Measuring Heterogeneity in Spatial Perception for Activity and Travel Behavior Modeling

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ABSTRACT

Travel demand models in the field of transportation have become increasingly sophisticated through the past several decades. The use of activity based modeling methods requires the integration of highly detailed information with statistical models but still substantial variation is unobserved. The inclusion of attitudes and preferences in our models and measures of accessibility is integral in teasing out some of this unobserved variation. Objective measures of opportunities, distance, cost, etc. can become marginalized if an individual has a negative perception of a place. With the inclusion of these attitudes, preferences and perceptions related to geography however, we may more accurately depict the potential behavior of an individual. In this research, we examine place attitudes and the possible role that such attitudes can have on destination choices. Various attributes of place are used in a latent class cluster analysis to explore differences among people and their perceived attraction to place. These clusters are then explored in relation to residential location to determine if there are neighborhood effects on attitudes and perceptions.
INTRODUCTION

Humans participate in activities as a part of daily life. These activities range on a spectrum from mandatory activities that might be fixed in time or place or both (for instance work for some individuals), or discretionary activities that have ultimate flexibility in the temporal and spatial domains. The mechanisms that individuals use to make decisions regarding their daily activities of life often involve both objective and subjective aspects of the physical environment, transportation system, social and cultural environment and the individual as a person. Deciphering these aspects and understanding their contribution to the choice process is wrought with complexities. However, it is imperative that proper attention is paid to unraveling these complexities to ensure that assumptions and theories of decision-making processes are truly representative of what actually takes place.

Many researchers have discussed the connections between spatial perception and travel behavior. Golledge (2006) for instance, states that as individuals age (both from a physiological and an intellectual perspective), they experience the environment, which leads to information accumulation and storage. This leads to a development of spatial knowledge and abilities. He then goes on to say that spatial decision-making is predicated on this knowledge. It is therefore important to recognize the role of spatial information and experiences in forming the perceptions about the environment that aid in decision-making. Spatial perceptions are formed on a variety of spatial aggregation levels. Destinations, for instance can be used in the formation of spatial knowledge and perceptions. On a larger scale, shopping centers, which are hubs of many point location
destinations, or regions, such as neighborhoods, blocks or communities can also be identified and spatial information can be built upon these geographic designations.

It is common practice in travel demand modeling to enumerate opportunities and include them as a description of attraction to a region or zone (see for instance Chen et al., 2010). However, the inclusion of objectively measured destination information, such as number of opportunities, cost, distance, travel time in models such as destination choice and accessibility indicators, inadequately captures differences in spatial knowledge and perceptions among individuals. These objective measures, to the best of our knowledge, have never been compared to spatial perceptions and attitudes of a geographic region. While attitudes and perceptions have been discussed in a travel behavior context (see Gärling, et al., Serai, et al., Kamargianni and Polydoropolou, Ben-Akiva et al., and Ettema and Verschuren), these discussions have largely focused on aspects such as mode choice, or incorporating attitudes into model formulations, and have not focused on comparing the objective and subjective measures used in decision making models and accessibility measures.

A person’s perception of access can be viewed as one aspect of the sense of place that one develops of a place or region. Work has been conducted to understand place level attitudes and the interaction of place attitudes and behavior, stemming from foundational work by both Tuan (1974, 1977) and Relph (1976). Given its roots in phenomenological theory, work to quantify sense of place has had a slow development. Many instances of these applications are centered on points of interest, or highly meaningful areas, and involve a variety of detailed aspects of sense of place (attachment, identity, dependence, etc). However, incorporating these attitudes and perceptions in
models of travel behavior presents challenges. For instance, within the discrete choice model framework, it would be difficult if not impossible to include this level of detail for each point location destination as an alternative to the choice. It would be infeasible to collect this point of interest data for every point from each respondent, and it would pose major computational hurdles due to the number of alternatives. For this reason, alternatives are often considered as zones in destination choice models.

Many researchers in GIScience explored the measurement of place, and have sought to create computational models of places. In fact, at the 2008 meeting of GIScience, a workshop (and subsequent special issue of Spatial Cognition and Computation) was dedicated to the discussion of computational models of place (Winter et al., 2008). These have ranged from using textual tags on photographs on popular sites such as Panaramio to create popularity distributions of certain areas or views (Schlieder and Matyas, 2009), to focusing specifically on place names (Davies, et al., 2009). However, little work has still appeared that focuses on the emotional connection of places and the motivation for travel to specific destinations.

Imbedded in discussions of sense of place and more broadly the acquisition of spatial knowledge is discussion regarding the multilevel aspects of place and psychological associations. The importance of the level of spatial aggregation and the psychological implications of considering place at different scales has been discussed in Montello (1993). This work claims that scale should matter when attempting to understand actions and behaviors of individuals. Most of this discussion centers around the impact of scale on the act of navigation and wayfinding, however, it is reasonable and testable that the use of scale should be considered in the examination of attitudes and
perceptions when selecting a destination, that both the actual destination at a point location, and a larger region (or perhaps several regions nested within a hierarchy are considered). Earlier literature on sense of place unveils this very concept, discussed and even debated, which is largely ignored in individual research attempts. Past discussions have centered on the existence of a hierarchy of places, in which one place is nested within another, larger place (see Rapoport, 1977). These larger places are surrounding the more personal inner places to the individual. In his framework, the hierarchical levels are a product of the experience at the prior, more personally associated level. In addition, Lynch in his discussion of the interpretability of landscapes and meaning presents an open ended question of the impact of geographic scale (buildings, cities, metropolitan areas) on the imagability of the place (Lynch, 1960). It is therefore necessary to have a multileveled approach to the understanding and application of the influence of place attitudes. To the knowledge of the authors, regional level place attitudes have never been examined and assessed for the level of attractiveness to destinations.

This research is a continuation of previous work conducted to understand attitudes as they relate to place and destination choices. The preceding study (Deutsch-Burgner, et al. 2014), involved computing, analyzing and visualizing weighted measures of subjective attraction to regions of Santa Barbara, and it’s relation to subjective well-being and happiness. The measures used include aspects of the landscape (attractiveness and opportunities that exist), possible detractors from an area (perception of danger) and the spatial knowledge of an area (familiarity). These attributes combine a variety of discussions on topics such as the development of cognitive maps and the influence of the physical landscape on psychological perspectives and human spatial interaction.
Attractiveness of the landscape can be seen as an element that contributes to cognitive aspects such as the legibility of places (Lynch, 1960) and the development of sense of place (Bjørn and Bjorke, 2002). Additionally, Rengert and Pelfrey (1997) discuss the influence of perception of danger on effective patrolling of police recruits, and the differences that exist between perceptions and reality. The familiarity of an area also provides indication of both the level of exposure to the region, and the attachment of meaning and organizing of spatial information (see for instance Golledge and Spector, 1978), that are integral to patterns of movement and decision making for activities. The following research continues the previous work by exploring differences and similarities in the attitudes and perceptions of individuals, and the influence of residential location on these attitudes. The motivation of this continued research is to both challenge and progress the assumptions and methodologies of destination choice modeling and measures of accessibility. This research explores how attitudes and perceptions vary by person, and residence, and can impact the choice set considered for destination choices.

**DATA DESCRIPTION**

The data used in this research is taken from a portion the Santa Barbara GeoTRIPS (Geography of TRavel, Interests, Places and Social ties) survey. This web-based survey was conducted in Santa Barbara, California. The portion of data used in this analysis is the result of a mapping exercise completed by each respondent. A full description of this survey component can be found in Deutsch-Burgner, et al. 2014. The resulting sample for this study was 561 respondents. A table of sample statistics is provided in Table 1.
TABLE 1 Sample Statistics (county data source and study area population statistics: US Census)

<table>
<thead>
<tr>
<th>Variable</th>
<th>County Population</th>
<th>Study Area Population</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Female: 49.8%</td>
<td>Female: 49.4%</td>
<td>Female: 57.6%</td>
</tr>
<tr>
<td>Years in house</td>
<td>30-34 years</td>
<td>Mean: 49 years</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Median: 33.6</td>
<td>30-34 years</td>
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<tr>
<td>Household income</td>
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<td>Median: $50,000-$74,999</td>
<td>Median: $50,000-$99,999</td>
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<td></td>
<td>Less than $10,000</td>
<td>$0 - $9,999</td>
<td>Less than $10,000</td>
</tr>
<tr>
<td></td>
<td>$10,000-$14,999</td>
<td>$10,000-$24,999</td>
<td>$10,000-$19,999</td>
</tr>
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<td>13.06%</td>
<td>4.63%</td>
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<tr>
<td></td>
<td>$15,000-$24,999</td>
<td>$25,000-$34,999</td>
<td>$20,000-$29,999</td>
</tr>
<tr>
<td></td>
<td>9.20%</td>
<td>8.12%</td>
<td>4.99%</td>
</tr>
<tr>
<td></td>
<td>$25,000-$34,999</td>
<td>$35,000-$49,999</td>
<td>$30,000-$39,999</td>
</tr>
<tr>
<td></td>
<td>9.10%</td>
<td>11.90%</td>
<td>8.20%</td>
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<tr>
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<tr>
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<td>15.40%</td>
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<tr>
<td></td>
<td>$150,000-$199,999</td>
<td>$200,000 or more</td>
<td>$80,000-$89,999</td>
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<td>6.70%</td>
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<td>$200,000 or more</td>
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<td></td>
<td>6.70%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Households w/ children</td>
<td>33.9%</td>
<td>25.0%</td>
<td>25.1%</td>
</tr>
<tr>
<td>Household members</td>
<td>Mean: 2.86 persons</td>
<td>2.57</td>
<td>Mean: 2.69 persons</td>
</tr>
<tr>
<td>Size</td>
<td>423,895</td>
<td>190,000</td>
<td>561</td>
</tr>
</tbody>
</table>

The mapping exercise required respondents to rank their agreement on a likert-like scale (of -3 being strongly disagree to +3 being strongly agree), with respect to four descriptive questions. The questions that were asked of respondents included:

1. This is an attractive area of Santa Barbara
2. This is a dangerous area of Santa Barbara
3. This area provides me with a lot of opportunities to do things I like to do
4. I am very familiar with this area of Santa Barbara

The respondents were asked to respond to the statement for a series of hexagons tessellating the study region of Santa Barbara. Figure 1 provides a screenshot of this mapping exercise.
Following this mapping exercise, respondents were also asked to score the importance of each of these aspects (attractiveness, perception of danger, familiarity, and perception of opportunities) when choosing a destination for an activity on a one through ten scale (with one being not important, and ten being very important). A full description of the methodology and reasoning behind the use of this hexagonal method can be found in Deutsch-Burgner, et al., 2014). A map of the hexagon regions and residential locations of respondents is provided in Figure 2. It is also important to note the numbering of hexagons in Figure 2, which will be used to refer to regions throughout the analysis and discussion.
DESCRIPTION OF PREVIOUS WORK

A previous study utilizing this data involved computing, analyzing and visualizing weighted measures of subjective attraction and it's relation to subjective well-being and happiness. A full report on hexagon values, importance rankings and findings can be found in Deutsch-Burgner, et al. 2014. Following this descriptive exploration, a weighted surface was calculated for each respondent for each attribute (attractiveness, perception of danger, familiarity, and perception of opportunities). Weighted surfaces were calculated for each person following Equation 1.

\[ A_l^{ijk} = x_{ijk} w_{jk} \]  

Equation 1

Where,

\[ i=1,\ldots, 23 \] (number of hexagons shown to respondents).
\( j = 1, 2, 3, 4 \) (for attractiveness, danger, opportunity, familiarity respectively).

\( k = 1, ..., n \) (n=561)

\( x \) is the attribute score from strongly disagree to strongly agree, rescaled on a 1-7 scale

\( w \) is the importance of that attribute in the decision process.

In addition, a weighted attraction surface was calculated for each respondent following Equation 2.

\[
I_i = x_{i1k}w_{1k} - x_{i2k}w_{2k} + x_{i3k}w_{3k} + x_{i4k}w_{4k} \quad \text{Equation 2}
\]

Where,

\( I_i \) is the overall attraction index

\( i \) and \( k \) are the hexagons and respondents respectively, as defined above

\( x \) is the attribute score from strongly disagree to strongly agree

\( w \) is the importance of that attribute in the decision process

and \( j \) from Equation 1 is replaced with specific attribute numbers

\( 1 = \text{attractiveness}, 2 = \text{danger}, 3 = \text{opportunities}, \) and \( 4 = \text{familiarity} \)

This is shown graphically in Figure 3.
FIGURE 3: Weighted Attributes and Weighted Attraction Surface

ANALYSIS

The previous investigation on the impact of attitudes on attraction to regions of Santa Barbara was conducted largely at an aggregate level. It is important however, to further investigate the attitudes of individuals from different perspectives to further understand how these attitudes impact individuals’ destination choices differently. The following analysis explores the attraction indices in three unique ways. First, we examine the influence of home location on an individual’s attraction to his or her home hexagon region. Second, the attraction indices for each individual are used to create latent class clusters to explain both response style and geographic preferences. Third, residence and
Home cluster region is once again examined, this time with respect to cluster membership.

**Home Location and Attraction**

Using the attraction index developed in previous work, the importance of home location was examined. To begin this exploration, geocoded addresses were assigned to the hexagons in which the respondent lives. Due to insufficient address information, seven respondents were excluded from this portion of the analysis (resulting in a sample size of 554). The average attraction index was computed for each hexagon in which respondents reside. The average attraction among all respondents living in each of the hexagons can be seen in Figure 4. Blank hexagons are those in which no respondents live. While the average values for attraction range from 72-114 for all respondents for the 23 hexagons, when examining home specific hexagons, the average values are much higher (from 102 to 180). Within this range, those respondents who live on the eastern and northern portions of the study area have higher attraction values for their own residential hexagons than those in the western portion. These higher attraction values coincide with higher priced real estate, both in the Montecito (eastern regions) and Santa Barbara foothills (northern regions). This finding points to the possibility of a higher likelihood of residents of specific areas to be more spatially selective in destination choices. An interesting result however is the relatively low home hexagon value that is observed in the Hope Ranch area of Santa Barbara. This area, like Montecito and the Foothills of Santa Barbara, has a high median home value and higher income residents. It must be noted however, that this region also has one of the highest standard deviations (indicated by the size of the circle within the hexagon). Caution should be used when
interpreting the standard deviation values, as a small standard deviation could also be a byproduct of a small sample within that hexagon.

**FIGURE 4 Home Based Attraction Index**

![Home Based Attraction Index Map](image)

Although examining the residential location and home hexagon region rating is helpful in untangling the nuances of attitudes, there are many questions still unanswered. In order to more fully understand the observed attraction indices and variation among the respondents, a latent class cluster analysis was utilized.

**Latent Class Cluster Analysis**

In order to understand the way in which people differ from each other in their attraction to areas of Santa Barbara, a cluster analysis was conducted using all 561 respondents. Using the framework of a latent class cluster analysis (LCCA) allows for the grouping of individuals into clusters exhibiting commonalities due to a latent, unobserved reason or factor. The latent class cluster model was estimated using Latent Gold 4.5. The analysis was conducted using the 23 continuous attraction index indicators.
(one for each hexagon), and was estimated using Maximum Likelihood and Posterior Maximization methods for parameter estimation. A discussion of LCCA can be found in Vermunt and Magidson (2002). The equation used to derive the latent clusters is provided in Equation 3.

\[
f(y_i | \theta) = \sum_{k=1}^{K} \pi_k f_k(y_i | \theta_k)
\]

Equation 3

where

\( y_i \) is the respondent’s score \((i=1,...,N)\) on the measured variables (in this case the 23 attraction scores - one for each hexagon)

\( N \) is the number of respondents (561)

\( K \) is the number of clusters \((k=1,...,K)\)

\( \pi_k \) is the prior probability of belonging to a latent class or cluster \( k \)

And \( y_i | \theta \) is the distribution of \( y \) given the model parameter \( \theta \)

Models were estimated iteratively and compared using a combination of fit statistics and parameters. After an evaluation of the fit statistics and resulting model profiles (for a discussion on fit statistics see (Nylund-Gibson, 2007), an eight-cluster model was selected as the most appropriate model (Log likelihood: -59701.32, BIC: 121776.29, Classification error: 0.0289). The eight clusters were interpreted by examining two aspects: first, the differences between clusters and the values of attraction surfaces were compared, and second a geographical interpretation was used. Table 2 provides the profile means for each hexagon, as well as the maximum, minimum and range of means for all eight factors.
### TABLE 2 Cluster Analysis Profile Means

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<tr>
<th>Cluster Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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<td>108.96</td>
<td>77.02</td>
<td>41.20</td>
<td>66.62</td>
<td>104.97</td>
<td>32.31</td>
<td>15.09</td>
</tr>
<tr>
<td>Max</td>
<td>96.18</td>
<td>162.10</td>
<td>109.91</td>
<td>126.20</td>
<td>134.45</td>
<td>132.09</td>
<td>81.24</td>
<td>30.79</td>
</tr>
<tr>
<td>Range</td>
<td>33.38</td>
<td>53.14</td>
<td>32.89</td>
<td>85.00</td>
<td>67.82</td>
<td>27.12</td>
<td>48.93</td>
<td>15.70</td>
</tr>
</tbody>
</table>

In addition, Figure 5 provides these values graphically, to better understand the differences that exist. Several aspects can be seen through the radar plot provided in this figure. First, there is a clear distribution of several clusters as being either “all high” values or “all low” values. For instance, clusters two and six are both hexagons that have values that are consistently high for all hexagons, and cluster eight has values that are consistently low for all hexagons. This can also be seen in the lower
plot of mean and range by hexagon. Secondly, in the radar plot, there is a visual trend that is noticeable among many of the clusters showing a lopsided circle, favoring the right side of the plot (clusters two and four are the most extreme cases of this). These hexagons are the eastern hexagons of Santa Barbara, as seen in the map of hexagon numbering provided earlier (Figure 2), and indicate a strong Montecito, downtown Santa Barbara attraction.

FIGURE 5 Cluster Means by Hexagon
It is important to note however, that there is a combination of several factors that are contributing to the emergence of these clusters. The development of these clusters appears to be a product of both the manner in which individuals answer the questions (for instance rating everything high or low), and the geographic attraction to different areas. To explore the geographic differences that exist in the clusters in combination with the examination of the attraction values, each cluster was mapped using the profile means for each hexagon. It is important to note that these maps are not normalized to a common scale. This was done in order to more easily compare hexagon to hexagon within a single cluster, rather than compare clusters to each other. Maps of each of the clusters are provided in Figure 6.
The results of this cluster analysis and interpretation of each cluster reveal some interesting aspects of the respondent’s attitudes.

*Cluster one:* Cluster one is comprised of values in the middle of the means when compared across all cluster values, with a range that is also in the middle across all eight clusters. Though there is less of a geographic trend, there is still a noticeable attraction to the coastal areas as well as downtown Santa Barbara, and
the lowest values of attraction being the mountain areas (Northern region) and UCSB/Isla Vista (hexagon 20).

Cluster two: Cluster two is comprised of the highest hexagon means across all clusters. This cluster has one of the larger ranges (as noted in Table 1) across the eight hexagons (it is the third largest). There is a noticeable geographic pattern within the hexagon mean values for this cluster, with a stronger attraction to the western portion of the Santa Barbara region. More specifically, this cluster has a higher attraction to downtown Santa Barbara and the surrounding hexagons, as well as the beach areas of Montecito.

Cluster three: Cluster three is comprised of hexagon means that are within the middle of the values across all clusters. It also has a range that is in the middle of the eight clusters. Geographically, downtown Santa Barbara can still be viewed as an area of attraction; however it is not as clearly defined when compared with other hexagons. Cluster three exhibits a lot of similarities with cluster one, but has a few noticeable differences. While cluster one showed higher attraction values along the east to west arterial of State Street, cluster three does not. Cluster three appears to have higher attraction values for small pockets of Santa Barbara that are perhaps either areas of residences, or more local activity centers. Further analysis is needed to understand exactly why these hexagons might have higher attraction values.

Cluster four: Cluster four has values ranging from the middle to high end of the spectrum of values across all clusters. It is the cluster with the highest range of values (approximately 85). Geographically, cluster four shows many
similarities with cluster two. It shows the strongest east to west pattern of differences between hexagon values. The eastern (downtown and Montecito) region of Santa Barbara clearly has a much higher attraction than the western region.

Cluster five: Cluster five has means that are within the middle range of values, and has one of the largest ranges across the eight clusters (second largest, with a range of approximately 68), indicating that there is a large spatial variation in the attraction to different hexagons. Within cluster five, there are both north to south and east to west patterns that can be seen in the attraction values. The northern regions of the study area that are comprised of more mountainous and residential areas are areas of lower attraction values. Similarly, the most eastern and western regions of the study area are also areas of lower attraction.

Cluster six: Cluster six has mean values that are on the higher end of the spectrum across clusters, indicating a higher attraction to the regions. In addition, cluster six has a lower range of values across the 32 hexagons (second lowest), indicating a high level of attraction across all hexagons. Cluster six shows the least geographic trending of any cluster. The areas of highest attraction fall along the coastal areas of Santa Barbara, and the areas of lowest attraction fall within the Goleta area.

Cluster seven: Cluster seven when compared to the other clusters is made up of individuals who have lower values of attraction to areas of Santa Barbara. The range of these values however is in the middle of the eight clusters. Like in cluster five, there is a noticeable trend of attraction in both the east to west and
north to south directions. While it is similar in that the border regions of the north, east and west have the lowest attraction values, the average values are lower, and the extremes within the values are not as large as cluster five.

*Cluster eight:* Cluster eight members have both the lowest attraction values and the smallest range of mean values across hexagons when compared to the other seven clusters. Within this cluster, there is only a very slight geographic trend that can be seen. More residential regions of Santa Barbara (western most and northern regions) tend to have lower attraction values. The coastal areas and downtown have slightly higher attraction values, although there is a noticeable dip in the attraction value for hexagon 7 (the lower eastside of downtown).

**Home Location and Cluster Membership**

To further the understanding of the cluster membership of respondents, the home residence was explored for each cluster. Figure 7 provides a map of cluster membership for each hexagon in which respondents live. In addition, these hexagons have been grouped into three regions: the Montecito and Summerland region (blue), the downtown and midtown region (tan) and the Goleta region (purple), and charts have been provided to display the total respondents in each cluster by these three regions. Additionally, Figure 8 provides the cluster by cluster membership with respect to these three regions of the study area. There are several notable aspects of the home residences with respect to cluster membership. First, cluster two and four have a much higher representation in the Montecito/ Summerland and the downtown/ midtown regions of the study area. This is consistent with the cluster interpretation, as members of these clusters have a stronger
attraction to the eastern portion of Santa Barbara. Additionally, cluster eight has the highest representation percent in the eastern portion (more specifically the coastal region of downtown Santa Barbara and Montecito. The members of this cluster were people who had a low attraction to all hexagons in a fairly uniform manner, but exhibited some bias toward the beach areas. This might be a reflection of the respondent’s preference toward the lifestyle and housing that the coastal areas have to offer. Clusters one, three, five and six on the other hand have a larger representation within the western portion of the study area (Goleta, and some parts of the downtown and midtown). With the exception of cluster 3 (which has approximately 46%), these clusters each have over 50% of the members living in the Goleta region of the study area. The members of clusters one, three and six showed the least amount of spatial trends with respect to cluster attraction. The Goleta region of Santa Barbara has lower housing prices and is further from the Santa Barbara downtown area, and these respondents are likely people who value their home location and surrounding community, but also enjoy the other regions of Santa Barbara. The high frequency of Goleta residents (approximately 52% of the cluster members) in cluster five is another interesting result. These cluster members show a higher attraction to the downtown area, and a much lower attraction to the mountain regions (the northern hexagons). Cluster five members are distributed primarily within the Goleta and downtown/midtown region hexagons. This is perhaps a certain segment of the population that is attracted to higher density regardless of what their home location is. Further analysis is needed to understand the membership and spatial patterns and preferences of these members.
FIGURE 7: Respondent Home Locations by Cluster Membership

FIGURE 8: Cluster Membership by Neighborhood
It is apparent through differentiating by location of residence, that where an individual lives can influence his or her views of different areas. This has implications for both the acquisition of spatial knowledge and in the use of information in travel related decision making. This challenges the practices of current state of the art models. Proximity to some areas does not completely capture the attraction to them. The overall attraction of an area depends on many other attributes that are subjective and weighted in differential ways among the people as seen in this sample, that are not solely based on their socio-demographics. In essence here we show that unobserved heterogeneity (in the random error terms) and taste variation (in random attribute coefficients) of discrete choice models is even more heterogeneous than originally thought and unraveling it requires a more carefully scrutiny of attractiveness factors as well as studies that in the pilot stage will be ad hoc but over time will become more conclusive about questions to ask, attributes to quantify, and model specification.

CONCLUSION

The development of spatial knowledge and use of spatial perceptions and attitudes are an integral component of decision making and travel behavior. Although this has been recognized in theoretical discussions, quantification of these perceptions and attitudes is limited. Furthermore, integration of these attitudes and perceptions with currently used objective measures of place is non-existent. It is important that we consider these attitudes and perceptions however, as it is possible that current practices misrepresent actual behavior by neglecting human preferences.
In this research, we use a set of subjective attributes to understand how residents view the South Coast of Santa Barbara County. Using innovative data collection methods, respondents were asked to respond spatially to attributes of destination choice. This research follows previous research that explored aggregate responses to these responses through the use of an averaged attraction index. Although the averaged attraction surface can provide insight into the views of residents at an aggregate level, it is also important to understand the differences that exist among individuals. Using a latent class cluster model, eight groups of respondents were extracted based on their subjective attraction potential. These eight clusters showed several aspects both at an aggregate level about attitudes regarding Santa Barbara as a whole, and at a disaggregate level (hexagon-by-hexagon). Preferences toward regions of Santa Barbara were noticeably different among clusters, as were the degree to which respondent’s attitudes across regions of Santa Barbara varied. When cluster membership was examined with respect to home location, noticeable trends were present. Residents of the Montecito and Downtown/midtown region had higher memberships in clusters that had a noticeable geographic preference toward the downtown and Montecito areas. Goleta residents however were less geographically biased. This result is consistent with indicators of attraction based on density of opportunities, as the downtown area has a higher density of businesses. However, the results reflect the fact that residents of Goleta might have a higher attraction to more opportunities than those who live in the eastern portion of Santa Barbara. In other words, members of less geographically biased clusters (who tend to be residents of Goleta) might avail themselves to a greater number of opportunities due to the fact that they have higher attraction values to all areas of the region.
There are several important future directions that must be addressed. First, cluster membership should be further explored to understand socio-demographic differences. A regression model of cluster membership explained by socio-demographics was not undertaken in this analysis, primarily due to sample size. Aspects of this analysis (for instance the rating of the individual attribute importance, or scoring of hexagons) however can be individually explored to understand how socioeconomic and demographic attributes can be used to further understand these subjective perceptions. Additionally, this research is motivated by the necessity to understand and predict destination choice. The results of the data collection should be compared to measures currently used in destination choices, or other objective measures or indicators of place. Lastly, destination choices often differ depending on the activity that is being conducted. A portion of the survey instrument that was not utilized during this analysis is a disaggregate rating of decision making criteria by various activity types (eating, spending time with family, shopping for groceries, etc.). These importance ratings in combination with the attraction surfaces and available opportunities can provide a powerful description of the most likely areas for conducting activities by individuals.
REFERENCES


