

Aggregate accessibility to population at the county level: U.S. 1940–2000*

M.E. O’Kelly¹, M.W. Horner²

¹ Department of Geography, The Ohio State University, 1036 Derby Hall, 154 North Oval Mall, Columbus, OH 43210-1361, USA (e-mail: okelly.1@osu.edu)

² Department of Geography, Southwest Texas State University, 601 University Drive, 139 Evans Liberal Arts Building, San Marcos, Texas 78666-4616 (e-mail: mark.w.horner@swt.edu)

Received: September 2002 / Accepted: January 2003

Abstract. A classic study by Harris (1954) shows a map of U.S. national accessibility. Harris argued that access to population and income represents a critical factor for location analysis. Such maps and analyses are now readily produced by geographical information systems, allowing experimentation with various parameters, and explorations of changes. By comparing changes in these measurements we can develop a synthetic picture of the impacts of population redistribution. This paper offers a comprehensive review of these calculations and illustrates their use with maps from county population in the continental U.S. from 1940 through to 2000.

Key words: aggregate accessibility, market potential, population distribution

JEL classification: R11

1 Accessibility indices

Accessibility or the relative *potential* of a given location is an important topic in urban and regional research (Craig 1987, Pooler 1987, Taaffe et al. 1996). The problem of measuring a given location’s accessibility is one of determining the magnitude of opportunities within some specified distance or threshold of the location. Thus, when regional accessibility is to be calculated, nearby population, income, or other measure of demand may serve as a proxy for the opportunity accessible to the location. Anecdotally, a great deal is made of claims based on accessibility: for example we see cities and counties claim that a given percentage of the nation’s population is

* Previous versions of this paper were presented to the Initiative in Population Research (IPR) workshop at the Ohio State University (Horner) and to the Center for Spatially Integrated Social Sciences (CSISS) Summer Workshop in Accessibility (O’Kelly). Thanks to the referees for helpful comments.

within a day's drive of their location, and such measures are often touted as an index of centrality, or suitability for market distribution. We feel that there is a need to offset this kind of local measurement with a more panoramic view of accessibility at the national scale. It is only by comparing and tracking changes in these measurements that we can have a synthetic picture of the impacts of population redistribution. Among other questions, we would like to know whether decades of migration and population dynamics have produced noticeable changes in the aggregate levels of access that Harris (1954) argued is a critical ingredient in locational and development studies.

Our work is an *exploratory spatial data analysis* (ESDA) of population. ESDA entails constructing informed summaries of spatial data; mapping and visualization of spatial phenomenon; and, uncovering underlying geographic processes (see Bailey and Gatrell 1995). ESDA approaches often include the calculation and visualization of summary statistics within GIS to identify spatial patterns of interest (Bailey and Gatrell 1995). In the present paper we show how accessibility indices may be used to explore spatial population issues in a GIS environment.

Operationally, a set of areas and their populations are easily input into an accessibility model such as the one used by Harris (1954) to measure US market potential. To demonstrate a similar model, we let A be the accessibility at area i and P be the population at area j . Further, we let d_{ij} define a matrix of straight-line distances between area centroids. The model is:

$$A_i = \sum_{j:j \neq i} P_j d_{ij}^{-1} \quad (1)$$

In the formulation above, distance between locations negatively impacts an area's accessibility. That is to say, if one holds population constant, proximal locations contribute more to an area's accessibility than do distant ones. Indeed, the most accessible places are those that are near many other large centers of population.

Unfortunately, the model of potential in Eq. (1) is formulated such that an area's own population is not counted in its accessibility score. This is a necessary exclusion because when $i = j$, $d_{ij} = 0$, which would lead to an invalid divide by zero in Eq. (1). See also Frost and Spence (1995) who discuss means to handle "self-potential." Although the Harris-type model appears to be a plausible approach to measuring locational accessibility, in practice, a model of the form in Eq. (1), where an area's own population is excluded from its accessibility score, may produce 'donuts' in the map pattern. For example, when these scores are visualized, it may be the case where highly accessible central areas actually appear to be *less accessible* than their peripheral neighbors. It is possible to circumvent this property of Eq. (1) by using strictly positive weights as a function of the values of distance. This might entail assigning each area's nearest neighbor distance to the diagonal of d_{ij} (Plane and Rogerson 1994). However, a different approach to accounting for an area's own population in the accessibility score is to model the deterrent effect of distance using the exponential function. Consider the following equation:

$$A_i = \sum_j P_j \exp(-\beta d_{ij}) \quad (2)$$

In Eq. (2), the exponential function is used to model the deterrent effect of distance on an area's accessibility score. Since $\exp(0) = 1$, the case of $d_{ii} = 0$ is easily handled, and therefore an area's entire population is counted into its own accessibility statistic. The decay of the exponential function in Eq. (2) is governed by the parameter β . The parameter β is shown with a negative sign by convention, as it is indicative of the deterrent effect of distance (Fotheringham and O'Kelly 1989). To apply Eq. (2) one need only choose a suitable value for β . Suppose that at a distance d from area i , we want Q (expressed as a fraction) of the j th area's population to be counted into i th area's accessibility score. Then,

$$\exp(-\beta d) = Q \quad (3a)$$

Taking the natural logarithm, rearranging terms, and solving for β explicitly yields:

$$\beta = -\frac{\ln(Q)}{d} \quad (3b)$$

The purpose of Eq. (3b) is to show that fixing any two of the three quantities β , Q or d will permit the third to be determined. For given β there is a downward sloping relationship between influence and distance. Shifts in β correspond to relaxation of the "ceteris paribus" assumption, and in effect relate to parametric shifts in conditions.

A second approach to measuring regional population accessibility is to impose some threshold to delimit which areas may count in the area's accessibility statistic (Plane and Rogerson 1994). Notice the model in Eq. (2) imposes no strict limitations on an area's accessibility score beyond those implied by the deterrent effect of distance. To remove this property from Eq. (2), we modify the formulas above such that only the population within some pre-specified distance, S is counted. This yields the following measure:

$$A_i^s = \sum_j P_j \quad \forall j \ni d_{ij} \leq S \quad (4)$$

Given this formulation, there are two subtle differences between the models in Eq. (2) and (4) that should be pointed out. First, because Eq. (2) uses continuous distance, it will always produce a more generalized map pattern than Eq. (4), unless one chooses a relatively large value for S in Eq. 4, or a very large value for β in Eq. (2). Second, a possible advantage of the model in Eq. (4) is that A_i^s is calculated in terms of population, whereas A_i calculated in Eq. (2) is a composite index with a slightly less direct interpretation: it measures weighted population, where the weights are governed by the exponential distance decay parameter. This kernel smoothing technique is familiar to geographers, and is now a standard operation in commercial GIS packages. Both the kernel and distance threshold models provide useful measurements of accessibility, especially when there is an opportunity to investigate changes in them over time.

While beyond the immediate scope of the present paper, there are a number of noteworthy methodological connections and linkages between the accessibility indices worked with here and the broader literature. We list some of these for the purposes of encouraging further cross-references between method and application. For example, Fotheringham, Brunson and Charlton (2000) have argued that spatial effects (e.g. accessibility) are

essential ingredients in statistical analysis. It is when these effects are ignored that traditional aspatial statistical analyses produce confusing or misspecified results. Thus, it is critical to be able to measure appropriate access scores. Obviously, we are simply using them descriptively here, but when we consider *kernels*, we open the possibility of kernel estimation. The term “kernel” is used to describe the idea that there are a series of spatial weights having a distance decay and a “bandwidth” (or maximum radius) within which effects are summarized. Bailey and Gatrell (1995) cogently describe the idea of spatially averaged or weighted observations, which they then show may be viewed as a kernel. In part then, this paper links a traditional spatial analysis smoothing technique with more complex kernel smoothers. Fotheringham, Brunson and Charlton (2002) also devise a powerful geographically weighted regression process, which they present and justify as a kind of spatial smoothing.

2 Properties of the exponential-based potential measures

The role of distance decay in trend and patterns of accessibility is described in this section, and several standard measures are devised to describe the changes in accessibility and the sensitivity of access measures to changes in the distance decay parameters.

To begin, assume we have i to n areal units. In general, the accessibility, or potential at unit i is given by

$$A_i = \sum_j P_j f(d_{ij}) \quad (5)$$

We will proceed by letting $f(d_{ij}) = \exp(-\beta d_{ij})$ as in Eq. (3a), and note that \mathbf{P} is the total regional population.

Differences in accessibility surfaces are governed by choices of spatial discount (β) parameters. The summation over all surrounding counties, weighted by a decreasing function of distance, has the effect of smoothing larger regional variation (if β is small in absolute value reasonably distant elements contribute to the score). Alternatively the surface generated using (5) can be quite spiky if the β parameter is large in absolute value and so the weights are primarily tracking the local summation of population. These properties of kernel smoothing operators are well known (see for example Bailey and Gatrell 1995). But what about the difference between these surfaces for a fixed time over different β values? We would like to be able to answer the following questions: how does accessibility increase when we decrease the role of distance decay, and how do variations of this measure show up across space? Further, what are the mathematical limits and expectations about such a measure? Another line of questioning might be about the difference for the same β value in different time periods. This would answer the following: how has a county changed in its overall access over time, given a constant distance decay rate?

While an enormous variety of effects can be accommodated through variations in the parameters, these parameters ought to be selected to relate to readily interpretable facts about the weighting scheme. It does not, in our opinion, make much sense to attempt to calibrate these values to any particular observation, and indeed it is hard to imagine what statistical

observation could be used as an empirical value in a maximum likelihood sense. Rather, we are going to present a tool for performing comparative statics. The tool should be capable of answering the “what if” kinds of questions that arise in changing landscapes of access, and should have sufficient parametric freedom to incorporate a large number of possible scenarios. Among these, we focus on reasonable encoding of probable trends in urban system accessibility. For instance, it is widely accepted that the deterrent effects of distance have declined over time (Janelle 1969). Instead of presenting the results in terms of β values, we might decide to fix β to achieve some specified degree of weighting at specific distances. What combination of β values, for example, gives a 50% weight to population at 100 miles and at the same time is contrasted with the surface that gives 50% weight to population at 200 miles? To explore this issue, we will stipulate that the population surface has a temporal subscript t and that β is given for two time periods: β_1 and β_2 . Throughout the following assume $|\beta_1| > |\beta_2|$.

Let

$$A_{it}^1 = \sum_j P_{jt} \exp(-\beta_1 d_{ij}) \quad (6)$$

$$A_{it}^2 = \sum_j P_{jt} \exp(-\beta_2 d_{ij}) \quad (7)$$

where A_{it}^1 is the accessibility of county i , at time t , under parametric assumption 1. A large β in absolute value (denoted β_1) corresponds to a steep distance discount factor, and by assumption the second value of β denoted β_2 is the smaller value (more weight attached to the larger distances).

Assume that the difference between (6) and (7) is taken to be a positive number, that is, $A_{it}^2 - A_{it}^1 =$

$$\sum_j P_{jt} \exp(-\beta_2 d_{ij}) - \sum_j P_{jt} \exp(-\beta_1 d_{ij}) \quad (8)$$

$$\sum_j P_{jt} [\exp(-\beta_2 d_{ij}) - \exp(-\beta_1 d_{ij})] \quad (9)$$

The question then is the location (d_{ij}) at which the weight contribution is largest to this contrasted surface. Differentiating with respect to d_{ij} yields:

$$\frac{d}{d(d_{ij})} (\exp(-\beta_2 d_{ij}) - \exp(-\beta_1 d_{ij})) = -\beta_2 \exp(-\beta_2 d_{ij}) + \beta_1 \exp(-\beta_1 d_{ij}) \quad (10)$$

To find the maximum value, we set the result of (10) equal to zero and solve for d_{ij}

$$-\beta_2 \exp(-\beta_2 d_{ij}) + \beta_1 \exp(-\beta_1 d_{ij}) = 0 \quad (11)$$

So,

$$\beta_2 \exp(-\beta_2 d_{ij}) = \beta_1 \exp(-\beta_1 d_{ij}) \quad (12)$$

Taking the natural logarithm of each side yields

$$\ln(\beta_2 \exp(-\beta_2 d_{ij})) = \ln(\beta_1 \exp(-\beta_1 d_{ij})) \quad (13)$$

Using properties of logarithms, we know that

$$\ln(\beta_2) - \beta_2 d_{ij} = \ln(\beta_1) - \beta_1 d_{ij} \quad (14)$$

Rearranging (9) and solving for d_{ij} , we obtain

$$d_{ij} = \frac{\ln(\beta_1) - \ln(\beta_2)}{(\beta_1) - (\beta_2)} \quad (15)$$

Further, if we combine the desire to have the weight at a specific distance, perhaps 50%, and the maximum contrast to occur at a specific distance, then the limited degrees of freedom require that the β_1 and β_2 values be determined to simultaneously solve Eq. (16)–(18):

$$D_{\max} = \frac{\ln(\beta_1) - \ln(\beta_2)}{(\beta_1) - (\beta_2)} \quad (16)$$

$$d(Q_1, \beta_1) = -\frac{\ln(Q_1)}{\beta_1} \quad (17)$$

$$d(Q_2, \beta_2) = -\frac{\ln(Q_2)}{\beta_2} \quad (18)$$

Interestingly, if we suppose that the β_2 value is a fixed percentage of the larger β parameter (say $\beta_2 = \alpha\beta_1$), we find that the ratio of the distance at which the either of the weights equals Q to the maximum contrast distance is a constant. A proof (demonstrated for Q_2) is in Appendix A.

Interpreting the result another way (A.5) shows that if β_2 is in a fixed ratio to β_1 then changes in β produce proportionate changes in many of the relationships between the surfaces. In practical terms, this result is useful to the analyst exploring a spatial data set with accessibility indices because it provides some guidance and expectation regarding choices of β .

To illustrate numerically, suppose for example D_{\max} (see Eq. 16–18) is required to be 120, $Q_1 = 0.5$, and $d(Q_1, \beta_1) = 35$, what then are the appropriate parameters? Clearly $\beta_1 \times 35 = -\ln(0.5)$, and so $\beta_1 = 0.0198$. With that constant, we see that $120 = [\ln(0.0918) - \ln(\beta_2)] / [0.0198 - (\beta_2)]$ which can be solved for $\beta_2 = 0.00248$.

Of course what cannot be independently selected in this context is the distance at which the second distance decay function reaches Q_2 [say 50%]. Once β_2 is selected to satisfy the first two conditions, we see that the second distance decay has a weight of 50% at about 280 miles. The difference between the two accessibility surfaces will show, graphically, the expected change in accessibility as (for example) the distance decay parameter is modified or the population weights are reconfigured. This would be useful to emphasize contrasts between urban systems under different parametric conditions.

The work stated above is in terms of trying to come to grips with two contrasted accessibility surfaces computed from different β parameters. What then about the contrast between two surfaces as computed from two different cut off radii (see Eq. (4)). One of the observations that is seen from map analysis of county level data is that the difference between the 100 mile cut-off surface and the 50-mile cut off surface seems to produce ring patterns around the major urban centers. This at first glance might be thought to be revealing something significant about the sprawl of populations. Nevertheless, once we delve into the mechanical details of the construction of these

measures we see that there is a more straightforward explanation. When the difference is taken from the point of view of a large population center (e.g. Franklin County, Ohio) the difference will be small (because the large core population is added and subtracted). However when a smaller peripheral county within perhaps 100 miles of a larger urban county is considered, the impact of the large accessible population inside 100 miles is added and there is no offsetting subtraction at the 50 mile radius (by hypothesis this is a small peripheral county). This county will therefore have a high positive contrast with its more central neighbors. The best way to think of this map is as one indicating those places that have high contrasts between their local (small) population and their accessible central nearby counties. In a way then these indices will help to identify the ex-urban fringe quite nicely.

3 Applications

Throughout the 1990's significant population growth and decline took place in the United States. With respect to metropolitan areas, suburban locations grew at the expense of central city cores (Ding and Bingham 2000). There has been increased suburban subcenter development, so-called 'edge city' development, and development beyond the rural-urban fringe known as exurban development (Lucy and Phillips 1997). Areas classified as being nonmetropolitan have also seen increases in their number of fast-growing communities (Beyers and Nelson 2000). At the national scale, regions experience vastly different population outcomes. The well-known Rust Belt to Sun Belt migration stream, which has sent mobile Americans southward in search of new residences, is a significant regional population shift where northern states have lost population to southern states (Plane and Rogerson 1994). Similar issues have been dealt with in Europe where the goal of closing the gap between core and periphery is tackled in studies of accessibility and economic development (e.g. Vickerman and Spiekermann 1999). Indeed very influential studies in the eighties by Keeble and collaborators led to the use of the same basic access scores as mentioned here, in measuring European accessibility variations. Further, those studies show the same kinds of contrasts between core and peripheral areas as characterize the US accessibility map.

The accessibility indices presented in the past section are excellent approaches for exploring regional population differences, both spatially and temporally. The release of the 2000 decennial census data provides a tremendous opportunity to investigate these issues. By analyzing 1990 and 2000 US county population data with these indices, we are able to identify broad trends over the past decade. The two measures population accessibility formulated in Eq. (1) and (4) are employed to understand how regional population change occurred during the period 1990–2000. To place these results in context, we also analyze data from past censuses 1940–1980 and report on historical county accessibility trends. Our measures are computed within GIS, allowing them to be mapped for the continental United States.

Using population accessibility indices to investigate regional population change is advantageous since population accessibility indices produce *spatial* summaries of population distributions, whereas simple change statistics do not take regional trends into account. Moreover, accessibility indices provide

an objective quantification of the opportunities relative to a given location since the indices illustrate an area's potential opportunity within larger urban and regional contexts. From a practical standpoint, these indices are easily computed and visualized using commercial geographic information systems (GIS) available today.

3.1 Past research using accessibility indices

Accessibility indices have been used directly in studies of urban and regional population issues (see Pooler 1987). As mentioned previously, the seminal work of Harris (1954) developed an index of market potential which was used to delineate economic agglomerations across the continental US. Since then, many studies have focused on aspects of accessibility. Work by Craig (1987), for example, discusses the interpretation of population accessibility measures, while Pooler (1987) provides an extensive history and review of potentials and related concepts. More recently, Geertman and Van Eck (1995) demonstrate how one may integrate accessibility indices with GIS for planning purposes. Given the ease of integrating population accessibility indices with GIS, indices such as the one by Harris (1954) have been recently applied in studies of urban and regional issues. For example, Horner and Grubestic (2001) incorporate a variant of the Harris potential model into a planning methodology that determines the locations of urban rail terminals. Similarly, Van Wee et al. (2001) adapt the basic accessibility measure to explore intrametropolitan employment patterns, with particular focus on competition effects among job locations.

Spatial analysis techniques are often applied to explore and elucidate changes in the distribution, composition or movement of population. In fact, numerous researchers have analyzed aggregate spatial data in an attempt to discern patterns in population and related phenomena. Seminal work by Vining and Strauss (1977) uses the Hoover concentration index to search for evidence of population concentration. Lichter (1985) computes similar indices of population concentration by race and region for the years 1950–1980. Fuguitt and Beale (1996) also review trends in US population, focusing on nonmetropolitan migration over the past thirty years. They note that migration trends have fluctuated during past decades, as migrants' residential preference for nonmetropolitan areas has varied. Rogers and Sweeney (1998) use the Gini index and the coefficient of variation to measure the *spatial focus* of migration streams in the US. Spatial focus is the degree of concentration of the migration streams between places. Rogers and Raymer (1998) consider the spatial focus of US interstate migration flows. They detail the differences in spatial migration patterns based on age, race, and other disaggregate characteristics by the time period of the move. Plane (1999a) develops the concept of *migration drift*, which is a summary of the average distance and direction moved by migrants in a country during a given time period. Plane finds that during the early 1990's the US's predominant east to west migration trend actually reversed itself, due in part to large amounts of out-migration from California. Other work by Plane (1999b) accounts for the effects of migrants' personal income on state economies. Plane finds that the states receiving the largest gains in absolute dollars from in-migrants (1993–1994) were Florida (\$3 billion), Arizona (\$1.3 billion), North Carolina

(\$1.2 billion) and Georgia (\$1.1 billion). Most recently, Beeson et al. (2001) model long term growth trends in US counties (1840–1990) as a function of education, transport and other factors.

To summarize, the aggregate spatial analyses reported in these research papers are of great interest to geographers, regional scientists and demographers interested in spatial population phenomena. Moreover, the ability of accessibility indices and their variants to summarize complex population distributions places them squarely within the family spatial analysis techniques useful for exploring population issues. To demonstrate the value of accessibility indices as tools for exploring population issues, we now move to describing the data and analysis performed.

3.2 Analysis

Data describing US county population from the 1990 and 2000 decennial census were obtained from the US census web site (www.census.gov). These data were imported into a GIS layer containing all of the US counties with TransCAD v. 3.2. For purposes of the study, only the counties of the continental US were included in the database.

A statistic familiar to those interested in spatial demographic issues is population change. Figure 1 shows a map of population change for the years 1990 and 2000. Darker shades are used to illustrate areas that have experienced greater positive population change. Although the map is quite varied in terms of spatial patterns, there are some trends to be pointed out. First, both the western and southeastern United States were among the fastest growing regions during the past decade. The five fastest growing counties during this time period were Douglas CO (191%), Forsyth GA (123%), Elbert CO (106%), Henry GA (103%) and Park CO (102%). Conversely, there were several regions that experienced flat or even negative population growth. Examples of these regions are found in the western plains states of Montana stretching southward to Texas, and the Appalachian core region extending from West Virginia into parts of eastern Ohio, western Pennsylvania and southern New York. Several of the counties along the Mississippi River in Louisiana and Arkansas also had little or no population growth. The regional trends illustrated in Figure 1 are taken up in more detail in the next section through application of accessibility indices.

3.2.1 County accessibility index results

Figures 2 and 3 show the maps of accessibility potentials as calculated by Eq. (2). For both years, we let the critical distance for .5 weight to be $d = 100$ (see Eq. 3), thereby counting half of the j th county's population at a distance of 100 miles away into the i th county's accessibility score. Each county's accessibility score is divided by an arbitrary scalar (1,000,000) to make them more manageable. The maps reveal very broad regional trends of accessibility, with the highest areas concentrated in the Northeast and Midwestern US. As one moves west, one generally finds declining accessibility until California is reached. Incidentally, the five most accessible counties in 1990

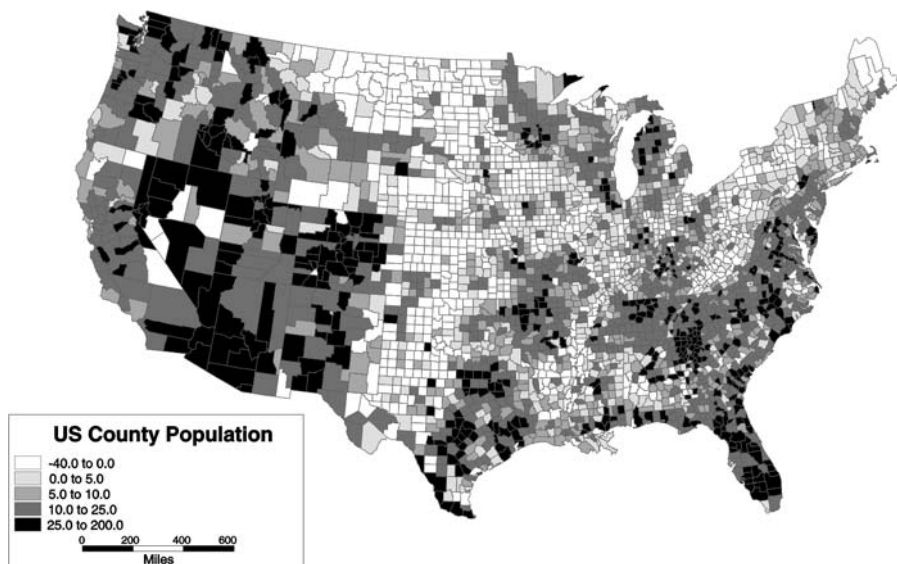


Fig. 1. 1990–2000 population % change

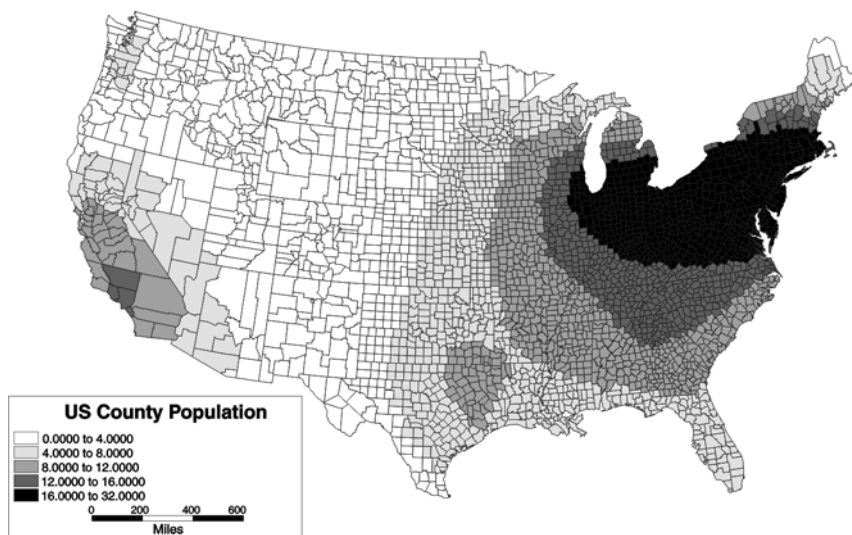


Fig. 2. 1990 relative accessibility scores

were Hudson NJ (1), New York NY (2), Essex NJ (3), Union NJ (4) and Kings NY (5). These five counties were also the most accessible in 2000.

Comparing Figs. 2 and 3, the dramatic increase of top-tier accessibility between 1990 and 2000 is particularly interesting. In fact, the leading edge of this classification (accessibility values = 16+) on Fig. 2 are further extended southward on Fig. 3 to include significant portions of North Carolina and

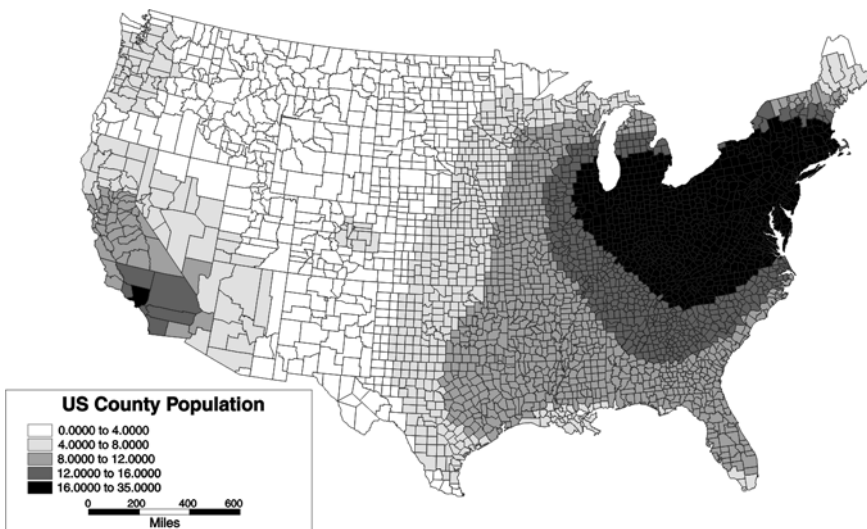


Fig. 3. 2000 relative accessibility scores

Tennessee. While it is difficult to determine the cause of this spatial shift, the increased prominence of southern locations in the top tier may be due to continued Frost-belt to Sun-belt migration that occurred throughout the 1980's (see Plane and Rogerson 1994). More concretely however, we do know that much of the population growth during the 1990's was concentrated in the South and the Western US (Perry and Macun 2001). In fact, the Census indicates that Texas, Florida, and Georgia were among the top five states in terms of the most people added during the 1990's. Further many of these same locations experienced dramatic increases in their levels of diversity. Smith et al. (2000) point out the rapid increases in the Hispanic and Asian and Pacific Islander populations in the southern US over the period 1990–1999. They note that the Hispanic and Asian and Pacific Islander populations more than doubled in Georgia, while the Hispanic populations North Carolina and Tennessee also grew by more than 100%.

Historically speaking, the spatial patterns of accessibility in both figures are very similar to those found in Harris' (1954) original work. Using data on county population from past censuses, we are able to discern temporal trends in the data and comment on long-term accessibility patterns. Just as was done for the 1990 and 2000 county population statistics, the exponential accessibility formula with $Q = 0.5$, and $d = 100$ (see Eq. 3) is calculated for each decade 1940 to 1980. Table 1 presents a summary statistic for each decade's average county accessibility score. Depending on how the statistic is calculated, one finds quite differing trends in average accessibility for the United States. If all counties' population and accessibility are each summed, and then the total accessibility is divided by the total population, one finds 'total per capita accessibility' ($\sum A_i / \sum P_i$). This quantity actually declines due to total population growing faster than total accessibility over the period 1940–2000. Conversely, if each county's accessibility score is divided by its population, and this ratio is added up for all counties, 'total average

Table 1. Summary of historical accessibility indices

Year	Population (millions)	A_i summary		A_i^f summary	
		Total of Accessibility Scores*	Total of Accessibility Scores (per capita)	Total of US Population within 50 miles*	Total of US Population within 50 miles (per capita)
Total accessibility per capita					
1940	131.67	191,469.77	147.87	1,714.24	13.02
1950	150.70	21,660.63	143.74	1,923.70	12.77
1960	178.46	24,762.16	138.75	2,210.92	12.39
1970	202.14	27,452.20	135.81	2,468.10	12.21
1980	225.18	29,852.98	132.57	2,667.41	11.85
1990	247.05	31,671.76	128.20	2,855.68	11.56
2000	279.59	35,333.00	126.37	3,194.28	11.42
Total average accessibility					
		A_i Summary	A_i^f Summary		
		Total of Local Ratios*	Total of Local Ratios		
1940	131.67	1.14	69,886.58		
1950	150.70	1.32	77,537.06		
1960	178.46	1.56	86,002.26		
1970	202.14	1.73	90,704.83		
1980	225.18	1.73	89,523.44		
1990	247.05	1.87	92,409.56		
2000	279.59	2.00	93,601.01		

*scaled by 1×10^{-6}

accessibility' generally increases from 1940–2000 ($\Sigma(A_i/P_i)$). The only anomaly in the trend is flat accessibility growth from 1970 to 1980 (both scores were about 1.73). This finding is perhaps explained by population deconcentration throughout the 1970's as discussed in Vining and Strauss (1977).

Returning to the most recent decade, the latest two years' potential scores may also be compared simply by calculating the percent change in relative accessibility indices from 1990 to 2000. When this operation is performed, one roughly finds the inverse map to those maps appearing in Figures 2 and 3. The analysis shows that the areas experiencing the greatest percent gains in population potential were relatively inaccessible areas in both 1990 and 2000. On the other hand, the already accessible urban regions, particularly in the northeast maintained their stature from 1990–2000. Table 2 reports that the counties experiencing the largest percent gains in relative accessibility (A_i) from 1990–2000 were Maricopa AZ (30.27%), Pinal AZ (29.87%), Gila AZ (29.41%), Pima AZ (28.48%) and Yavapai AZ (28.28%). If we consider the data from 1940 and calculate the percent change in accessibility from 1940 to 2000, we find a more varied set of fast-growing regions. Broward FL had the largest percent change in accessibility (721.46%), while other counties in Florida and Arizona rounded out the top five counties in Table 2. Table 2 also shows that the counties around New York City have been among the most accessible over the last 60 years.

3.2.2 County population accessible within 50 miles results

To differentiate among the broad regional trends depicted in Figs. 2 and 3, the model in Eq. (4) is calculated using $S = 50$. This choice of S represents a small radius, which should produce maps more generalized than the simple population change map (Fig. 1), yet the maps should exhibit a higher level of regional variation than exponential-based accessibility maps (Figs. 2–3). Figure 4 shows the map of population accessible within 50 miles for 1990 (Eq. 4). Most of the major metropolitan areas in the United States appear as dark clusters of counties. The most interconnected urbanized counties appear as large expanses of darkly shaded counties in the northeast, midwest and southwestern United States. Eq. (4) is calculated for the 2000 population data and mapped in Fig. 5. In general, the map pattern of the 1990 statistic persists for the 2000 statistic. As shown in Table 2, the top 5 counties for largest population within 50 miles were the same for 1990 and 2000 (Middlesex NJ, Somerset NJ, Nassau NY, Bergen NJ, New York NY). However, when comparing individual counties from map to map, many times it is the case that metropolitan areas have expanded in terms of the number of counties that comprise them. For example, looking at the Atlanta area for 1990, one can see that the number of counties that are *visually* a part of the metropolitan area actually increased in 2000.

Focusing on the case of Atlanta, application of the accessibility index highlights spatially the pressures of its growing suburbs and exurbs. Recent work by Helling (1998) describes the changing nature of urban form in Atlanta, where residences and employment continue to decentralize. At the same time, Atlanta has become one of the most congested places in the US (TTI 2002). Proposed solutions to dealing with congestion entail reorienting

Table 2. Historic accessibility trends for specific countries

Top 5 accessible countries based on A_i			
1940	1950	1960	1970
1 Hudson, NJ	Hudson, NJ	Hudson, NJ	Hudson, NJ
2 New York, NY	New York, NY	New York, NY	New York, NY
3 Essex, NJ	Essex, NJ	Essex, NJ	Essex, NJ
4 Kings, NY	Kings, NY	Kings, NY	Kings, NY
5 Union, NJ	Union, NJ	Union, NJ	Union, NJ
1980	1990	2000	
1 Hudson, NJ	Hudson, NJ	Hudson, NJ	
2 New York, NY	New York, NY	New York, NY	
3 Essex, NJ	Essex, NJ	Essex, NJ	
4 Union, NJ	Union, NJ	Union, NJ	
5 Kings, NY	Kings, NY	Kings, NY	
Largest % cng. (1940–2000)	Largest % cng. (1990–2000)		
1 Broward FL (721.46%)	Maricopa AZ (30.27%)		
2 Miami–Dade FL (712.32%)	Pinal AZ (29.87%)		
3 Maricopa AZ (704.86%)	Gila AZ (29.41%)		
4 Monroe FL (690.56%)	Pima AZ (28.48%)		
5 Pima AZ (657.79%)	Yavapai AZ (28.28%)		
Top 5 accessible counties based on A_i^2			
1940	1950	1960	1970
1 Somerset, NJ	Middlesex, NJ	Middlesex, NJ	Middlesex, NJ
2 Middlesex, NJ	Somerset, NJ	Somerset, NJ	Somerset, NJ
3 Westchester, NY	Westchester, NY	Bergen, NJ	Nassau, NY
4 Bergen, NJ	Bergen, NJ	Nassau, NY	Bergen, NJ
5 New York, NY	New York, NY	New York, NY	New York, NY
1980	1990	2000	
1 Middlesex, NJ	Middlesex, NJ	Middlesex, NJ	
2 Somerset, NJ	Somerset, NJ	Somerset, NJ	
3 Nassau, NY	Nassau, NY	Nassau, NY	
4 Bergen, NJ	Bergen, NJ	Bergen, NJ	
5 New York, NY	New York, NY	New York, NY	
Largest number of persons added within 50 miles (1940–2000)	Largest number of persons added within 50 miles (1990–2000)		
1 Los Angeles CA (7.41 million)	Morris NJ (1.43 million)		
2 Ventura CA (7.41 million)	Richmond NY (1.39 million)		
3 Contra Costa CA (6.14 million)	Somerset NJ (1.38 million)		
4 Nassau NY (5.58 million)	Bergen NJ (1.37 million)		
5 Fairfield CA (5.55 million)	Union NJ (1.36 million)		

land uses to support more efficient travel (see Horner and Murray 2003). However, these plans will be come increasingly challenging to implement as metropolitan functional regions expand as they have in the case of Atlanta.

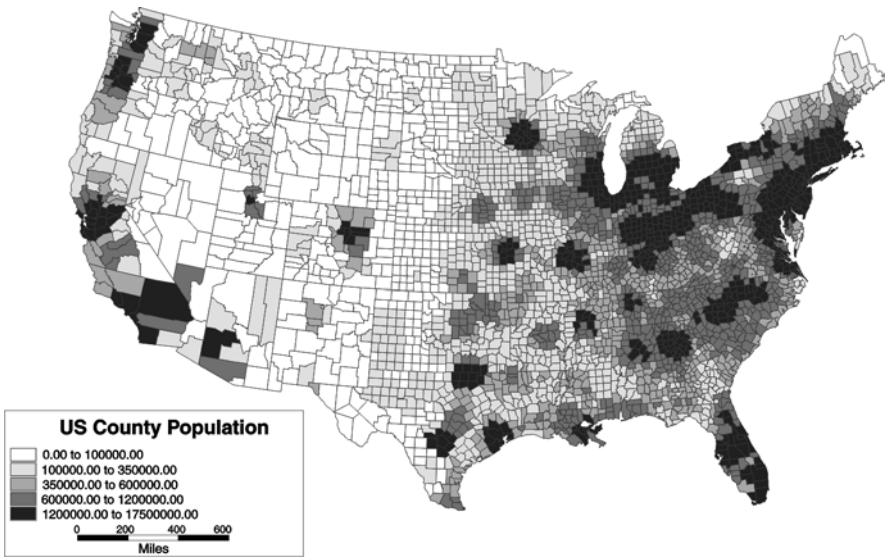


Fig. 4. 1990 population within 50 miles

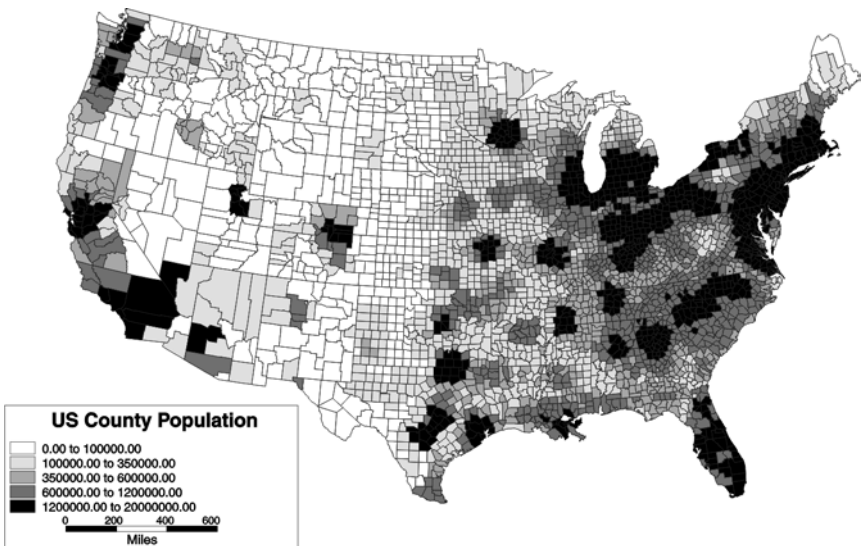


Fig. 5. 2000 population within 50 miles

We may also look at A_i^s from a historical perspective. Returning to Table 1, it is noted that the trends in county population within 50 miles virtually mirror the trends in the accessibility index (A_i). For the ‘total accessibility per capita’ approach, we find that the summary statistic of population within 50 miles *decreases* over time, while for the ‘total average accessibility’ approach, we find that the summary statistic of population within 50 miles *increases* over time.

These trends may be visualized for the entire set of counties simply by subtracting the 1990 population within 50 miles from the 2000 population within 50 miles. From this operation, we know how many people within 50 miles a county added, or lost in some cases. These values are mapped in Fig. 6 and reveal some very interesting patterns. First, one notices that several regions have lost population as evidenced by the Appalachian region and some of the plains states. Conversely, the coastal areas of the mid Atlantic States and the southeastern United States systematically added population. Similar gains in regional population were made for the Midwest, Florida and California. As listed in Table 2, the counties adding the largest number of persons within 50 miles from 1990 to 2000 were Morris NJ (1.43 million), Richmond NY (1.39 m), Somerset NJ (1.38 m), Bergen NJ (1.37 m), Union NJ (1.36 m). Using the historical data and performing the same calculations, we found that that the counties of southern California and Nassau NY added the most people within 50 miles from the period 1940–2000, as shown in Table 2. The difference in county population within 50 miles is also shown in Fig. 7. The Plains States, the Mississippi River Basin and Appalachian region all appear to have lost population. In contrast, regions such as the Piedmont stretching from North Carolina to Georgia, the east Lakes of the Midwest, and Northeast all gained population. Similar to the 1990–2000 pattern in Fig. 6, Fig. 7 also shows that California and Florida made significant gains in population within 50 miles from 1940–2000.

4 Discussion and conclusions

The present paper has concerned itself with (1) reviewing selected measures of accessibility, (2) examining properties of exponential based accessibility

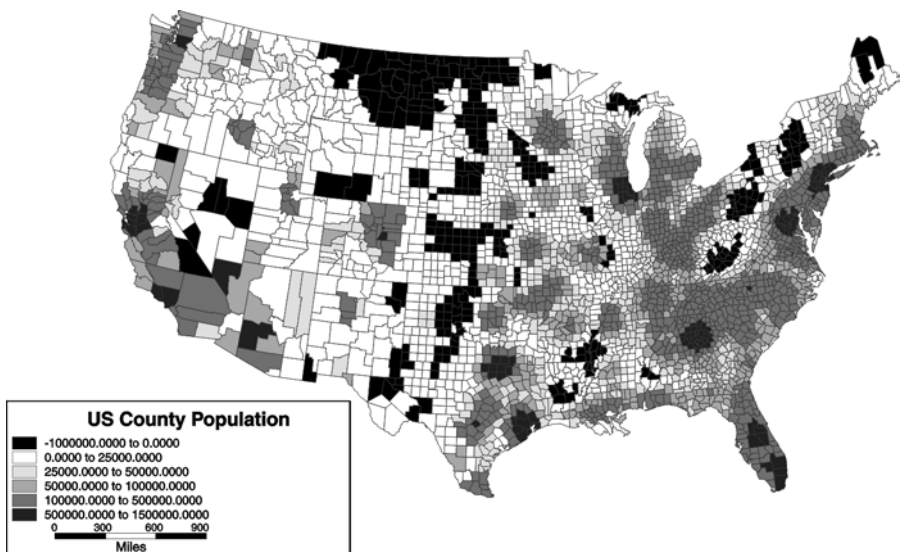


Fig. 6. Difference in 2000–1990 population within 50 miles

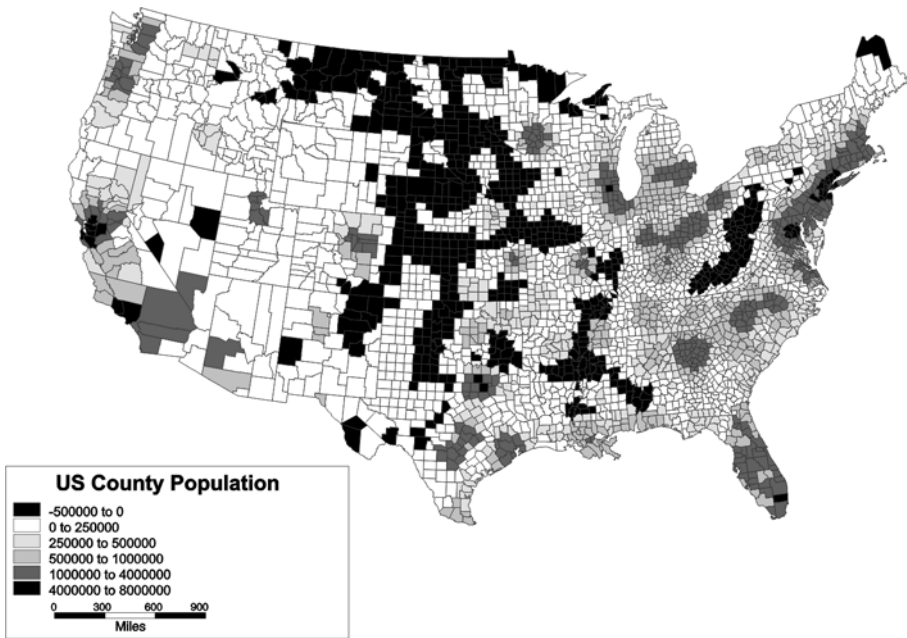


Fig. 7. Difference in 2000–1940 population within 50 miles

formulations in detail, and (3) applying accessibility indices to newly released county level census data to discern trends in the US population distribution. Our analysis of the 2000 decennial census and census data from prior years illustrates regional US population trends using county-based accessibility measures. Changes in regional population patterns during past decades are quantified. Substantive findings from examination of maps show that certain regions of the United States, particularly the ‘sun-belt’ areas, continue to be high-growth areas, while other US regions have lost population over the last decade (e.g. the plains states and Appalachia).

Taken in total, we have demonstrated approaches for the *exploratory spatial data analysis* of population issues. As previously stated, ESDA approaches often include the calculation and visualization of summary statistics within GIS to identify spatial patterns of interest (Bailey and Gattrell 1995). With the present data-rich environment, one need not be constrained to simply county level analysis as we demonstrated here. For example, future exploration at the *intraurban* level is especially valuable as researchers seek understandings of sprawl and metropolitan population change (see Ding and Bingham 2000). It is hoped that our work would be helpful in these and other research efforts to come.

References

- Bailey T, Gattrell A (1995) *Interactive Spatial Data Analysis*. Longman Scientific and Technical, London

- Beeson PE, DeJong DN, Troesken W (2001) Population Growth in US Counties, 1840–1990. *Regional Science and Urban Economics* 31(6):669–699
- Beyers WB, Nelson PB (2000) Contemporary Development Forces in the Nonmetropolitan West: New Insights from Rapidly Growing Communities. *Journal of Rural Studies* 16(4):459–474
- Craig J (1987) Population Potential and Some Related Measures. *Area* 19(2):141–146
- Ding C, Bingham RD (2000) Beyond Edge Cities: Job Decentralization and Urban Sprawl. *Urban Affairs Review* 35(6):837–855
- Fotheringham AS, O'Kelly ME (1989) *Spatial Interaction Models: Formulations and Applications*. Kluwer Academic Publishers, The Netherlands
- Fotheringham AS, Brunson C, Charlton M (2000) *Quantitative Geography: Perspectives on Spatial Data Analysis*. Sage Publications, London
- Fotheringham AS, Brunson C, Charlton M (2002) *Geographically Weighted Regression*, Wiley, Chichester
- Frost ME, Spence NA (1995) The Rediscovery of Accessibility and Economic Potential: The Critical Issue of Self-potential. *Environment and Planning A* 27(11):1833–1848
- Fuguitt GV, Beale CL (1996) Recent trends in Nonmetropolitan Migration: Toward a New Turnaround? *Growth and Change* 27(2):156–174
- Geertman S, Van Eck J (1995) GIS and Models of Accessibility Potential: An Application in Planning. *International Journal of Geographic Information Systems* 9:67–80
- Harris C (1954) The Market as a Factor in the Localization of Industry in the US. *Annals of the Association of the American Geographers* 44(4):315–348
- Helling A (1998) Changing Intra-Metropolitan Accessibility in the U.S.: Evidence from Atlanta. *Progress in Planning* 49:55–108
- Horner M, Grubestic T (2001) A GIS-Based Planning Approach to Siting Urban Rail Terminals. *Transportation* 28(4):55–77
- Horner M, Murray A (2003) A multi-objective approach to improving regional jobs-housing balance. *Regional Studies* 37(2):135–146
- Janelle DG (1969) Spatial Reorganization: A Model and Concept. *Annals of the Association of the American Geographers* 59:348–364
- Keeble D, Owens PL, Thompson C (1981) The Influence of Peripheral and Central Locations on the Relative Development of Regions, Department of Geography, Cambridge University
- Lichter DT (1985) Racial Concentration and Segregation across US Counties, 1950–1980. *Demography* 22(4):603–609
- Lucy WH, Phillips DM (1997) The Post-Suburban Era Comes to Richmond: City Decline, Suburban Transition, and Exurban Growth. *Landscape and Urban Planning* 36:259–275
- Perry M, Mackun P (2001) Population Change and Distribution: Census 2000 Brief. US Census Bureau, Washington DC. On: <http://www.census.gov/prod/2001pubs/c2kbr01-2.pdf>
- Plane DA (1999a) Migration Drift. *The Professional Geographer* 51(1):1–11
- Plane DA (1999b) Geographical Pattern Analysis of Income Migration in the United States. *International Journal of Population Geography* 5:195–212
- Plane DA, Rogerson PA (1994) *The Geographical Analysis of Population with Applications to Planning and Business*. John Wiley and Sons, New York
- Pooler, JA (1987) Measuring Geographical Accessibility: a Review of Current Approaches and Problems in the Use of Population Potentials. *Geoforum* 18(3):269–289
- Rogers A, Raymer J (1998) The Spatial Focus of US Interstate Migration Flows. *International Journal of Population Geography* 4:63–80
- Rogers A, Sweeney S (1998) Measuring the Spatial Focus of Migration Patterns. *The Professional Geographer* 50(2):232–242
- Smith A, Bashir A, Sink L (2000) *An Analysis of State and County Population Changes by Characteristics: 1990–1999*. Working Paper Series, No. 45, Population Division: U.S. Census Bureau, Washington, D.C. <http://landview.census.gov/population/www/documentation/twps0045/twps0045.html>
- Taaffe EJ, Gauthier HL, O'Kelly ME (1996) *Geography of Transportation*, Second edition. Prentice Hall, New Jersey

- Texas Transportation Institute (2002) *The 2002 urban mobility study*. Texas A&M University. Summary tables on: <http://mobility.tamu.edu/ums/>.
- Van Wee B, Hagoort M, Annema JA (2001) Accessibility Measures With Competition. *Journal of Transport Geography* 9:199–208
- Vickerman R, Spiekermann K (1999) Accessibility and economic development in Europe. *Regional Studies* 33(1):1–15
- Vining DR, Strauss A (1977) A Demonstration that the Current Deconcentration of Population in the United States is a Clean Break with the Past. *Environment and Planning A* 9:751–758

Appendix A

If the β_2 value is a fixed percentage of the larger β parameter (say $\beta_2 = \alpha\beta_1$), we find that the ratio of the distance at which the either of the weights equals Q to the maximum contrast distance is a constant. Demonstration for Q_2 :

$$\frac{d(Q_2, \beta_2)}{D_{\max}} = - \frac{(\ln(Q_2))/\beta_2}{(\ln(\beta_1) - \ln(\beta_2))/((\beta_1) - (\beta_2))} \quad (\text{A.1})$$

$$- \frac{\ln(Q_2)}{\beta_2} \times \frac{(\beta_1) - (\beta_2)}{\ln(\beta_1) - \ln(\beta_2)} \quad (\text{A.2})$$

substituting a β_1 for β_2 everywhere:

$$- \frac{\ln(Q_2)}{\alpha\beta_1} \times \frac{(1 - \alpha)(\beta_1)}{\ln(\beta_1) - \ln(\alpha\beta_1)} \quad (\text{A.3})$$

$$- \frac{\ln(Q_2)}{\alpha\beta_1} \times \frac{(1 - \alpha)(\beta_1)}{\ln(\beta_1) - (\ln(\alpha) + \ln(\beta_1))} \quad (\text{A.4})$$

$$- \ln(Q_2) \times \frac{(1 - \alpha)\alpha^{-1}}{-\ln(\alpha)} = \text{some constant, C} \quad (\text{A.5})$$