becoming extremely important in assessing policy actions that change land use to influence travel behavior and attempts to steer it away from using automobiles. The assessment of these policies, in large metropolitan organizations, is done with urban simulation software that employs discrete choice models (see the review by Waddell, 2002). These models predict location choices (e.g., residence, workplace, school, or possibly other major pegs at which activities take place) using as explanatory variables a variety of location attributes in more or less complex forms of accessibility indicators. In this area we see an increasing sophistication of techniques such as multi-scale approaches that account for spatial and behavioral heterogeneity while attempting to solve some problems with spatially correlated explanatory variables and counteract potential fallacies. A sample of recent advances are papers by Bhat and Guo, 2004, Guo and Bhat, 2004 and 2007, Mohammadian et al., 2005, Sivakumar and Bhat, 2007, Sener, Bhat, and Pendyala, 2011. In parallel, in policy oriented circles and among advocates of specific land use actions to change travel demand, we also see growing literature offering an emerging typology of spatial structure indicators (e.g., land use density, diversity of land uses, characteristics of the highway infrastructure, proximity to public transportation). The review and meta-analysis of Ewing and Cervero (2010) provide a comprehensive report of the use of these indicators provides a link between the policy literature and provides an estimate of the impact of these indicators on a limited set of travel indicators. As one would expect spatial structure is very important in studies about the historical evolution of settlements (typical example is the urban growth application of Stanilov and Batty, 2010).

In all these studies we find accessibility to opportunities for employment and/or activity participation explaining the location choices of households. Accessibility indicators can take a variety of forms but they almost always include some measure of location attractiveness (e.g., amount of activity, number of stores, variety) weighted or buffered by measures of impedance (e.g., travel time to reach activities). Location choice is also a function of a variety of other factors including cost (e.g., price of homes), spatial ethnic segregation (e.g., immigrant ethnic enclaves or other social processes that motivate people of similar cultural traits to co-locate), social exclusion (e.g., specific groups may be excluded from different areas of an urban environment by policy or tradition), or temporary co-location for education or other reasons (e.g., attending a specific college, serving in the military).

Underlying all this, a hierarchy exists in the spatial organization of opportunities that characterizes each living environment. In fact, large urban environments are no longer monocentric but show clear emergence of polycentrism (Giuliano and Small, 1991, and the review by Anas et al., 1998). It is important then to identify and describe underlying spatial structures (Hughes, 1993) but this is not a trivial task and should account for transportation infrastructure. Hierarchies are based on geographic space (e.g., region, city, neighborhood, city-block, land parcel), time (e.g., historical time, day of the week, time of day), in-situ social networks (e.g., ethnicity, religious meeting places), and type of activity opportunities (e.g., retail, arts and entertainment, leisure). To the best of our knowledge a method that recognizes this hierarchy explicitly and provides classification of locations using accessibility and segregation, as well as, employs informative opportunity indicators does not exist or it is done in a somewhat ad-hoc opportunistic way. A more systematic approach is useful in developing choice sets, creating new type of explanatory variables for discrete choice models, estimating models tailored to localities of special character, and helps us characterize spatial structure and its evolution for urban simulation models. It may also help us understand, explain, and support the input to and output from urban simulation models.

To partially fill this gap we report in this paper findings from a pilot research project with focus on the Southern California five county region (which is also the largest MPO in California) that takes advantage of accessibility indicators computed at a fine level of spatial resolution (the US Census block), for fifteen types of employment, and different times during a day (accounting for opening and closing of businesses and the presence of congestion in different parts of the region at different times of a day). We use these indicators to develop spatial clusters that are able to classify each block based on its own intensity of activity availability and the opportunities available at its adjacent (contiguous) blocks. In this way we derive spatial clusters for a selection of activity opportunities for each block by first computing this value from each land parcel within the block. These spatial clustering indicators are then used in another clustering process, using Latent Class Cluster Analysis, to classify different parts of Southern California into five categories that range from high accessibility, to medium accessibility, and finally to very low accessibility. We repeat this using the same method for four time periods of a day to describe the evolution of the region during a day and how different localities change in their ability to provide services to their residents. We also study these different groups of blocks in terms of their resident characteristics.

In the next section we describe the accessibility indicators used here followed by a section on the spatial cluster analysis and the Latent Class Cluster Analysis together with a description of the time-of-day dynamics. Then we review the findings in the correlation between spatial structure and resident characteristics. The paper concludes with a summary of findings and next steps.

2. ACCESSIBILITY INDICATORS AND THE REGION

The block-level accessibility measures described in Chen et al., 2011 are the main source of information to describe the spatial structure of Southern California. These measures are computed at a fine level of spatial disaggregation, which is the US Census block. As described in Chen et al., 2011, we used multiple databases to describe the opportunities available at different levels of spatial aggregation and converted all data into information for each block while rectifying any missing or miscoded information through comparisons of different sources of data. The end result is an account of the number of persons at each block working in any of fifteen different and mutually exclusive industry types that are: a) Agriculture, forestry, fishing and hunting and mining; b) Construction; c) Manufacturing; d) Wholesale trade; e) Retail trade; f) Transportation and warehousing and utilities; g) Information; h) Finance, insurance, real estate and rental and leasing; i) Professional, scientific, management, administrative, and waste management services; j) Educational; k) Health; l) Arts, entertainment, recreation, accommodation and food services; m) Other services (except public administration); o) Public administration; p) Armed forces. All blocks are connected to a roadway network that includes for each of its links estimated speed for different periods of a day. This network is used to compute shortest paths among all the blocks. There are approximately 203,000 blocks that cover the entire (mega)region surrounding Los Angeles (called the Southern California Association of Governments region). Using these shortest paths we identify for each block all the other blocks that are within 10, 20, and 50 minutes to create travel time buffers. Then, for each period in a day and for each of the fifteen industries we count the number of persons employed by each industry type within each buffer. To account for the different opening and closing times of activity opportunities the number of employees that are reachable in the accessibility indicators changes for each hour in a day. To derive this time of day profile we use information of arrivals and departures from work sites available in a travel survey. In this way the resulting accessibility indicators change with space and time to reflect the rhythms of activity in the region for which they are defined. More details about the method are reported in Chen et al., 2011 and an application to neighborhood analysis in Dalal and Goulias, 2011.

Due to the region's size and vastly varied land use, population for any given block can range from zero to over 7,000 residents. However, the attributes of the built environment described are not equally distributed over the county. For example, the density of transportation infrastructure increases with population density. This creates different levels of network connectivity and accessibility between urban and rural neighborhoods (Chen, et al, 2011). Other attributes include the distribution of opportunities, which are often more dense in more urban areas of Southern California (Dalal and Goulias, 2011). In this analysis we use accessibility indicators as the core material in developing groups of similar spatial structure. We selected to work with four periods in a day that follow the current SCAG four-step model that provides travel speed and time for each roadway segment for four time periods, AM peak (6 AM to 9 AM), PM peak (3 PM to 7 PM), Midday off-peak hours (9 AM to 3 PM), and Nighttime off-peak hours (7 PM to 6 AM). This allows the calculation of shortest path travel time between blocks for each of these four different periods in a day and analyze blocks in terms of the 10 minute accessibility indicators of all fifteen types of industries. In this way we have fifteen continuous variables for each of the 203,000 blocks covering the entire Southern California.

Similarly, the population of Southern California is as varied as the landscape. Within the study region, there exists a certain amount of social and demographic stratification. The average density, age, household income, and household size differ between sub-regions and between neighborhoods as shown in Table 1. One example is in race/ethnicity, which can be very diverse, as in Pasadena, or very homogenous, as in Boyle Heights. Thus, while the built environment varies over space, persons with different socio-demographics populate different spaces. In our study, we consider the anisotropic spread of environmental attributes and population characteristics as an underlying preference for choice for residences, workplaces, and other activity destinations. This is accomplished by first accounting for the variation in opportunities and persons over space through spatial clustering methods. Second, the clusters of opportunities are associated with persons to describe a probable set of choices based on household survey data.

Table 1 Socio-demographics of selected neighborhoods in Southern California

Region	**South Bay**		**San Gabriel Valley**		**Westside**	**Southeast**	**Eastside**
Neighborhood	Rancho Palos Verdes	Inglewood	Pasadena	Glendale	Santa Monica	Compton	Boyle Heights
Persons/mi	3,084	12,330	5,366	6,368	9,817	9,199	14,229
Median hh size	2.7	3	2.5	2.7	2	3.9	3.8
Median hh income	128,321	46,574	62,825	57,112	69,013	43,157	32,253
Rented housing	18.1	63.6	54	61.6	70.2	43	75.9
Single parent hh	4.8	26.5	13.4	9.4	12.8	22	21.2
Median age	44	29	34	37	38	24	25
% White	62.8	4	39.1	54.1	71.3	1	2
% Latino	5.6	46	33.3	19.6	13.5	57	94
% Black	2.1	46.4	13.9	1	3.5	40	0.9
% Asian	25.2	1.1	10	16.3	7.1	1	2.4

Source: US Census, 2000

3. G* ANALYSIS

This study examines spatial clusters of opportunity access aiming at representing subregions within Southern California that display spatial homogeneity, such as a neighborhood of blocks with high accessibility to arts opportunities. We account for spatial heterogeneity from large-scale regional effects by using a local indicator of clustering. In addition, we consider spatial dependency in our data. For any spatial outcome, such as land prices, the values in one location are more influenced by the values of nearby locations than values of far locations. However, it is unlikely that any urban phenomenon is spatially independent, so our approach is to describe spatial dependency through spatial clusters.

Spatial clusters are built on the concept of spatial dependence, in which things closer to each other are more related than things farther apart (Tobler, 1970). A cluster measures the concentration (or dispersion) of values over space, a simple measure of positive spatial dependence or autocorrelation. In our analysis, a positive cluster specifies when a block which is surrounded by more similar blocks than expected at random. Conversely, a negative cluster specifies when a block is surrounded by dissimilar blocks, more than expected at random, indicating negative spatial autocorrelation. Thus, our first step is to measure the concentration or dispersion of urban attributes by locating and defining the spatial extent of spatial clusters (Jacquez, 2008).

However, it is important to note that urban processes, including the distribution of activities, are widely considered to be spatially heterogeneous, in that the outcomes of the processes vary over space (Anselin, 1995; Paez and Scott, 2004; Jacquez, 2008). Spatial heterogeneity is especially true for extensive study areas where large-scale regional effects can influence the mean and variance of spatial processes, thereby biasing spatial clustering analysis of values (Miller, 1999; Buliung and Kanaroglou, 2007). In our study of Southern California, large variation can be found in the number and density of opportunities available to blocks throughout the day (Figure 1 shows box-plots of the sum of all fifteen accessibility indicators). High-density areas such as downtown Los Angeles would affect estimation in a global cluster analysis, such as Moran's I, thus the use of a local indicator of clustering is highly relevant in a large study area like Southern California. By using a local measure of spatial association, we are able to estimate clusters without large-scale regional bias, and show significant local clusters in rural or outskirt areas (Anselin, 1995).

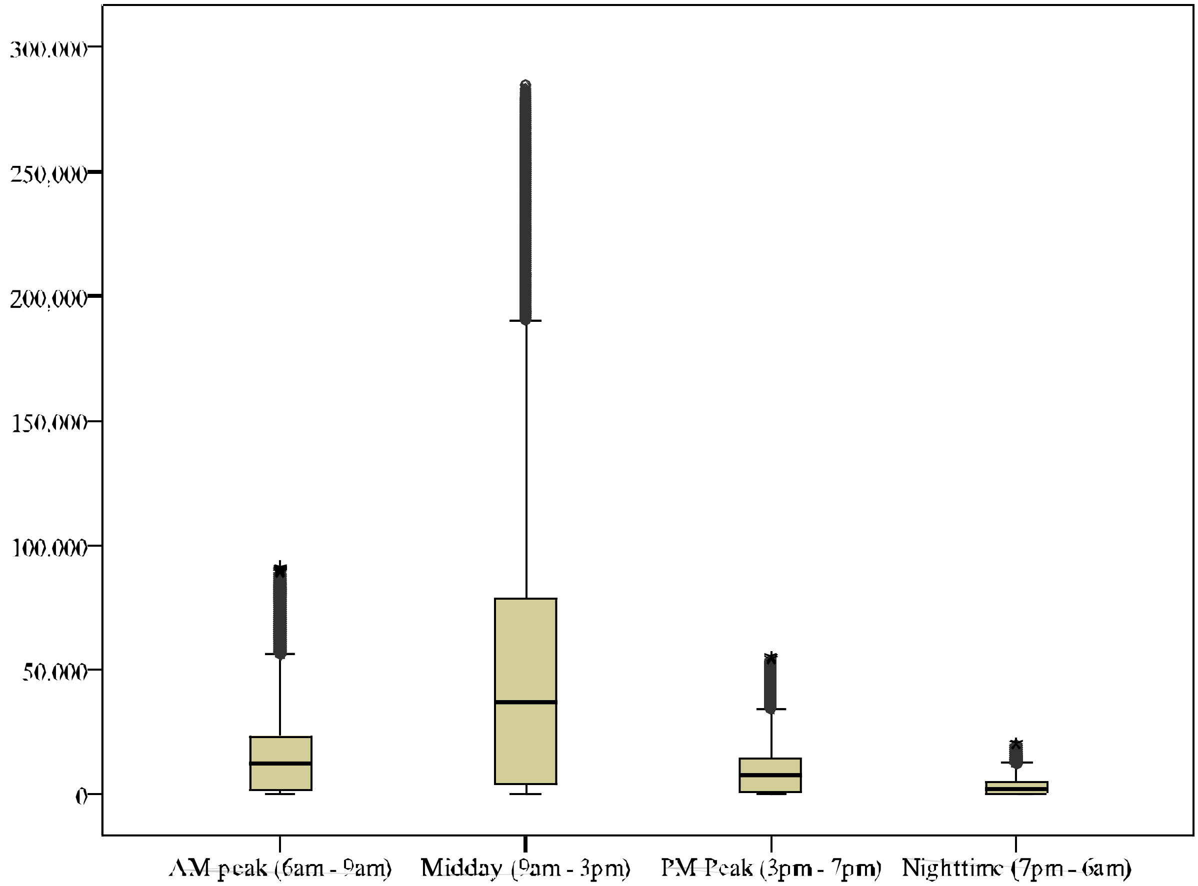


Figure 1 Total opportunities during different time periods for Southern California study regions

In our spatial cluster analysis, we use the *G* statistic, developed by Getis and Ord, to quantify local spatial autocorrelation and dependency and reveal block-level clusters (Getis & Ord, 1992). This measure was selected for its attractive properties and based on a preliminary pilot study using Los Angeles county data alone. The output of the repeated application of G* to each of the fifteen accessibility indicators are fifteen continuous variables of z-scored spatial cluster accessibility indicators. These are in turn used as criteria variables to identify latent classes (*LC*) using Latent GOLD® 4.5 software (Vermunt and Magdison, 2005), which is a model-based latent class cluster model building system. The analysis starts with a 1-dimensional LC baseline model (one cluster), followed by fitting successively LC models with adding one dimension (additional cluster) each time. The goodness of model fit is assessed using the Bayesian Information Criterion (BIC) value which is a penalizing statistic for excessive estimated parameters and it is a function of the log-likelihood statistic (LL). The final cluster spatial structure is defined as the model with a low BIC value and less parameters. Taking into account parsimony and model fit statistics a 5-class latent cluster model is estimated with the accessibility indicators for each time of day.

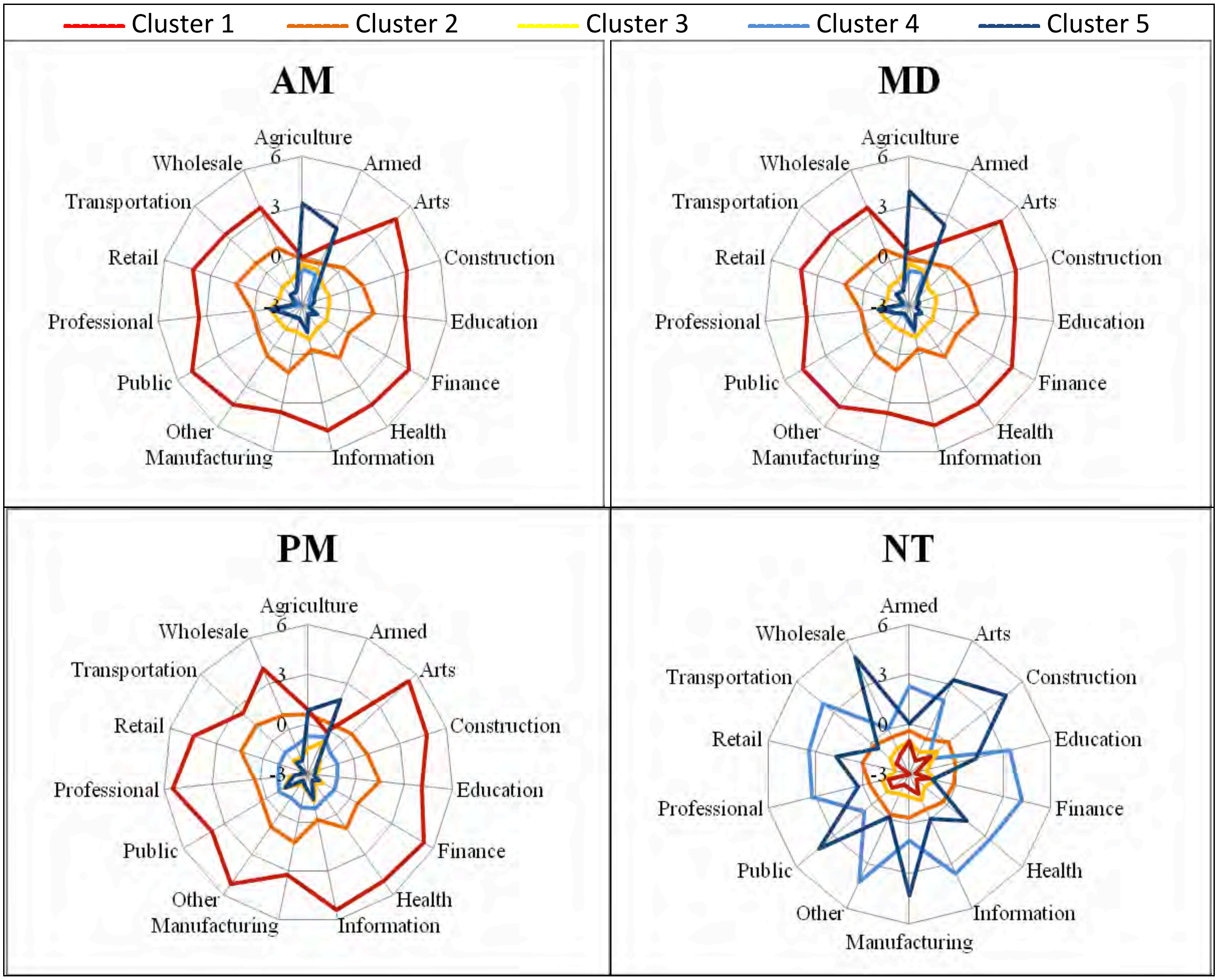


Figure 2 Latent Class Cluster characteristics

Figure 2 shows the mean (in z-scores) spatial clustering values of industries for the five clusters and Table 2 shows the cluster sizes during the AM, MD, PM, and NT. The largest cluster is Cluster 1 (Crimson), which accounts for a third of all blocks in the study region. Cluster 1 shows high accessibility for all industry types except agriculture and armed forces. It is lowest during the nighttime which may be explained by store operating hours. Cluster 2 (Orange) is the second largest class and shows an average accessibility to all industry types. The third largest class is Cluster 3 (Gold) and has lowered access to all industries over all times of day. Cluster 4 (Cyan) experiences very low access to all industries and is fourth in size. This cluster is largest during the midday, but then shrinks during the PM peak. The smallest cluster is Cluster 5 (Blue) which experiences very low accessibility to all industries except agriculture and armed forces. This cluster expands during the nighttime and may include blocks that have higher accessibility in other time periods. This outcome shows the temporal variability of accessibility is captured by the LCCA outcome.

Table 2 Size of Latent Class Clusters for time of day

Cluster Size	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
AM	35.84	20.12	18.13	16.07	9.83
MD	33.1	22.7	18.3	18.3	7.6
PM	36.07	21.86	18.5	13.06	10.5
NT	29.3	20.81	18.4	17.76	13.73

In Figure 3, a map of the blocks classified by cluster membership shows a much clearer spatial structure. There is a clearly definable region in Southern California of high accessibility that stretches along the Pacific Ocean and east to west to the center of the city of Los Angeles. Accessibility is in fact enhanced by the presence of freeways as backbone to this structure. In addition, these maps show the polycentric/multimodal character of the spatial organization of the SCAG region (recall this region includes 190 cities). The four maps together also show that the role of these centers (nodes) is for some centers dynamically homogeneous and for some other centers heterogeneous. For example, the coast has many centers that provide high accessibility throughout the day and even at night time (lower right hand map) maintains good the best accessibility but for a smaller number of industries than in the day time. Similarly, some areas in the far northeast of the region have poor accessibility all the time. In contrast, there are groups of block (e.g., North Orange County) that have dramatic changes of accessibility at night fall.

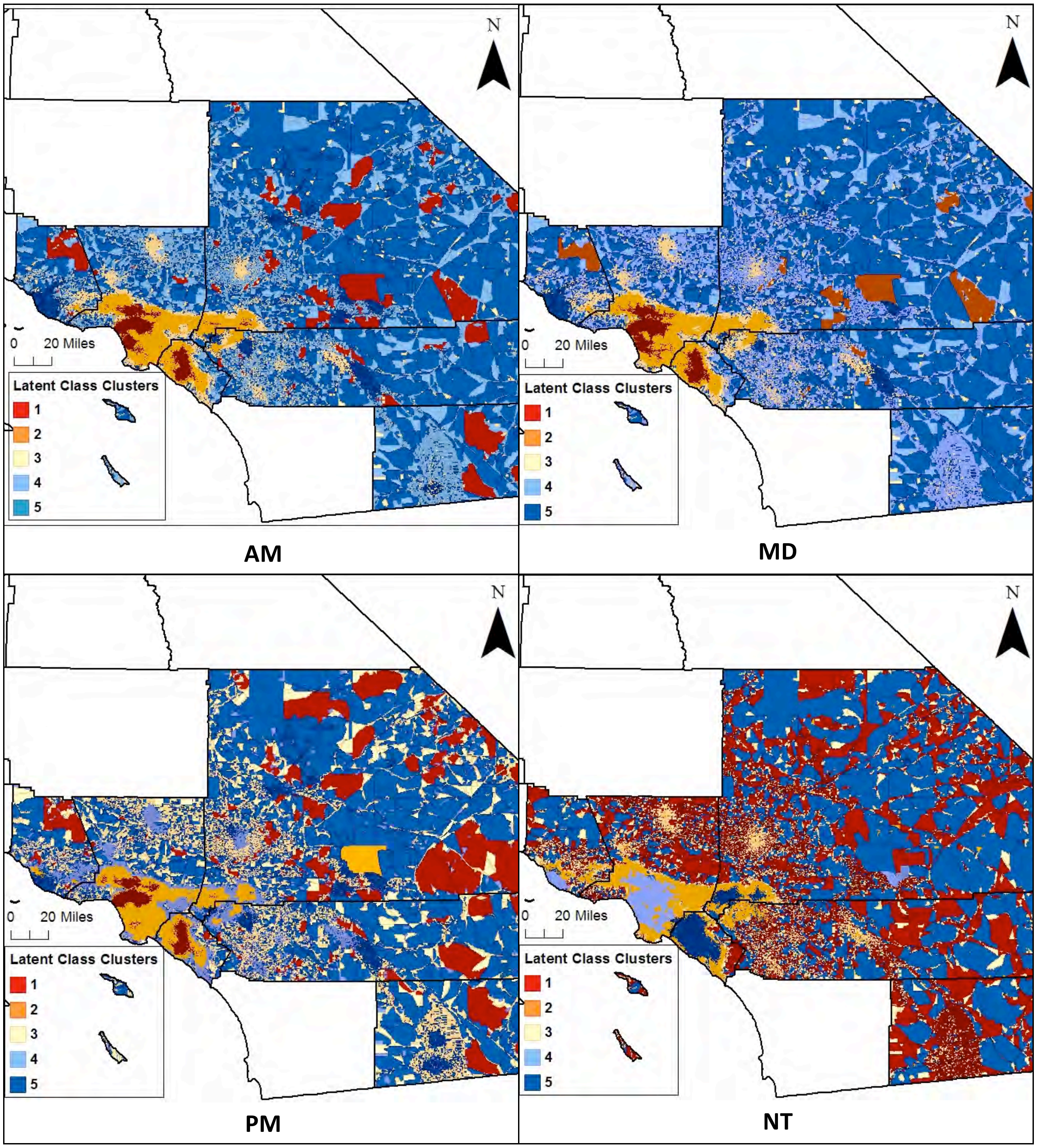
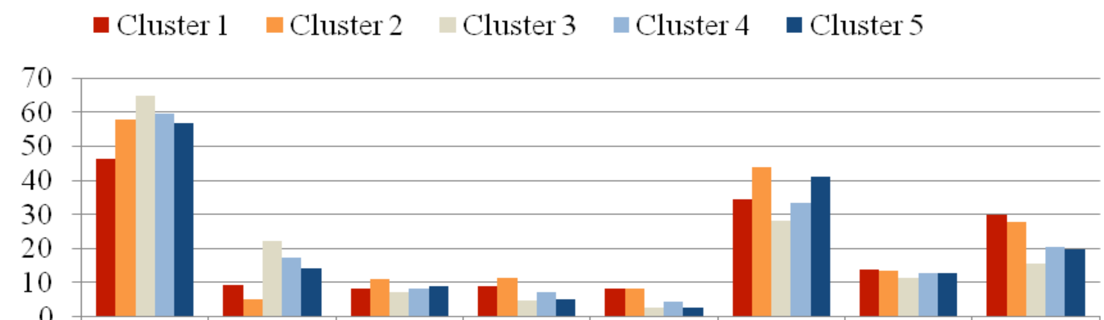


Figure 3 Map of Latent Class Cluster output for time-of-day

Another reason that clusters show significantly different patterns of accessibility during the nighttime is also the inclusion of a large portion of zero opportunities for industries at this time, which can bias the clustering outcomes. This is likely why the clusters show a major shift in pattern during the NT, as shown in Figure 3. Cluster 1 is found where clusters of high opportunities are found, with the exception of armed forces and agricultural industries. Cluster 1 is found in the downtown Los Angeles region and a few locations in the east. When comparing the time periods, Cluster 1 is more pronounced in the east in the PM peak, though public and manufacturing opportunities decline. Cluster 2 experiences more heterogeneity in opportunity access with neither high clustering nor high dispersion. In space, Cluster 2 is largely found in the suburban Central Valley extending until the eastern deserts. Importantly, Cluster 2 represents the average heterogeneity in the distribution of opportunities based on the local and global mean in the study region. Cluster 3 shows low levels of dispersed opportunities and is found in small pockets consistent with locations of outer rural towns. Cluster 4 is found in clusters of high dispersion, seen in the Central Valley exurbs and along outer transportation networks. Similarly, Cluster 5 experiences high dispersion, with the exception of high clustering of armed and agricultural opportunities.

Near the coast, Cluster 1 clearly represents mixed land use in high density urban areas. However, Cluster 1 also represents high clustering, or rural centers, when found near areas of dispersed armed and agricultural lands in the east. The dynamics in accessibility are more pronounced in these rural areas, with more high clusters in the AM and PM peak than during work hours. Next, Cluster 3 experiences much more dispersion in the PM peak than in earlier time periods. Translated on a map, the exurbs of Los Angeles Valley lose access to many opportunities during the PM peak possibly from congestion or early store closing hours. This is in contrast to Cluster 4 in rural areas which show no change in low clustering values.



	Home owners	Vacant housing	Female head of hh	% Black	% Asian	% Hispanic	Poverty level	Foreign born
Cluster 1	46.48	9.16	8.17	8.90	8.37	34.52	13.80	30.02
Cluster 2	57.80	4.97	10.96	11.30	8.10	43.87	13.51	27.95
Cluster 3	64.77	22.11	7.03	4.76	2.81	28.04	11.31	15.43
Cluster 4	59.60	17.16	8.09	7.22	4.27	33.49	12.83	20.49
Cluster 5	56.76	14.23	8.93	5.20	2.72	41.23	12.94	19.68

Figure 4 Cluster socio-demographic characteristics

These clusters can be related to socio-demographic characteristics of the resident populations. As shown in Figure 4, high accessibility clusters have the highest level of percent renters, black, asian, and foreign born residents (which is an indication of the different immigration waves in this area). In contrast, low accessibility clusters are higher in home owners living in areas with high levels of vacant housing. The contrast between these two clusters suggests high accessibility may not be an immediate proxy for desirability, and low accessibility may not describe undesirability. In fact, we find an 11.31% to 13.80% of poverty level residents in all clusters with the highest percent in the two best access clusters. Interestingly, Cluster 3 with low levels of dispersion has the highest percent of home owners and lowest minority and poverty rates. These are the areas in the outer rim of Los Angeles which experience a decrease in accessibility into the PM peak. Cluster 3 may describe an older, white population that has moved to the exurbs far away from the urban core and then services followed them but did not reach the same high levels as along the coast.

4. SUMMARY AND CONCLUSIONS

In this paper we present one way to analyze complex spatial systems enhancing our understanding of the dynamics of polycentric cities and of residential, work, and school location choice processes. We first classify a large region into a multilevel nested spatial structure using information from regional models, US Census blocks, and from highway and local road networks. We also employ multiple sets of indicators including resident population and its characteristics, infrastructure provision, activity opportunities by type of opportunities, and housing supply, and synoptic measures of activity and travel behavior. Finally, we introduce time of day as a fundamental element in classifying spatial units at different observation levels. The primary objective of this paper, to illustrate the creation of realistic space-sensitive and time-sensitive fine spatial level accessibility indicators that attempt to track availability of opportunities, is met using largely available data. These indicators support the development of the Southern California Association of Governments activity-based travel demand forecasting model that aims at a second-by-second and parcel-by-parcel modeling and simulation. They also provide the base information for mapping opportunities of access to fifteen different types of industries at different periods during a day reflecting clearly the polycentric nature of the urban landscape of this region. To accomplish this task classification of units within each level is preformed in two distinct ways: a) cluster analysis using observed variables to derive groups and their taxonomy; and b) cluster analysis using a set of latent constructs to derive groups and their taxonomy. In our spatial analysis, we include the spatial dependency and homogeneity attributes as latent descriptors of the environment, which are then used to classify Southern California into block clusters. The method used and our findings improve center identification techniques of the type found in McMillen (2001) and Redfearn and Giuliano (2008).

The methods here reduced a complex spatial environment into groups that share similar attributes but also share spatial patterns and provided new insights. What is uncertain is the appropriate scale of the spatial analysis, as the scale of our spatial units and the scale of neighborhood definitions. In our analysis, we use the Census block which varies in size over Southern California. To compensate for resident population size, urban blocks are quite small while parks and rural areas are much larger. Smaller blocks often have more neighbors within a given distance. Likewise, the shape of rural blocks is rarely regular resulting in more contiguous neighbors. The size and shape affect the value of the local mean derived from 'neighboring' blocks of neighbors in the spatial clustering analysis. This is a classic geographic concern known as the Modifiable Unit Problem (MAUP) in which spatial analysis is inherently biased by the data. The MAUP effect is most clearly seen during the nighttime when most blocks report no open businesses. The nighttime clusters are unusual in their size, spatial distribution, and industry characteristics. Interpretation is aided with more descriptive statistics on block-specific attributes like socio-demographics. We need to expand the research reported here and test the use of land parcels as spatial units to reduce the bias from MAUP.

However, when applied as a way to describe the environment and identify subcenters of activity during multiple time points. As a pilot study, we find spatial structures related to the hierarchy of transportation networks and industry agglomeration. The next steps are to enhance the inventory of land use, expand travel modes to transit, account for public lands, and add other indicators that describe the built environment. We also expect to correlate the dynamic accessibility clusters with synthetic daily activity schedules for the 19 million residents within the study region developed within SimAGENT, an urban simulation model for Southern California.

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