

**Comparing Transit Accessibility Measures:
A Case Study of Access to Healthcare Facilities**

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ABSTRACT

Despite the continued interest in transportation accessibility, it is still unclear how different types of accessibility measures relate to one another and which situations are best for each. The current study undertakes a statistical comparison among four transit accessibility measures (representing three main categories of accessibility models) to determine whether they are comparable and/or interchangeable. Specifically, this analysis considers a case study to measure individuals' access to healthcare via paratransit. Results indicate that the three categories of accessibility measures provide drastically different interpretations of accessibility that cannot be duplicated by each other. Furthermore, the more closely accessibility models capture individuals' perceptions and true access to activity opportunities, the more consistent and evenly distributed the results.

1. INTRODUCTION

Transit accessibility, or the measure of how easy it is for an individual to travel to a desired destination using public transportation, is a critical issue for transit captive populations for whom it is a key determinant of the ability to access activities, as well as for non-transit captive populations for whom it is an important consideration in travel mode choice. In fact, higher levels of regional public transit accessibility have been tied to enhanced quality of life (1), potential growth (2), and economic strength (3). As a result, transportation and regional planners are continually attempting to make their transit systems more efficient, connected, and easy to reach. At the same time, planners are also developing measures to evaluate how effective changes to their transit system and service are in improving the region's transit accessibility.

Accessibility is rooted in many transportation system decisions and characteristics, including land-use planning, network design, system operations, and population demographics. Consequently, accessibility measures are most effective when they are sensitive to these factors (3, 4). Accessibility measures are especially important for transit agencies and planning organizations as they currently face reduced budgets, limited workforces, and increased demands for service (5, 6). Even within these constraints, agencies can apply accessibility measures to optimize their resources to provide the highest levels of service possible. Many government agencies recognize the importance of accessibility measures and encourage their use in long-term transit planning (5). In fact, it has even been suggested that policies affecting the equity of accessibility should be examined with *multiple* measures in order to confirm their validity (7).

Even as accessibility is being increasingly used for system-level planning, it is critical to recognize that accessibility is inherently an individual construct. After all, each individual views how accessible a mode or destination is differently. For instance, while one individual might have a high value of time and may feel inconvenienced if she needs to travel long distances to reach an activity opportunity, another individual might have such a high preference for that activity that he does not mind traveling a long distance to reach it. It follows that while accessibility is dependent on transportation systems, it should really be evaluated in terms of individuals' perceptions of their experience *within* the transportation system. Therefore, the most effective and accurate transit accessibility measures should consider individuals' perceptions for activity participation and travel.

Even though many researchers recognize the need to consider patrons' perspectives, most transit accessibility measures used in the literature fail to do so (6, 8, 9). The main reason for this is the fact that measures based on transit patrons' perspectives require extensive supporting data based on stated and revealed preference surveys. Instead, researchers have developed a number of simplified measures that require much less information (at the cost of increasing the number of assumptions regarding individuals' preferences and perceptions of accessibility). Certainly, one underlying assumption of all measures is that individuals are constrained by space-time limitations, and more research has been conducted in this area recently with the help of Geographic Information Systems (GIS) (10). For example, the simplest method of counting activities reachable by transit within a certain buffer distance from an individual's home can easily be implemented using address information in GIS, but it assumes that all the activities are preferred equally, that there are no isolated congestion or convenience considerations, and that all individuals perceive travel times similarly. In the category of these simplified measures, transit accessibility can be defined in terms of miles, number of opportunities, dollars, and even minutes of delay.

While one can argue that “no one best approach to measuring accessibility exists, (and) different situations and purposes demand different approaches,” (5) it is still unclear exactly how these different types of accessibility measures relate to one another and which situations are the best for each. Transit practitioners need reliable, accurate, and responsive accessibility measures from which to make decisions. However, if different measures are not comparable (and thus provide inconsistent results) planners may run the risk of making inaccurate or unreliable conclusions about accessibility and the effectiveness of policy/operational decisions. As accessibility becomes increasingly important to transit planning, it is essential to determine if different measures are interchangeable, as that will dictate the level of effort and data required. This issue is especially relevant for the recently introduced individual-level methods (e.g. utility-based measures) that assess accessibility for individuals based on their specific trip characteristics and personal assessments of their trip. Even though these measures are promoted as being able to more realistically describe individuals’ behavior and be more responsive to policy/operational changes, they require considerably more development and data collection than other methods. As a result, it is valuable to specifically assess whether these methods provide significantly more accurate evaluations of accessibility relative to previous techniques.

In the context of the above discussion, the transportation planning field routinely accepts that individual-level accessibility measures with preference components are preferable, but these conclusions are mainly based on qualitative descriptions. Similarly, researchers tend to agree that measures which aggregate data, regardless of type, are less accurate and should be avoided when possible (5). Considerably less work, on the other hand, has focused on quantitatively distinguishing between accessibility measures (11). Even the few quantitative studies to date have been unable to identify if and which methods are more sound than others (12, 13). Clearly more work in this field, especially in the area of transit planning, is necessary, which motivates the research in this paper. In particular, the current study undertakes a statistical comparison among four commonly applied transit accessibility modeling techniques to determine whether or not they are comparable and/or interchangeable.

The rest of this paper is structured as follows: Section 2 discusses and defines three standard “schools of thought” on accessibility modeling, including data needs and assumptions associated with each. Section 3 introduces an access-to-healthcare case study and develops four accessibility formulations spanning the three different “schools of thought” to measure paratransit service in the case study region. Section 4 compares and evaluates the performance of the four accessibility formulations using predictive validation as well as environmental inequality statistics. Section 5 explores how accessibility measures can be used to evaluate the impact that changes in paratransit planning and operations can have on patrons’ access to healthcare. Section 6 concludes the paper with a summary of the findings and future thoughts.

2. METHODS FOR MEASURING INDIVIDUALS’ ACCESSIBILITY

An array of accessibility measures have been introduced over the past decade. Not surprisingly, each is tailored to a specific focus, level of aggregation, situational dataset, and computational requirement. While these measures can be grouped in a number of ways (13, 14), three common categories stand out: cumulative, gravity, and utility-based models. Measures from each category have their own benefits and challenges, which will be discussed in this section. One common issue applicable to measures from all three categories, however, is that of aggregation. Accessibility measures can significantly lose sensitivity as results are aggregated by transportation mode (4) and zone system scale (15). Specifically, while larger zone systems may be easier to work with, they often assume a greater level of population and demographics

uniformity, which in most cases is not accurate and can lead to biases (5). As a result, it is important to focus studies on a specific mode, a specific activity opportunity, and a detailed spatial zoning system regardless of the chosen accessibility measure, even though this may be data-intensive.

2.1 Cumulative Models

Cumulative models, also labeled as count or isochronic models, are the simplest accessibility measures to calculate. As the name suggests, these measures evaluate individuals' accessibility as the cumulative number of activity opportunities within a specific radius of time or distance from his/her home or the shortest distance an individual must travel to get to the closest activity opportunity. Search-radius and travel distances can be calculated as either *straight-line distances* between zones, *network distances* along the shortest path between zones, or a combination of these two. Straight-line distance is perhaps best suited for walking trips where travel is not restricted to roadside sidewalks. On the other hand, while network distance may be a more difficult measure to define and quantify, it may also be a more realistic measurement for vehicular travel because it uses the actual road network between the two points and better represents travel times and/or distances. High levels of cumulative model accessibility are described by higher counts of total number of activity opportunities or lower shortest distance travel costs, depending on the specific model.

The cumulative models are desirable because they require relatively minimal data and results are straightforward to interpret. Unfortunately, the cumulative models' relative simplicity is also their most significant limitation. These models assume that all activity opportunities are equally attractive and that individuals do not have preferences beyond the activity opportunity that is the closest. For example, neither the quality of care nor physician reputation, important factors affecting individuals' choice of healthcare provider, are considered in these models. Cumulative accessibility models do give a sense of the scale of available activity opportunities, but are not responsive to any factors beyond network characteristics and shortest straight-line distances.

2.2. Gravity Models

The most widely used accessibility measures are those described as gravity models (6, 16). These measures are very similar to the transportation gravity models of the four-step planning model. As such, individuals' accessibility is calculated based on zones as a function of activity opportunity attractiveness, and the travel distance between other zones and the individual's resident zone. A zone's activity opportunity attractiveness can be described in many ways, including number of employees of each of several industry types, number of facilities of each industry type, square-footage of facilities, or a scaled ranking. Travel distances between zones can again either be straight-line or network shortest path. However, in this model, distances are scaled by a friction factor to "penalize" activity opportunities that are further away. This friction, or impedance, factor is often predetermined and can be region-, activity-, or trip-specific (17). As a result, the closer individuals are to more attractive activity opportunities, the higher their gravity accessibility (3, 5).

There are many advantages to using the gravity model beyond the fact that it is the most widely used accessibility measure (3). These measures are relatively easy to interpret (though not as easy as the cumulative model measures), are based on widely available data, and require rather undemanding calculations (6, 18). Gravity models can also be adjusted to account for

individuals' mode choices and travel distances on the mode-specific networks (3, 14). Still, while gravity models are frequently used, they are not without shortcomings. First, gravity models assume that each destination location is equally attractive to all individuals (14). Second, individual traveler behavior and time constraints are not considered in gravity models (6). Third, a major difficulty with gravity models is defining the friction factor for different types of trips (3, 17, 19).

2.3 Utility-based Models

Utility-based measures are the third, and most complex, method of measuring accessibility. They are unique because they incorporate individuals' behavior and decision-making preferences into the accessibility calculation (in fact, the gravity model formulation is a simple type of utility-based model formulation; see 20). Individuals' accessibility is calculated as either the level of utility, or satisfaction, they have for their preferred activity opportunity or the average of their utilities for all activity opportunities. This utility is calculated using a model that weights various characteristics of the trip to reach activity opportunities by individuals' perceived level of importance (derived from travel survey responses). For example, travel distance between an individual's origin zone and activity opportunity zone, a common factor across accessibility models, can be weighted differently for women and men to reflect potential differences in perception between men and women in how vexing traveling long distances is for them. Regardless, the higher an individual's calculated utility, the higher their level of accessibility. Additionally, utility-based models are often included as part of larger microsimulations that predict individuals' travel patterns in relation to traffic conditions and regional development.

The main benefit of utility-based models is the fact that individuals' accessibility is calculated based on their preferred activity opportunities, rather than just the nearest one. These measures recognize that just because an activity opportunity is close does not mean it contributes to accessibility if the individual does not prefer to go there. Utility-based accessibility measures are not too difficult to interpret as well, although utilities are an abstract number without units. That being said, utility models also effectively incorporate costs, which can be used to translate the accessibility measures into dollar amounts that are easy to understand and use (19). These models also remove many of the assumptions present in the previous two model types. Because they model travel choices at the individual level, utility-based accessibility is a more representative measure of the individual's actual choices as opposed to assuming that each individual has similar preferences and behaves identically (6, 19). Unfortunately, however, a major disadvantage of utility-based models is the complexity of developing them. These models require extensive data collection of individuals' travel patterns and opinions, which can be difficult and expensive to obtain (6).

3. METROACCESS HEALTHCARE CASE STUDY

As mentioned previously, accessibility measures are more accurate and meaningful when they focus on a specific mode, activity opportunity, and spatial zoning system. Therefore, in this study, we consider the case study of *MetroAccess* in Austin, Texas to quantify and measure individuals' access to healthcare providers via paratransit service.

Paratransit (also referred to as demand-response transit or dial-a-ride) is a critical form of transportation that operates on-demand, utilizing different routes each day depending on when and where patrons request service. In many small and medium-sized communities that cannot support fixed-route transit, paratransit functions as an independent mode available to the entire

population. In urban areas with fixed-route transit, however, paratransit is often incorporated as a complementary service for ADA-approved elderly or mobility impaired patrons. Cumulatively, paratransit serves over 86 million patrons in the US each year, many of whom are dependent on this service (21). As the national population continues to age and move away from dense urbanized cores, paratransit operators will need to ensure that they are able to provide adequate access for future population's travel needs.

Not surprisingly, one of the most common types of paratransit trip requests that operators must plan for, both currently and in the future, is access to healthcare. While preventative care and routine medical visits are essential for all age groups and populations, these are especially important activities for paratransit patrons who tend to be older or mobility impaired (22). Unfortunately, healthcare facilities (e.g. doctor offices, physical therapists, hospitals, etc.) are typically located away from where many of these older populations live, making access to healthcare difficult. Furthermore, individuals tend to select healthcare facilities based on reputation and specialty, meaning that preferred healthcare facilities are often not the nearest options (23). As a result, captive paratransit patrons may have to endure long travel times to reach their preferred healthcare facility, or they may not be able to reach it at all if the service does not extend that far. In fact, a Los Angeles study found that those who were able to drive themselves had access to nearly twenty times more healthcare facilities than those who relied on transit (4). Healthcare providers have appropriately begun to use accessibility measures to equitably locate their practices (23). Paratransit operators must likewise continue to understand (and accommodate) these issues to provide accessible service.

3.1 Case Study Region and Data Formation

MetroAccess, a subsidiary of the regional *Capital Metropolitan Transportation Authority* of Austin, Texas, provides paratransit service within $\frac{3}{4}$ mile radius of all fixed-route bus routes in the metropolitan area. (24). Similar to other paratransit services, *MetroAccess* operates on significant subsidies (e.g. using over 20% of *Capital Metro*'s annual budget and contributing less than 2% to its revenues) (25). The service operates 124 vehicles, of which approximately 80% are utilized and 20% are in maintenance at any given time (25). Each vehicle is capable of picking up an average of 2 persons per hour and operates for roughly 9 hours per day, which equates to nearly 1,800 passengers served daily (25). As expected, a sizeable proportion of *MetroAccess* patrons' requests are trips to access healthcare, which includes physical therapy, doctor appointments, and hospital visits. *MetroAccess* was selected as a case study for this research because it is a successful representative paratransit service with extensive spatial data available to the research team in the area of the paratransit coverage.

In order to evaluate the region's accessibility, spatial data was collected from a variety of sources and compiled in ArcGIS. The zone system, defined as Census 2000 block groups, was acquired from the Environmental Systems Research Institute (ESRI) along with its associated census SF1 demographics database. Travis County zoning records, county roadways, point locations of healthcare facilities, and healthcare facility footprints were then downloaded from the City of Austin's Communication and Technology Management Department website (26). Finally, fixed-route transit lines and the paratransit service region boundary were collected from Capital Metro (27). Additionally, fleet composition data (e.g. number, type, capacity, and operating hours of vehicles) was solicited from *MetroAccess*' operations manager (25).

Next, the complete spatial service region data was constructed through a number of steps. First, all of the spatial data was combined and projected to the NAD 83 Texas Central State

Plane projection and coordinate system to ensure that any spatial calculations were accurate and consistent. Second, the 2000 census demographic data was joined to the 516 census block groups in the zone system. Third, the zoning data was aggregated into the five zoning types required by the accessibility measures, classified as residential, apartments, commercial/ public, retail, and manufacturing/industrial. Census block groups outside the Austin city limits that lacked zoning were assigned a base of 5% on its land being used for all zoning types. Fourth, spatial characteristics, such as zonal areas and inter-zonal distances, were calculated. This step further required that zones were first converted into centroids, and distances (in miles) were calculated from these zone centroids to the nearest fixed-route transit line, to every other zone centroid, and to the nearest healthcare facility. Finally, the data was exported and four accessibility measures (detailed in the following section) were calculated for each zone in the service region.

3.2 Calculating Healthcare Accessibility

Four unique healthcare accessibility measures were selected to characterize *MetroAccess* patrons' access to healthcare. These measures represent commonly used forms of the previously discussed cumulative, gravity, and utility-based models. All of these measures are computed at the zone level, which in the current analysis corresponds to census block groups.

Minimum Distance Measure

The simplest of the four, the *minimum distance measure* is a common cumulative model that is best at describing, with minimal data requirements, patrons' residential location relative to healthcare facility locations (14). As such, this measure defines accessibility from each zone i as the straight-line distance (in miles) from the centroid of each zone to the nearest healthcare facility k :

$$A_{MD,i} = \min_{\forall k} d_{ik} \quad (1)$$

Straight-line distances were used because previous research has shown that these distances can be more accurate than network distances in metropolitan areas, such as Austin, where streets form grid-like patterns (11). It is important to recognize that this measure is not based on distances to patrons' preferred healthcare facilities, but simply the nearest ones to the centroid of the zone in which individual patron's reside. Lower values from this measure (i.e. shorter distances) correspond to higher levels of accessibility.

Healthcare Facility Gravity Measure

The second accessibility measure, introduced by Knox (4), takes the form of a traditional gravity model. In the *healthcare facility gravity measure*, all healthcare facilities are evaluated in relation to each zone. By definition, accessibility is proportional to the attractiveness of each facility as well as inversely proportional to the distance patrons must travel to each facility. The resulting measure is calculated as follows:

$$A_{HCFG,i} = \sum_{k=1}^N \left(\frac{S_k}{d_{ik}^\delta} \right) \quad (2)$$

Accessibility from each zone i is calculated by summing gravity values for each facility k ($k = 1, 2, \dots, N$). These gravity values are estimated by scaling the square footage, S_k , of each facility k (an indicator of the attractiveness or quality of the location) by the distance d_{ik}

between zone i and facility k (in miles from the centroid of each zone to the healthcare facility). How much facilities are penalized by distance is controlled by the distance decay function δ . The authors assumed a value of -1.285 for δ , the recommended standard for home-based other trips (28). In this measure, higher values of $A_{HCFG,i}$ (i.e. more closer and attractive facilities) correspond to higher levels of accessibility for zone i .

Two-Step Cluster Gravity Measure

The *two-step cluster gravity measure* considers patrons' access to healthcare facilities in relation to the facilities' overall availability for the entire population (22). This measure recognizes that facilities that serve too large a population may not be preferred destinations because it becomes difficult to schedule desired appointment times or receive personal service. Therefore, an additional component is included in this gravity model that reduces the accessibility score for facilities located in the densest areas of the region. Because the measure also includes the square footage of each hospital, large hospitals that can handle more patients are less affected by this component than those that are smaller but are expected to serve as many patients. This measure takes the form:

$$A_{TSCG,i} = \sum_{k=1}^N \left(\frac{S_k d_{ik}^{-\beta}}{\sum_{j=1}^M P_j d_{jk}^{-\beta}} \right) \quad (3)$$

Similar to the previous measure, accessibility from each zone i is calculated by summing gravity values for each healthcare facility k ($k = 1, 2, \dots, N$). In this measure, however, gravity values are composed of two parts. The numerator, or base measure of facility attractiveness tempered by travel distance, is identical to the basic gravity model measure. The denominator, which describes each facility's availability relative to the region's population, is represented by the total population size, P_k , of each region zone j (an indicator of the level of demand) and the distance, d_{kj} , between facility k and zone j (in miles from the centroid of each zone j to the centroid of the zone in which the healthcare facility k is located). The denominator is summed for each region zone j ($j = 1, 2, \dots, M$). The recommended value of -1.285 for home-based other trips was also used for β (28). Again, higher values (i.e. with closer and more attractive facilities) correspond to higher levels of accessibility.

Patron Microsimulation Measure

The final utility-based accessibility model is by far the most computationally and data intensive. The *patron microsimulation measure* is composed of a series of behavioral discrete choice, regression, and probabilistic models that predict individual paratransit patrons' travel decisions and trip characteristics for a given day (for a complete description of the measure and its models, please refer to 29). These models are developed based on travel logs from paratransit service in Brownsville, Texas, and, as a result, they provide a more realistic description of patrons' desired destinations and trip characteristics. When the measure is applied to a region, it first forecasts where all the patrons requesting service on a given day need to be picked up. It then proceeds to predict when, where, and why each patron needs to travel. As each patron is scheduled, trip characteristics, including pick-up delay, travel times, etc., are calculated.

Accessibility for each patron l is calculated in minutes of delay by weighting and scaling each of their forecasted paratransit trip characteristics, based on findings from a survey conducted in Tyler, Texas (22). Ultimately, accessibility for each zone i is calculated by averaging the accessibility values across individuals from that zone. In this study, only those trips to access healthcare were included in the analysis. Because accessibility is calculated in equivalent minutes of delay (delay, as defined here, is the difference in travel time between taking the paratransit mode and a personal vehicle), lower values (i.e. less personal delay) correspond to higher levels of paratransit mode accessibility.

4. COMPARING ACCESSIBILITY MEASURES

In this section, the four common accessibility measures presented previously are evaluated to determine whether they are comparable and/or interchangeable. This is accomplished using three techniques. First, the accessibility results are mapped and spatial accessibility distributions are compared. Second, forecasting evaluation statistics are used to test how similar each measure is to the others. Third, environmental justice inequality statistics are employed to describe how each measure distributes accessibility across zones. These analyses are undertaken using the 281 census block group zones (of the 518 total census block groups zones in the paratransit service region) identified in the patron microsimulation measure as having requests to access healthcare. The remaining zones cannot be compared because they did not receive accessibility values from the microsimulation measure (due to the fact that no patrons were expected to travel from them).

4.1 Spatial Accessibility Distribution

Figure 1 presents four maps of the service region, with each map displaying the results for one of the four accessibility measures. Healthcare facilities are identified as white circular dots on the maps. Zones are classified as high accessibility, high-average accessibility, low-average accessibility, or low accessibility. Classification thresholds vary by map and are based on four natural-break quantiles within each measure. Higher levels of accessibility are represented by darker gray shading, and lower levels are identified by lighter gray shading.

As one would expect, the *minimum distance* map shows that zones closest to healthcare facilities have the highest levels of accessibility. However, because there are many healthcare facilities throughout the region, most zones tend to be close to at least one facility. As a result, the map shows relatively high levels of accessibility evenly throughout the populated areas. The *healthcare facility gravity* map, on the other hand, considers access to all healthcare facilities, so those that are closest to the majority of facilities have the highest accessibility measures. Again, as one would expect, these zones are the ones most centrally located (i.e. where populations are the densest and healthcare facilities are typically situated). This measure is represented by bands of accessibility, with higher levels of accessibility in the urban core and decreased values the further one moves out. The *two-step cluster gravity* map is similar to the healthcare facility gravity map, but with narrower bands of accessibility. This is due to the fact that, while still a gravity model, this measure penalizes facilities if it serves too large a population. Finally, the *patron microsimulation* map presents a drastically different picture of paratransit accessibility. Rather than just consider distances to facilities, this measure considers where patrons are coming from and their preferred facilities. The range of accessibility values in this map highlights that the closest facility is not always the preferred activity opportunity. In fact, some of the most highly accessible areas are in the outer areas of the service region, where more older and

mobility-impaired populations typically reside and from where a large fraction of requests to access healthcare originate. By simply comparing these spatial accessibility distributions, one can see that each measure evokes a different interpretation of accessibility and that one measure cannot easily be interchanged with another. However, while helpful from a visualization perspective, the maps themselves do not provide any quantitative metrics of the closeness of each pair of accessibility measures, which is the focus of the next two sections.

4.2 Prediction Evaluation Statistics

In response to the variety of travel demand methods introduced over the past decade, researchers have developed a number of methods for evaluating a model's ability to match current travel patterns. These statistics have also been used to examine how effective two different prediction measures are at describing the same travel situation. As such, this study applies five of the most commonly-utilized statistics to quantitatively evaluate how similar the four accessibility measures are. In order to compute the statistics, each measure is scaled between 0 and 1, relative to its own maximum and minimum values and oriented so that 1 indicates its highest level of accessibility. The evaluation statistic formulas are presented in Table 1, where N is the number of zones (i.e. 281 in our case). The final values describing each pair of measures are also presented in Table 1. Diagonals are not shown in Table 1, as they are perfectly correlated.

Percent Root Mean Square Error (PRMSE)

The PRMSE focuses on forecasting bias and precision by comparing the variance between two accessibility measures. Typical values of the PRMSE range between 0 and 100%, with 0% corresponding to the lowest levels of variation between the two measures. However, the PRMSEs calculated between almost every pair of measures are greater than 100%, indicating that there is considerable variation between these measures. The PRMSE value comparing the two gravity measures, however, is 48.166. This means that the two gravity measures are and provide similar accessibility results, as one would expect.

Correlation Coefficient

A common statistical measure, the correlation coefficient calculates the amount of variation or dependence between two measures that can be explained by the data. Values range between 0 and (+/-) 1, with 1 indicating that the two measures are perfectly correlated. Here, the results show that the patron microsimulation measure is highly uncorrelated with all other measures. The minimum distance measure is moderately correlated with the two gravity measures, with correlations of 0.504 and 0.520 respectively. Most significant, however, is the correlation between the two gravity models, with a coefficient of 0.862. Again, this result would suggest that the two gravity models can be used interchangeably.

Theil's Inequality

Theil's inequality, or uncertainty coefficient, uses information entropy to describe the overall association or expected values between pairs of accessibility measures. Theil's inequality values can range between 0 and 1, with 0 corresponding to low entropy (or high association between measures) and 1 corresponding to high entropy (or less association between measures). Once again, the two gravity models prove to be extremely similar, with very low entropy value of 0.175. Interestingly, the simplest measure of minimum distance and the most complex measure of patron microsimulation also have a relatively low score of 0.420, indicating that both

measures have relatively similar patterns of accessibility measures across zones. The other pairs of measures all have scores greater than 0.500, which reveal a low level of association.

Mean Absolute Deviation (MAD)

Similar to PRMSE, the MAD indicates the *absolute* magnitude of variability between accessibility measures, which provides additional perspective on the differences between them. Again, MAD values can fall between 0 and 1, with 0 associated with minimal variability (or the best relationship between measures). These results again highlight how small the error is between the two gravity models, with an extremely low MAD value of 0.051. Interestingly, this statistic also reveals that the patron simulation measure has moderately low variability relative to the two gravity measures, with MAD values of 0.359 and 0.358 respectively.

Tracking Signal

Finally, tracking signal statistics use MAD values to evaluate measures to see if they track high or low through comparing accessibility values for pairs of zones. As such, values can extend from positive to negative infinity, but between 2.5 and -2.5 is preferred. Unfortunately, every pair of measures' tracking signal statistics fail to be significant. This may be because it is hard to distinguish a reliable pattern to accessibility measures in the region. The closest one can come to a reoccurring pattern across measures is with the two gravity models, but even then the tracking signal score is rather high.

Overall, the prediction evaluation statistics reveal two important trends regarding the comparability and interchanging of accessibility measures. First, the two gravity measures performed consistently in the same way. Even though the two-step cluster gravity measure incorporates an additional weighting factor, both models produced statistically comparable results. Second, the other measures are statistically incomparable with each other. Each has distinctly different interpretations of accessibility that cannot be duplicated by any other measure.

4.3 Environmental Justice Inequality Statistics

While the previous statistics evaluated relationships *between* pairs of accessibility measures, the environmental justice inequality statistics focus on the variation *within* each measure. These statistics provide additional insight into how each measure's interpretation of accessibility is distributed among the zones (i.e. whether there is significant differences in the average accessibility or if a few zones are considerably better/worse than others). The environmental justice inequality statistic equations and the final values describing the inequality of each measure are presented in Table 2.

Coefficient of Variation

The coefficient of variation is a simple evaluation of variation within an accessibility measure, similar to standard deviation. This statistic, however, is unitless, which allows us to compare them. Values less than 1 indicate less variation within the measure (i.e. accessibility is more evenly dispersed across the regions) and values greater than 1 indicate higher levels of variation within the measure (i.e. accessibility is skewed towards different regions). The results show that the patron microsimulation has more evenly dispersed accessibility throughout the region, whereas the gravity measures and minimum distance measures have increasingly skewed

regional accessibility. This is confirmed by the more concentrated rings of higher accessibility in the accessibility maps.

Relative Mean Deviation

This statistic describes the mean deviation from the mean, or, on average, how different each zone's accessibility is from the regional average. Smaller relative mean deviation values indicate more evenly distributed levels of accessibility. Again, the patron microsimulation may be described as promoting a more even distribution of accessibility across Travis County. The other measures perform similarly, with the minimum distance measure offering a highly inequitable interpretation of accessibility.

Variance of Logarithms

Another statistic that compares each zone's accessibility relative to the average accessibility is the variance of logarithms. Due to the logarithm, this statistic is more sensitive to outlying accessibility values. Similar to the previous statistic, smaller values indicate that accessibility is more evenly distributed throughout the region. The patron microsimulation stands out as the exceedingly even distribution of accessibility values. Furthermore, there are few outlying zones with extreme accessibility values in any of the measures because each of the variances is low.

Theil Index

The Theil index is based on entropy and measures the probability of selecting high accessibility measures from specific zones. As such, this measure provides a good weighted average within and across subgroups of high and low accessibility. Values for the Theil index can range between 0 to the 5.628 (the natural log of the number of zones, or 281), with 0 meaning that all zones have the same measure of accessibility and 5.628 meaning that there is a significant discrepancy in measured accessibility values. Again, indices are relatively low for all measures, implying that they have small ranges of accessibility values.

Gini Index

Finally, the Gini Index returns values between 0 and 1, with 0 indicating total equity across the region and 1 indicating worst inequality. The index measures statistical dispersion, which considers proportions of measures allocated within different ranges of high, average, and low accessibility. Slightly higher than the last index, these values denote relatively high levels of equity among the zones, with the minimum distance measure having the largest statistical dispersion.

Overall, the environmental justice inequality results show that each measure provides a unique interpretation of accessibility in terms of how equitably accessibility is distributed. Both gravity measures describe similar accessibility trends, as they again performed similarly throughout all the statistics. Minimum distance measures, however, provides the most skewed interpretation of accessibility. Overall, the simplified model leads to more drastic and extreme accessibility results. On the other hand, the patron microsimulation measure provides more streamlined and equitable version of accessibility.

5. POLICY-RESPONSIVE SCENARIO ANALYSES

While it may be useful to benchmark regional accessibility at a specific point in time, the main purpose of accessibility measures is to evaluate how changes in regional policies, demographics, and operations will affect individual's access to activity opportunities. This section uses the case study region to assess how two common issues (changing demographics and reduced budgets) will affect regional access to healthcare facilities. Unfortunately, the results from the first three accessibility measures will not change based on these issues because they do not incorporate these parameters into their calculation. The patron microsimulation measure, however, is sensitive to these issues and can be applied to evaluate the impact that changing demographics and reduced budgets have on accessibility.

5.1 2015 Population Demographics

One of the most common concerns for paratransit agencies is ensuring that their fleet operation can accommodate future demand. Travis County, like many other counties in Texas, is expected to grow within the next decade, causing shifts in both the number and location of paratransit patrons. In order to evaluate the effectiveness of the current fleet to meet these future demands, the patron microsimulation measure was used to run a scenario based on projected population data for 2015. In this scenario, the Travis County population was aged using the most likely 'one-half 1990-2000 migration' projection for 2015 from the Texas State Demographer (30). This projection was prepared based on averages between 1990 and 2000 population estimates and assumes net migration rates half of those seen in the 1990s. As such, this projection suggests slower, but still steady, growth rates compared to the 1990s. Specifically, the number of individuals aged 18-29 is increased by 0.921%, the number of individuals aged 30-49 is increased by 1.177%, the number of individuals aged 50-64 is increased by 2.160%, and the number of individuals aged 65 and greater is increased by 1.764% in each zone.

The first two maps in Figure 2 present the zone-based accessibility to healthcare facilities for the current conditions as well as for this first demographic shift scenario. It is important to recognize that the thresholds identified in the base scenario are also used in scenario 1, so the shading classification remains consistent. Again, higher levels of accessibility are represented by darker gray shading, and lower levels are identified by lighter gray shading. One can see that as the population changes by 2015, there is a slight decrease in the overall regional accessibility. There are fewer zones with accessibility scores in the high accessibility category, but many more in the average-high accessibility category. This is due to the fact that (1) there are more patrons requesting service, (2) the number of individuals requesting service increased in the periphery of the urban core, and (3) this demand is being served with the same fleet currently being used. Fortunately, most of the zones with the average-high accessibility levels are within the periphery of the urban core, where we see the most growth. These results might indicate that purchasing additional vehicles or circulating paratransit service around the urban core, rather than the outer regions, might be valuable means for improving future accessibility.

5.2 25-Percent Reduction in Service Hours

Another timely concern for paratransit operators is how reductions in operating budgets will affect regional accessibility. Paratransit operation costs a considerable percentage of transit providers' annual income, and, as a result, they are significantly affected when transit providers' federal funding is reduced. One option *MetroAccess* might consider to save funds is to reduce hours of operation by twenty-five percent. A considerable portion of *MetroAccess'* budget pays

for vehicle drivers, so reducing hours is a drastic but efficient means of saving funds. The patron microsimulation measure was again used to run a scenario in which fleet hours were reduced from 9 to 6 $\frac{3}{4}$ hours per day.

The last map in Figure 2 presents the zone-based accessibility to healthcare facilities for this second scenario. The thresholds identified in the base scenario apply to this map as well, and one can see that the reduction of service hours has significantly decreased paratransit patrons' access to healthcare facilities. There are almost no zones with high levels of accessibility and very few designated as average-high accessibility. Even those centrally located zones, which were conveniently located to facilities and well served in the base scenario see a drastic drop in access levels. These results highlight how important the availability of paratransit service is to patrons. These significantly reduced levels of accessibility are caused by operators simply being unable to meet the current demand. There are still many patrons in the outer regions of Travis County, and *MetroAccess* would be unable to serve them all with reduced hours. Not only does this appear to be an ineffective way to deal with the budget, but these results suggest that it might make operations worse by spreading patrons out over more time and increasing daily demand for service.

6. CONCLUSIONS

Despite the continued interest in transportation accessibility in both the literature and in practice, it is still unclear exactly how different types of accessibility measures relate to one another and which situations are best for each. Therefore, the current study undertakes a statistical comparison among four commonly applied transit accessibility modeling techniques to determine whether or not they are comparable and/or interchangeable.

Specifically, this analysis considers a case study of *MetroAccess* in Austin, Texas to quantify and measure individuals' access to healthcare providers via paratransit service. The four transit accessibility measures considered in this study (minimum distance, healthcare facility gravity, two-step cluster gravity, and patron microsimulation) represent the three main categories of accessibility models: cumulative, gravity, and utility-based. These measures were then compared using spatial accessibility distributions, which spatially describe how accessibility varies through the region; prediction evaluation statistics, which quantitatively evaluate how similar pairs of accessibility measures are; and environmental justice inequality statistics, which describe how each measure's interpretation of accessibility is distributed among the zones.

The results highlight a number of important conclusions regarding the comparability and interchange of accessibility measures. First and foremost, the three categories of accessibility measures provide drastically different interpretations of accessibility that cannot be duplicated by each other. When planners or policy-makers employ accessibility measures to support decisions, they must be careful and explicit about what measures they select, as they can offer quite different results. That being said, measures within the same category are often times comparable and interchangeable because they describe accessibility in similar terms. For example, the added complexity of the two-step cluster gravity measure did not provide significantly different results than the much simpler healthcare facility gravity measure.

Finally, the inequality statistics showed that the more closely accessibility models capture individuals' perceptions and true access to activity opportunities, the more consistent and evenly distributed the results. The simplified measures lead to more drastic, skewed, and extreme accessibility results for zones. However, the patron microsimulation measure provided a more streamlined and equitable version of accessibility. Furthermore, the patron microsimulation

measure provides a more realistic description of patrons' desired destinations and trip characteristics that are sensitive to changes in regional policies, demographics, and operations. The real purpose of accessibility measures is to evaluate how these changes will affect individual's access to activity opportunities, and it makes sense to develop measures of accessibility that can achieve this, as shown through the policy-responsive scenario analyses.

Ultimately, this study focused on one specific mode, activity opportunity, and spatial zoning system. While these conclusions are consistent and reliable, it is critical for researchers to continue to evaluate accessibility measures for other modes and activity opportunities.

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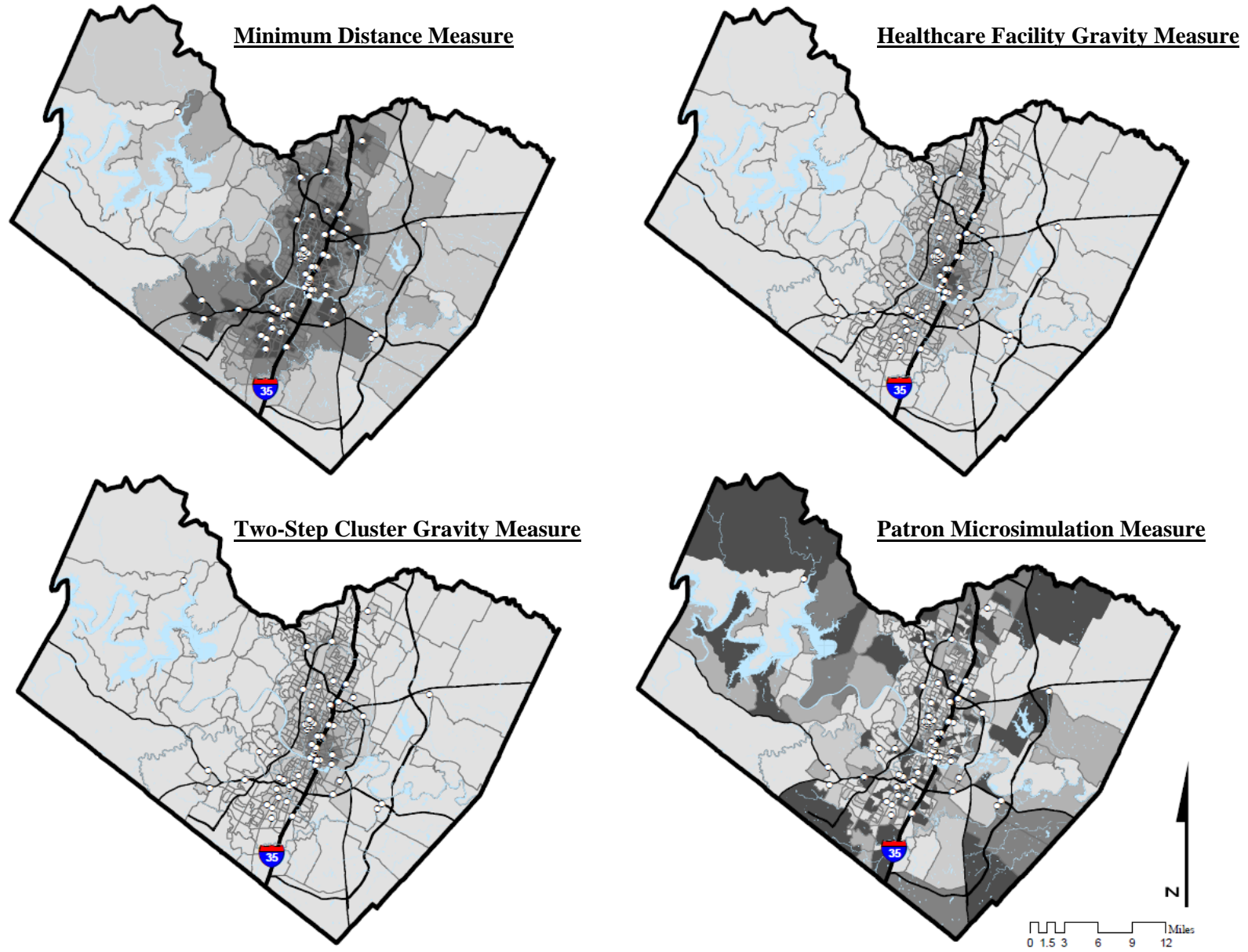


FIGURE 1: Healthcare Accessibility Measure Results

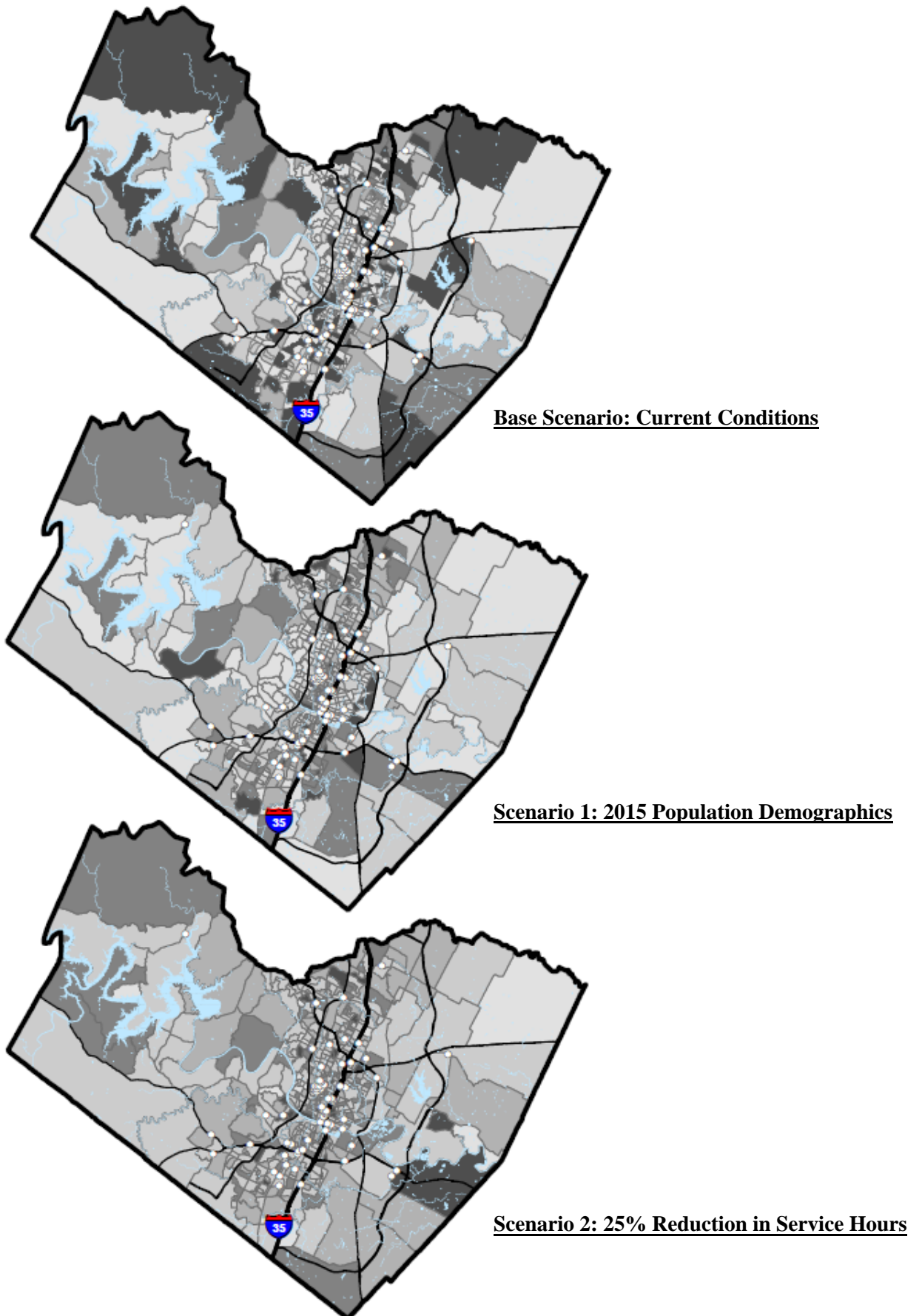


FIGURE 2: Healthcare Accessibility Changes Across Scenarios

TABLE 1: Prediction Evaluation Statistics Definitions and Results

Evaluation Statistic		Definition			
Percent Root Mean Square Error (PRMSE)		$PRMSE = \frac{1}{\bar{x}} \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - x_i)^2} \times 100 (\%)$			
Correlation Coefficient		$r^2 = \frac{1}{N} \sum_{i=1}^N \left(\frac{(y_i - \bar{y})(x_i - \bar{x})}{\sigma_y \sigma_x} \right)$			
Theil's Inequality		$U = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - x_i)^2} / \left\{ \sqrt{\frac{1}{N} \sum_{i=1}^N y_i^2} + \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \right\}$			
Mean Absolute Deviation (MAD)		$MAD = \frac{1}{N} \sum_{i=1}^N y_i - x_i $			
Tracking Signal		$TS = \frac{1}{MAD} \sum_{i=1}^N (y_i - x_i)$			
		Compared With...			
Evaluation Statistic For...		Minimum Distance Measure	Healthcare Facility Gravity Measure	Two-Step Cluster Gravity Measure	Patron Microsimulation Measure
Percent Root Mean Square Error (PRMSE)	Minimum Distance Measure	-	303.063	354.823	141.606
	Healthcare Facility Gravity Measure		-	48.166	107.492
	Two-Step Cluster Gravity Measure			-	108.690
	Patron Microsimulation Measure				-
Correlation Coefficient	Minimum Distance Measure	-	0.504	0.520	-0.167
	Healthcare Facility Gravity Measure		-	0.862	-0.157
	Two-Step Cluster Gravity Measure			-	-0.176
	Patron Microsimulation Measure				-
Theil's Inequality	Minimum Distance Measure	-	0.573	0.609	0.420
	Healthcare Facility Gravity Measure		-	0.175	0.550
	Two-Step Cluster Gravity Measure			-	0.579
	Patron Microsimulation Measure				-
Mean Absolute Deviation (MAD)	Minimum Distance Measure	-	0.642	0.668	0.503
	Healthcare Facility Gravity Measure		-	0.051	0.359
	Two-Step Cluster Gravity Measure			-	0.358
	Patron Microsimulation Measure				-
Tracking Signal	Minimum Distance Measure	-	280.855	280.970	246.533
	Healthcare Facility Gravity Measure		-	142.038	-157.008
	Two-Step Cluster Gravity Measure			-	-177.497
	Patron Microsimulation Measure				-

TABLE 2: Environmental Justice Inequality Statistics Definitions and Results

Inequality Statistic	Definition			
Coefficient of Variation	$c = \frac{\sqrt{\sigma^2}}{\bar{y}}$			
Relative Mean Deviation	$M = \frac{1}{N} \sum_{i=1}^N \left \frac{y_i}{\bar{y}} - 1 \right $			
Variance of Logarithms	$v_{log} = \frac{1}{N} \sum_{i=1}^N \left(\log \frac{y_i}{\bar{y}} \right)^2$			
Theil Index	$T = \frac{1}{N} \sum_{i=1}^N \left[\left(\frac{y_i}{\bar{y}} \right) \log \left(\frac{y_i}{\bar{y}} \right) \right]$			
Gini Index	$G = \frac{1}{2n^2\bar{y}} \sum_{i=1}^N \sum_{j=1}^N y_i - y_j $			
Accessibility Analysis Measure				
Inequality Statistic	Minimum Distance Measure	Healthcare Facility Gravity Measure	Two-Step Cluster Gravity Measure	Patron Microsimulation Measure
Coefficient of Variation	1.120	0.735	0.729	0.100
Relative Mean Deviation	0.740	0.524	0.497	0.089
Variance of Logarithms	0.195	0.113	0.101	0.002
Theil Index	0.191	0.101	0.096	0.002
Gini Index	0.498	0.375	0.248	0.057