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Measuring Traffic Congestion

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Abstract: We develop a traffic congestion index using data for California highways from 1976 through 1994. The technique yields a congestion measure which has several advantages. The index developed here can be applied to counties, urbanized areas, highway segments, or other portions of geographic areas or highway networks. The index allows cross-sectional and time series comparisons which have only rarely been possible. Most importantly, the congestion index developed here is based on data which are readily available. We compare our index to others based on Highway Performance Monitoring System (HPMS) data, and illustrate similarities and differences. We also discuss important issues for future research and data collection efforts which can contribute to more refined congestion measurement.

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While traffic congestion is an important policy issue in most urban areas, the phenomenon remains surprisingly poorly measured. In the early 1990s, Meyer (*1*) found that twenty-two of thirty large metropolitan planning organizations (MPOs) had no information on roadway congestion within their jurisdiction. While in some instances organizations other than the MPO might have information on congestion, there are few standard indices of congestion and policy-makers often have little or no ability to compare congestion levels across metropolitan areas and years. Yet the need to measure highway congestion has possibly never been greater.

The Intermodal Surface Transportation and Efficiency Act of 1991 (ISTEA) has increased the visibility of policies that require or could benefit from congestion measures. For example, ISTEA instructs metropolitan planning organizations to reduce congestion and implement congestion management plans. Furthermore, congestion pricing is increasingly being discussed in policy circles, and has been implemented on State Route 91 in Orange County, California. One implication is that research and policy analysts will need information on congestion levels on highway segments and highway systems throughout urban areas. This will increasingly require that highway congestion be measured in ways that are both theoretically sound and are based on readily available data. In this paper we demonstrate how data which are routinely available from the California Department of Transportation (Caltrans) can be used to construct a congestion index for counties, urbanized areas, highway segments, or other geographic areas or portions of highway networks.

BACKGROUND

There are three issues that must be addressed in measuring congestion. A congestion index should reflect the full range of highway performance, the index should be based on data that are widely available, and analysts must carefully interpret the results of any index. Congestion measures have been discussed since the 1950s, but most indices have been developed for individual metropolitan areas, vary widely in complexity and theoretical soundness, and do not allow comparisons across locations or times (*1,2,3*). Of the congestion indices that allow comparisons across urban areas, the ones developed by Lindley (*4*) and Schrank, et. al. (*5*) are the most similar to the index developed here.

Lindley's index is based on peak hour traffic volume data obtained from the Highway Performance Monitoring System (HPMS). Lindley used those data to generate twenty-four hour volume profiles for a sample of urban highways. Once the volume profiles were calculated, Lindley compared volume to capacity (V/C), designating any V/C value greater than 0.77 as congested. Estimated congestion delays were then converted into travel delays (in minutes), assuming average uncongested travel speeds of 55 miles per hour (or 88.55 kilometers per hour) and average travel speeds of 20 mph (32.2 kph) when V/C equaled one.

The most important shortcoming in Lindley's technique is that it does not measure the full range of highway system performance. Lindley followed much past convention by truncating the analysis at V/C equal to one, allowing no comparison with more severe congestion levels. He further truncated the analysis for uncongested highways, drawing no distinction between any V/C less than 0.77. This truncation is undesirable from a policy perspective. Analysts might wish to draw distinctions between different roads that are both uncongested, one with considerable excess capacity and another with less excess capacity. Similarly, a more complete ranking of congested roadways is desirable to distinguish those highways with the most extreme excess of volume compared to capacity.

Of the indices which have been proposed, the only one which measures the full range of system performance and which allows comparisons across metropolitan areas is the index developed by Schrank, et. al. (*5*) and refined by Schrank and Lomax (*6*) of the Texas Transportation Institute (TTI). The TTI index is a weighted average of vehicle miles traveled and lane miles of freeway as shown below.

$$RCI = \frac{(FwyVMT / Ln - Mi) * VMT + (ArtVMT / Ln - Mi) * ArtVMT}{13{,}000 * FwyVMT + 5{,}000 * ArtVMT} \quad (1)$$

where RCI = TTI's Roadway Congestion Index
FwyVMT/Ln-Mi = Freeway daily vehicle miles traveled per lane miles
FwyVMT = Freeway daily vehicle miles traveled
ArtVMT/Ln-Mi = Principle arterial daily vehicle miles traveled per lane mile
ArtVMT = Principle arterial daily vehicle miles traveled
13,000 and 5,000 are estimates of capacity per lane mile on freeways and principal arterials, respectively

The TTI index assumes a capacity of 13,000 daily vehicle miles traveled (VMT) per lane-mile (or 20,917 vehicle kilometers traveled per lane-kilometer) on freeways and 5,000 daily VMT per lane mile (or 8,045 vehicle kilometers traveled per lane-kilometer) on principle arterials, and then compares measured VMT to capacity.

Both the TTI index and the index developed here are weighted averages of a V/C measure that is not truncated. The important differences between the TTI index and the one we develop below are twofold. First, TTI used only two definitions of highway capacity -- one for freeways (13,000 daily VMT per lane mile or 20,917 vehicle kilometers traveled per lane-kilometer) and the other for principle arterials (5,000 VMT per lane mile or 8,045 vehicle kilometers traveled per lane-kilometer). The data for our congestion index correspond to six different capacity levels that correspond to highway classifications that range from principal arterials in rural areas to major urban expressways. Second, the TTI index is based on daily VMT, while our congestion index is based on peak hour traffic flow. By comparing the values for the two indices, we can get insight into the importance of using different capacity levels and observing peak hour travel in measuring congestion. If the two indices give similar values, then a congestion index (ours or TTI's) might not be sensitive to distinctions in road capacity and peak versus off-peak travel. This would be useful because it would suggest that congestion indices developed with administrative state data or with more widely available HPMS data can give similar information.

Yet once a congestion index is developed, an important and relatively overlooked issue is how to interpret the results. Schrank, et. al. (*5*) have been criticized by Gordon, Richardson, and Liao (*7*), who note that the rank order correlation between the TTI index for metropolitan areas and self-reported commute times (from the National Personal Transportation Study) is only 0.09. This underscores the fact that congestion levels need not correspond directly to travel times. We simply wish to note that policy-makers often care about both travel times and traffic congestion, especially if congestion itself becomes a policy objective as suggested by ISTEA and the recent serious discussion of congestion pricing. Thus adequate congestion measures are needed.

Yet while congestion indices can identify areas and locations where demand exceeds capacity, the appropriate policy response is often subtle. TTI has suggested that their index can be used to identify capacity expansions which are necessary to relieve congestion (*6*). Yet that approach ignores the possibility that identifying congestion does not necessarily imply that road building must follow. Much recent thinking has focused on demand management schemes, including pricing (*8,9*). A necessary precursor to implementing and monitoring the effectiveness of demand management schemes is the ability to consistently measure congestion levels across urban areas and at different points in time (1). We present here an index which is based on data which are available from Caltrans for 1976 through 1994 for all 58 California counties. This allows a level of standardization, across counties and years, which is rare when measuring congestion.

A CONGESTION INDEX BASED ON CAPACITY ADEQUACY DATA

The most common way to measure congestion is with a volume to capacity (V/C) index which gives a ratio of traffic volume over rated capacity. These data are compiled by most state departments of transportation, but V/C is usually truncated at one. Once traffic on a road exceeds the rated capacity, there is no distinction between differences in congestion levels. For congestion management policies that aim to reduce but not eliminate congestion, a truncated measure gives no information about the effectiveness of the policy.[1] For research, the similar point holds. Very severe congestion might have different economic, social, or safety implications than more moderate congestion, but a truncated measure often cannot distinguish between the two. Thus the first step is to start with some measure of congestion that is not truncated.

For California highways, such a measure is the capacity adequacy index. Capacity adequacy is reported annually for approximately 4,000 locations on the state highway system, which includes all interstate, federal, and state highways in California. Capacity adequacy (CA),

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[1] Some analysts, such as Lindley (*4*), have classified roads as congested when V/C equals 0.77. Thus the range of V/C from 0.77 to 1.0 provides some distinction between levels of congestion. Yet these measures still truncate V/C at 1.0, and thus cannot compare differences in congestion among roads where volume exceeds capacity.

defined below, is the inverse of a V/C measure, but importantly, CA is not truncated.

$$CA = \left(\frac{\textit{rated volume capacity}}{\textit{volume during present design hour}}\right) * 100 \qquad (2)$$

Capacity adequacy is the ratio of the highway's rated capacity divided by a measure of peak hour travel flow (volume during the present design hour), multiplied by 100. Rated capacity is based on level of service criteria that take into account the type of highway, lane width, geometry, terrain, and other conditions that affect traffic flow. The present design hour is the 30th highest volume hour for rural highways and the 200th highest volume hour for urban highways. While this definition cannot be changed by the researcher, the present design hour is intended to represent a peak hour, with extreme outliers excluded. Larger CA values imply less congestion. Locations with CA less than 100 are congested at the present design hour; locations with CA greater than 100 are not congested.

It is often important to understand congestion along a route segment, several routes, or within a geographic area such as a city, county, or metropolitan area. Below we suggest a technique for aggregating CA to the county level, but the same methods could be used to aggregate to any level of geography. Also, as will be clear when we present the aggregation technique, congestion indices for route segments are calculated as part of the process of deriving a county congestion index, so that the techniques below can be applied to measure congestion on particular routes or portions of routes.

Developing a county congestion index requires aggregating CA to the county level. That aggregation is done in two steps. First, for each county, CA is summed for each highway. The resulting highway aggregates are then summed for each county. Both sums are weighted by average daily travel (ADT). This is done to weight each CA value in a way that incorporates information on the relative importance of each location on the highway network. Each location is judged to be important in proportion to the ADT that passes through that point. Congestion at high ADT locations, because that congestion affects more drivers, is weighted more heavily. The first summation, which creates a congestion index for highway segments, is shown below.

$$HWYCA_{j,k} = \sum_{i=1}^{N} \frac{ADT_{i,j,k}}{HWYADT_{j,k}} CA_{i,j,k} \tag{3}$$

where $HWYCA_{j,k}$ = congestion measure for highway "j" in county "k"
$CA_{i,j,k}$ = CA at location "i" on highway "j" in county "k"
$ADT_{i,j,k}$ = average daily travel at location "i" on highway "j" in county "k"
N = the number of mile locations which report CA and ADT data on highway "j" in county "k"
and

$$HWYADT_{j,k} = \sum_{i=1}^{N} ADT_{i,j,k} \tag{4}$$

such that $HWYADT_{j,k}$ = sum of the ADT at each location "i" on the segment of highway "j" that is in county "k".

The second sum, which aggregates the $HWYCA_{j,k}$ variables for each county, is shown below.

$$ACCESS_k = \sum_{j=1}^{M} \frac{HWYADT_{j,k}}{CNTYADT_k} HWYCA_{j,k} \tag{5}$$

where $ACCESS_k$ = the congestion measure for county "k"
M = the number of highways in county "k"
and

$$CNTYADT_k = \sum_{j=1}^{M} HWYADT_{j,k} \tag{6}$$

such that $CNTYADT_k$ = sum of highway segment HWYADT's for county "k".

Note that, in equation (5), $HWYCA_{j,k}$ is weighted by $HWYADT_{j,k}$, where $HWYADT_{j,k}$ is the sum of the ADT on the highway segment rather than an average ADT for the segment. One reason to prefer a summed ADT for the weight in equation (5) is that this makes longer highways more important in the $ACCESS_k$ variable. For two highways with the same average ADT, if one is longer, it is arguably more important in the network. This suggests that HWYCA for the longer highway should be weighted more heavily, and the formula in (5) does that.

The result of the sums in equations (3) - (6), ACCESS, is a weighted average of CA within the county. ACCESS is an inverse congestion measure. Larger values of ACCESS imply less congestion, and hence easier travel (or access) to locations throughout the network. The name "ACCESS" is simply a mnemonic to denote the opposite of congested travel, and is not meant to imply any broader definition of accessibility. Because the CA variable is constructed such that values smaller than 100 imply congestion, and because ACCESS is a linear combination of CA variables, county ACCESS indices below 100 imply county highway networks which are, on average, congested.

The CA data used to calculate ACCESS cover the entire state and provide generally good coverage of the state highway network. Many urban counties have more than 100 CA observations; Los Angeles County has the most data points, with observations on CA for 292 locations in 1994. For 1990, we divided the total state highway miles in each county by the number of CA reporting locations to get an average distance between reporting locations. The urban counties generally had CA reporting locations that were more closely spaced. Many of the larger urban counties (e.g. Alameda, Contra Costa, Los Angeles, Orange, San Diego, San Francisco, Santa Clara) report CA at locations which are, on average, two to three miles apart. Of the counties in the state's six largest urban areas, only two (Riverside and San Bernardino) had more than an average distance of 3.2 miles between CA reporting locations. Both Riverside and San Bernardino contain large portions of very sparsely populated land, and CA reporting locations are more widely spaced in those regions and drive up the average spacing in those counties.

Sampling theory gives some insights into the network coverage available in the data. We calculated the ADT weighted average of CA and the standard deviation of that ADT weighted average for all the counties in the state in 1994. The standard error of the sample weight mean CA, $\sigma/\sqrt{N}$, was less than 10 for 32 of the 58 counties, and for virtually all of the urbanized counties in the state. Yet this ought not be taken as a literal basis for statistical hypothesis tests. CA data are not likely to be a random sample of all locations on the highway network, because CA is often measured at locations where congestion problems are expected to occur. Even if the CA observations constitute a random sample, calculations of standard errors of the sample mean would have to be adjusted to match the aggregation scheme in equations (3) through (6). Yet even if the standard errors ought not be used for hypothesis tests, this exercise is informative because it illustrates that large differences in summations of CA (e.g. differences of more than 20 to 30 points) are unlikely to occur randomly due to lack of information at all network locations, while smaller fluctuations ought to be viewed with some caution.

RESULTS

First consider cross-sectional comparisons of county ACCESS variables. Maps 1 through 3 show, respectively, county ACCESS variables in 1976 (the first year in the data set), 1985 (the mid-point of the data set), and 1994 (the last year in the data set). Table 1 list ACCESS and population density for all counties in the state in 1991. Note first that the urbanized counties are, as a group, more congested than the rural counties. In 1994, seven of the ten most congested counties were in the greater San Francisco Bay area. The counties with the ten lowest ACCESS variables in that year (e.g. the highest congestion) had ACCESS values that ranged from 58 to 76. Los Angeles County's ACCESS value of 74 ranked that county as the ninth most congested (out of a total of 58 counties in the state) in 1994. Also note that the maps display a geographic broadening of congestion problems over the study period. This is especially clear in the San Francisco Bay Area, where more counties are in the lowest range (50-75) in 1994 than in 1976. These results are generally intuitive and probably not surprising.

Yet the maps, especially Map 1, reveal surprisingly congested counties which are either rural or on the fringe of urban areas. The most congested county in 1976 was El Dorado (ACCESS = 57), in the mostly rural Sierra foothills east of Sacramento. The most congested county in 1994 was Sonoma (ACCESS = 58), on the exurban (but rapidly growing) fringe of the San Francisco metropolitan area. In general, the rural counties of Calaveras, El Dorado, and Placer in the Sierra foothills and the partly rural counties of Napa and Sonoma on the fringe of the San Francisco greater metropolitan area consistently have among the lowest ACCESS variables (i.e. highest congestion) in the state.

We believe that these low density/high ACCESS counties reflect one of the pitfalls of using the 30th highest volume hour as a present design hour in non-urban areas. Many of the partly rural counties with low ACCESS in Table 1, such as Sonoma, Napa, El Dorado, and Placer, accommodate large amounts of seasonal tourist traffic. (Sonoma and Napa are in the wine country of the Napa Valley. El Dorado and Placer are on the primary highway route to the ski resorts around Lake Tahoe.) Thus CA, and ACCESS, for those counties might be driven by seasonal tourist traffic and might not represent typical driving conditions. Yet this point of caution does not appear to apply to urbanized counties. Recall that, for urban highways, the present design hour is the 200th highest volume hour, which is less likely to be an outlier.

Figures 1 through 3 show the time series pattern of ACCESS for selected counties. Figure 1 shows ACCESS from 1976 through 1994 for five selected Bay Area counties. Figure 2 shows ACCESS for the five counties in the Los Angeles Consolidated Metropolitan Area. Figure 3 shows ACCESS for five selected other counties in the state, including counties in the San Joaquin Valley (Fresno, Kern), Sacramento County (which contains the state capitol), Placer County in the Sierra foothills, and rural Humboldt County in far northern California. Because data for 1988 were unavailable, the ACCESS values for those years are the average of the 1987 and 1989 values. All other values are based on CA data.

ACCESS trends downward in most, but not all, of the counties in Figures 1 through 3. The trend toward lower ACCESS is most consistent for the urban counties in Figures 1 and 2 and for the smaller urbanized counties of Fresno and Sacramento. By 1994, most urban counties have ACCESS variables which are below 100, indicating, on average, congested highway networks.

Because ACCESS is similar to the roadway congestion index (RCI) developed by TTI, we compared the two measures. The RCI was developed by TTI for census urbanized areas, which are typically not coterminus with counties. We modified the summations in equations (3) - (6) to correspond to urbanized areas, and then calculated ACCESS for the six California urbanized areas for which TTI reports RCI values in the report by Schrank and Lomax (*6*). Our ACCESS variable and TTI's RCI are plotted, for each of the six California urbanized areas, in Figure 4. Because the RCI was only available for 1982 through 1994, Figure 4 shows only those years. We converted the RCI into units that are comparable to ACCESS by inverting the RCI and multiplying by 100. This converts TTI's measure of volume to capacity into a variable that corresponds to CA, which is capacity divided by volume multiplied by 100. See equation (1) for the definition of the RCI and equation (2) for the definition of CA that forms the basis of our ACCESS variable.

Note first from Figure 4 that ACCESS and RCI are qualitatively similar. Both suggest that California's urbanized areas are, on average, congested by the 1990s, and both show that congestion is, for most urbanized areas, growing worse over time. Yet there are some differences between ACCESS and RCI. The time trends for the ACCESS and RCI variables differ somewhat for the Riverside-San Bernardino urbanized area, especially in the 1980s. More interestingly, while the ACCESS and RCI values are close for Los Angeles, Riverside-San Bernardino, and San Diego, RCI is consistently higher than ACCESS in the other three urbanized areas (Sacramento, San Francisco, and San Jose). Because we have transformed the RCI to be comparable to ACCESS, this means that ACCESS shows more severe congestion than does RCI in the Sacramento, San Francisco, and San Jose urbanized areas.

The difference in the San Jose urbanized area is large; ACCESS and RCI differ by over 40 points in 1982 and over 30 points in 1994. This is likely due to the differences between the

CA data and the VMT data that form the basis for ACCES and RCI, respectively. Among those differences, the fact that CA is a peak hour measurement while VMT is a daily average is probably most important. It is possible that congestion in San Jose county is more severe when attention is restricted to peak hour, which the ACCESS variable does.

CONCLUSION

Our results suggest that the ACCESS variable is a useful indicator of congestion within geographic areas and over time. Yet measuring congestion has generated some recent controversy, such as the criticisms in Gordon, Richardson, and Liao (*7*). Our analysis leads us to conclude that the controversy lies mostly in a lack of care about how congestion indices are developed and interpreted.

The concept of a network average is most meaningful for places with similar road and travel conditions. Developing congestion indices for urban areas or portions of urban areas can give insights into system performance. Yet larger geographic aggregates, which include urban and rural locations, lose meaning as the average obscures important variations in network performance.

One potentially important application of congestion indices is in focusing on individual links in a highway network. For example, as the first step in creating the county ACCESS variable, equation (3) develops a congestion index for highway segments. This could be used to pinpoint chronically congested highway segments, and the policy applications could be more profound than gauging average network performance. For example, one could use a highway segment ACCESS variable (or similar measure) to evaluate the effectiveness of congestion pricing schemes, or to identify highly congested routes which are candidates for demand management policies or capacity expansion.

More generally, while ACCESS and similar variables are useful indicators of congestion, some cautions are in order. Whenever data are aggregated into congestion indices, the researcher should communicate the details of the data, including the number of observations and the extent of network coverage. More attention needs to be given to the statistical reliability of congestion indices; small variations might not be meaningful. Instead, the value of congestion indices is in their ability to distinguish broad trends. Furthermore, the policy applications of these indicators require careful consideration. Congestion indices, by themselves, can only measure highway network performance; they do not suggest policy solutions.

Still, there is a pressing and growing need to measure congestion levels in a consistent manner across places and time. The ACCESS variable provides a useful way to do that with available data. In some cases (the Southern California urbanized areas of Los Angeles, Riverside-San Bernardino, and San Diego) the ACCESS variable compares closely to TTI's RCI index. This suggests some scope for using HPMS data (of the sort used by TTI) as a substitute in states where CA or comparable data are not available. Yet some caution is appropriate, because choices about capacity measurement and time of day apparently lead to important differences between ACCESS and RCI in the northern California urbanized areas.

Future research should examine how to expand the HPMS dataset to better support congestion indices throughout the United States. Including data that are comparable to CA would be a start. Future research should also examine in detail the implications of different measures of capacity and the distinction between peak hour and daily volume. The results can hopefully someday guide efforts to augment the HPMS and other data sources in ways that can better support congestion measurement. At least as important would be to expand the number of reporting locations, thereby increasing the statistical reliability of aggregate indicators. Along the same lines, there is a need for formal sampling theory regarding the statistical properties of congestion indicators -- a point that has been somewhat overlooked in the past. Lastly, the data to support congestion measurements should be made broadly available to the research community, so that the task of measuring congestion and refining the indices can continue.

Overall, the scope for congestion management policy has been and will continue to be constrained in the absence of readily available methods to measure congestion (1). The ACCESS variable constructed above allows a comparison of congestion in California counties for almost a two decade span. The same or similar techniques, applied in other states, hold the promise of improving the measurement of what remains one of the more poorly quantified transportation phenomena.

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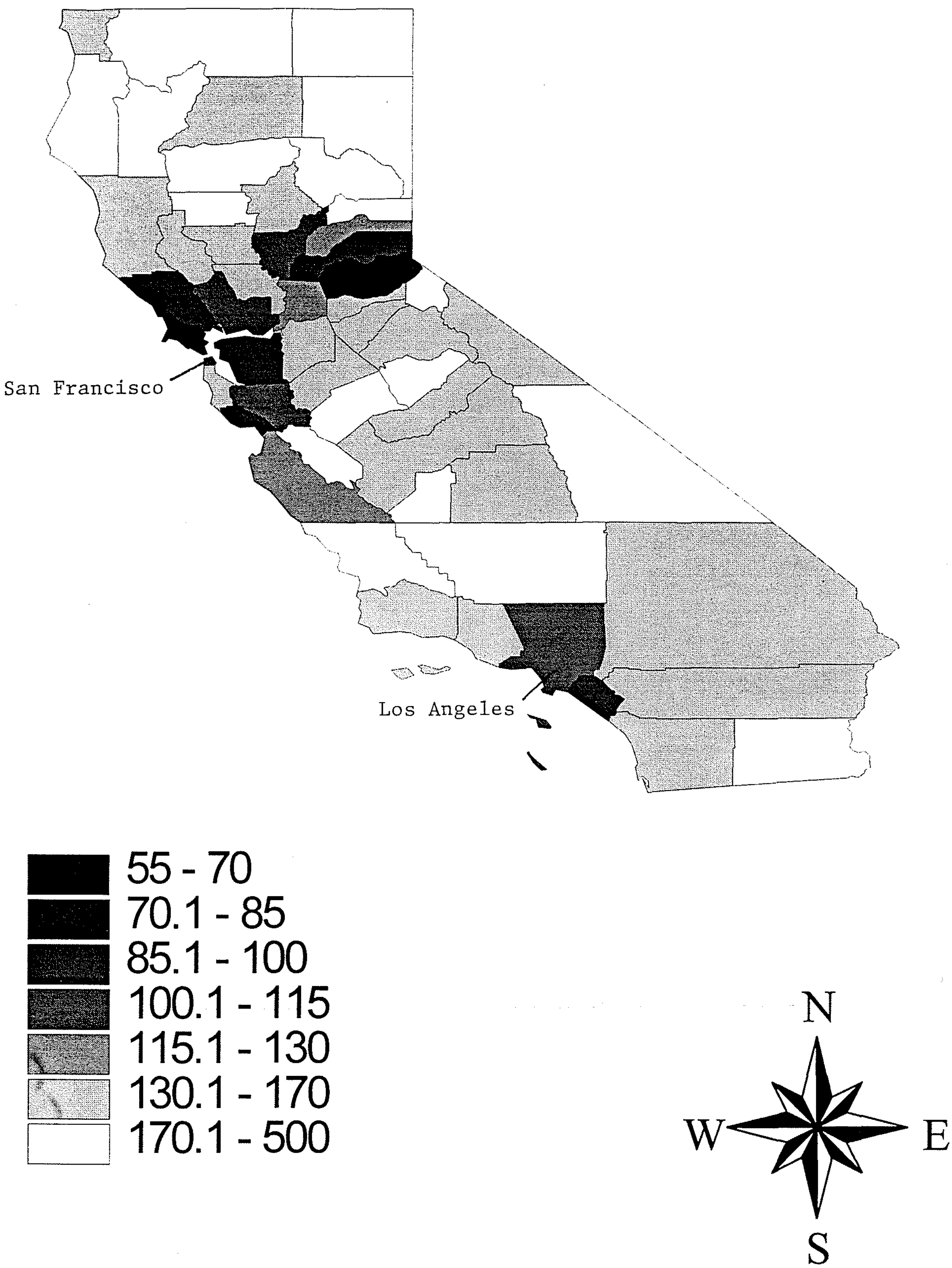
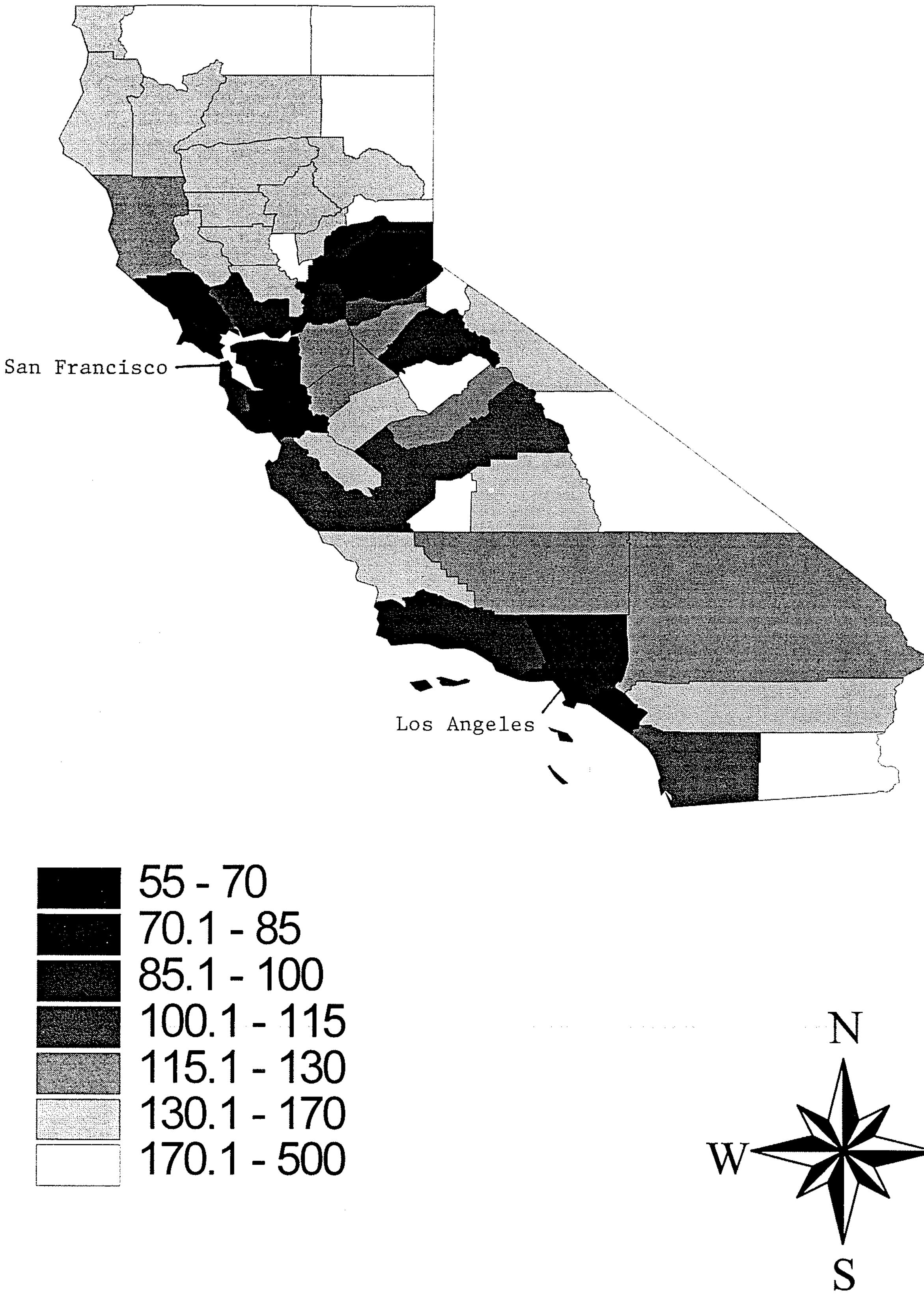
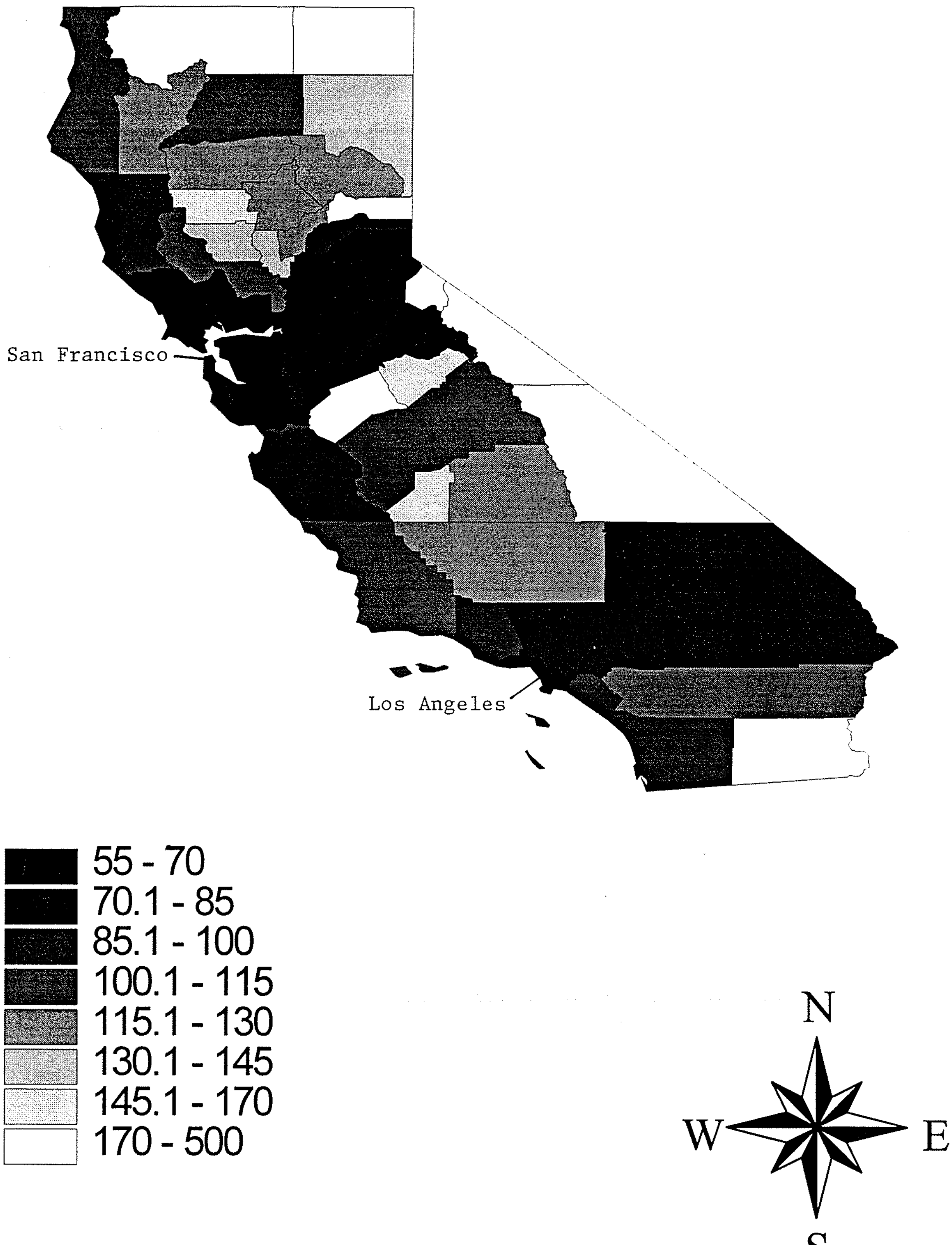
MAP 1:
ACCESS for California Counties (1976)



MAP 2:
ACCESS for California Counties (1985)



MAP 3:
ACCESS for California Counties (1994)



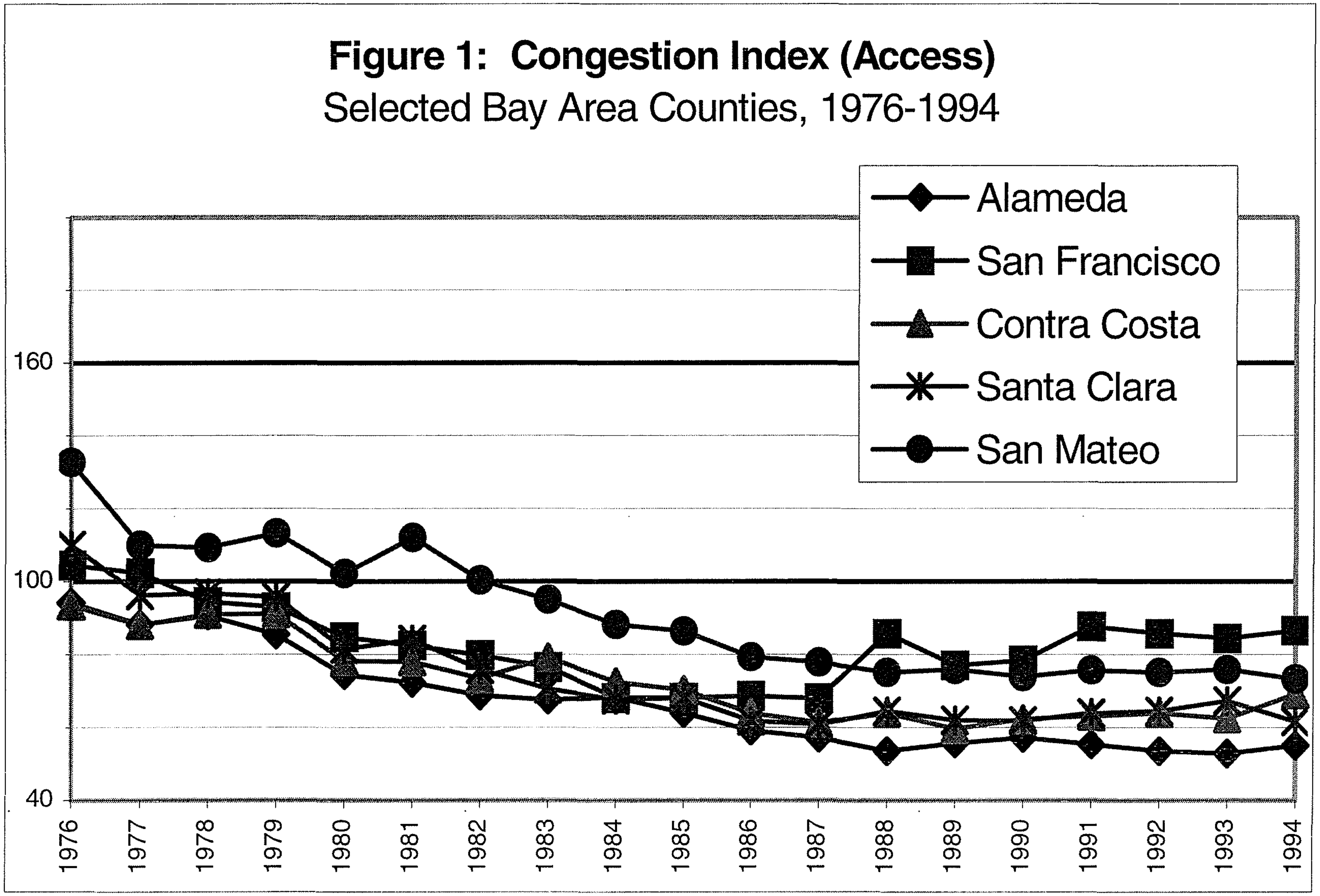


Figure 1: Congestion Index (Access)
Selected Bay Area Counties, 1976-1994
Alameda
San Francisco
Contra Costa
Santa Clara
San Mateo
160
100
40
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994

Figure 2: Congestion Index (ACCESS)
Los Angeles Metropolitan Area, 1976-1994

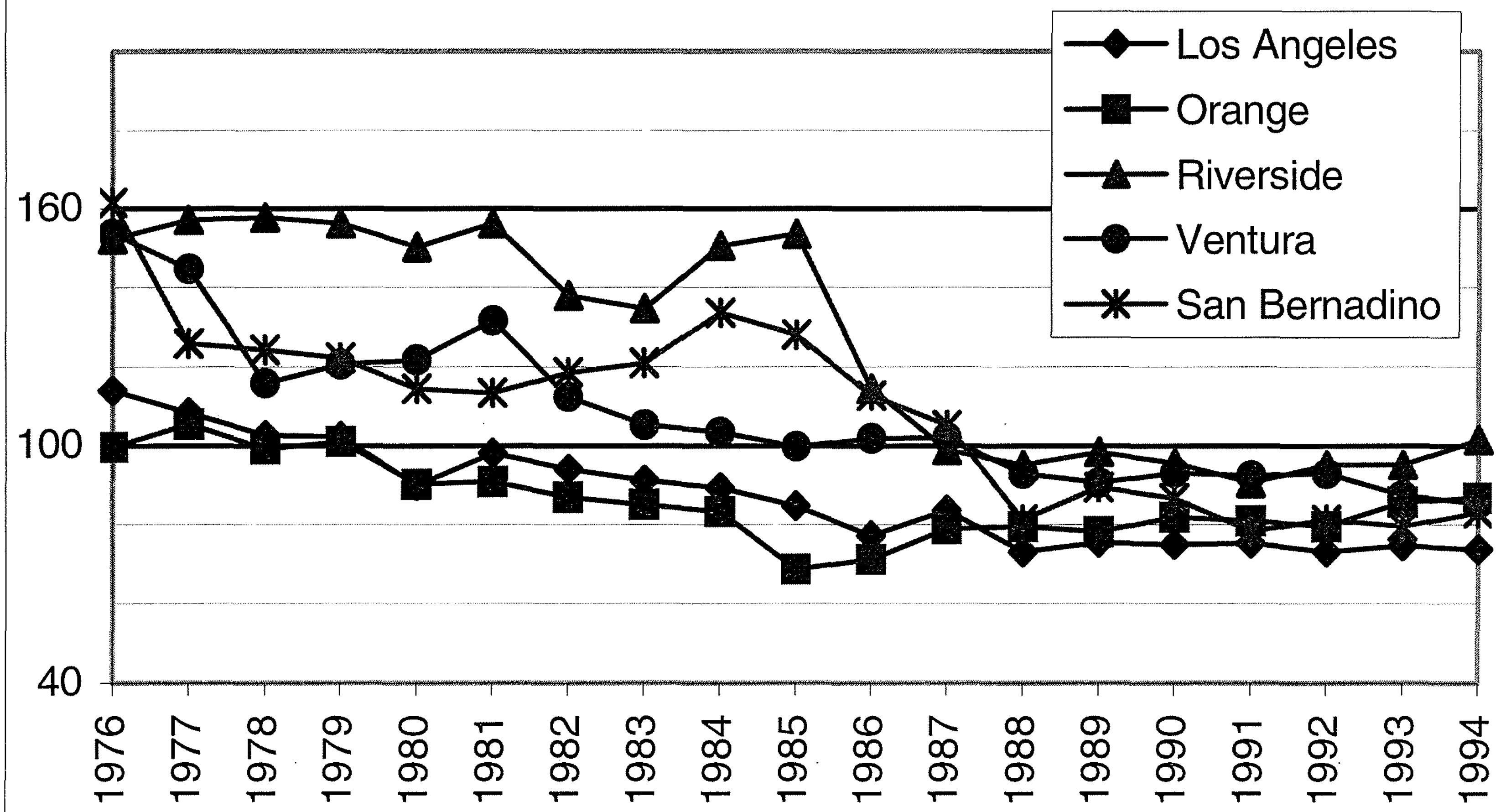
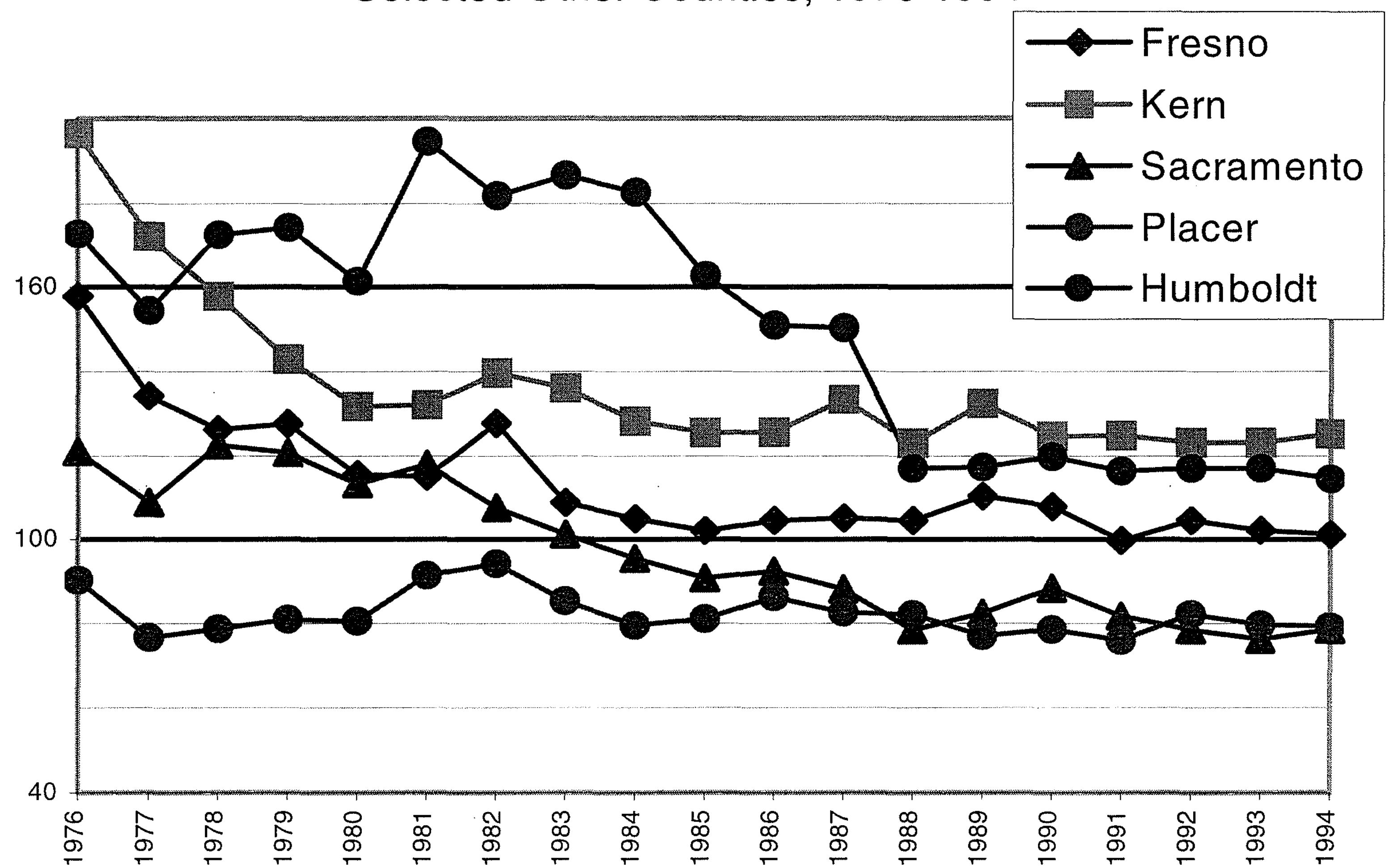


Figure 3: Congestion Index (Access)

Selected Other Counties, 1976-1994



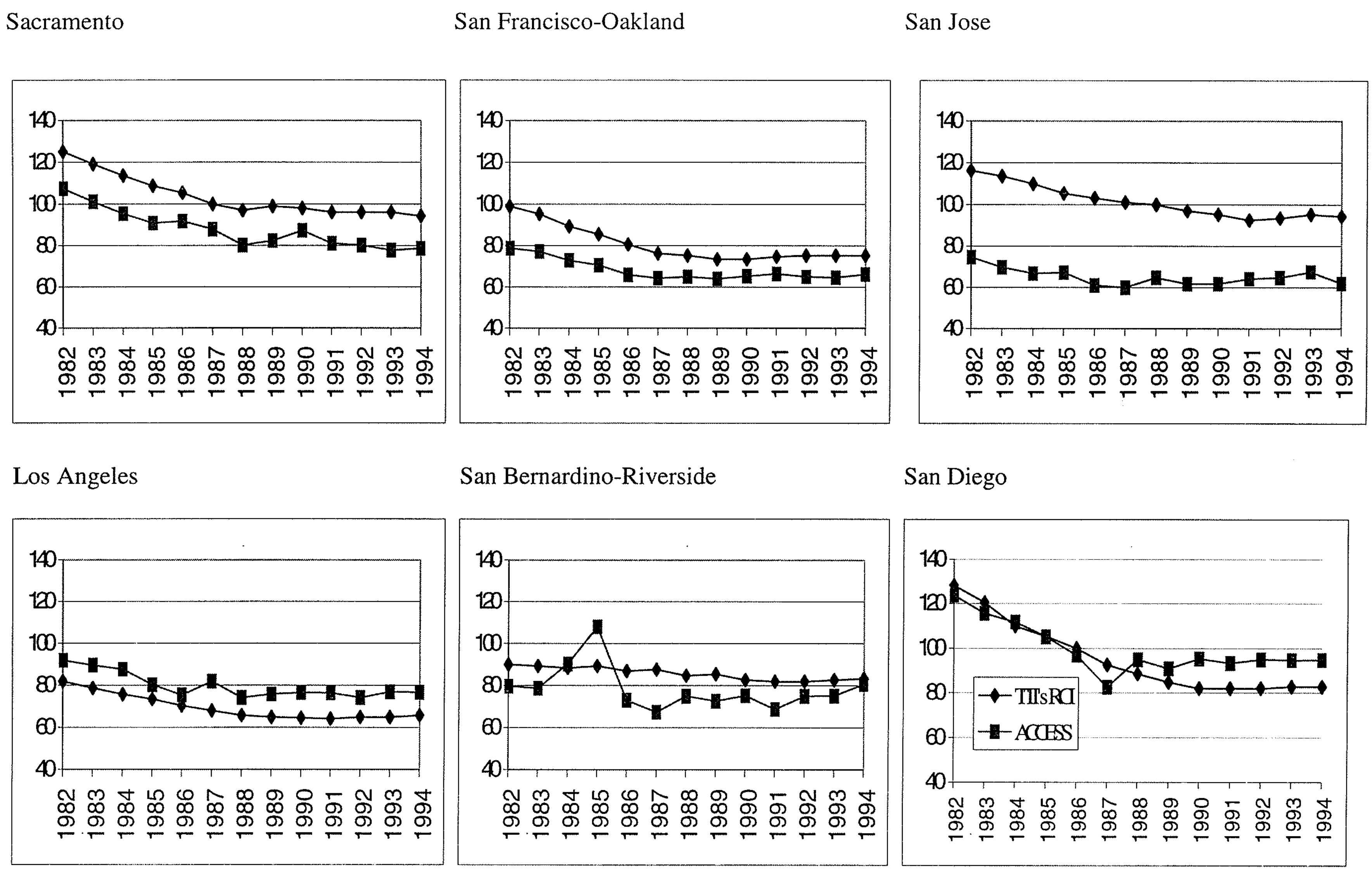


Figure 4: Comparing ACCESS with TTI's RCI Index

Table 1: Access and Population Density, 1991

County	ACCESS	Population Density (Persons/Acre)
Sonoma	53.87	0.397
Alameda	55.32	2.785
Santa Cruz	57.17	0.830
Marin	60.32	0.706
Contra Costa	63.09	0.036
Santa Clara	63.94	1.829
Calaveras	67.68	0.052
Napa	71.22	0.233
El Dorado	73.28	0.122
Los Angeles	75.26	3.470
San Mateo	75.64	2.283
Placer	75.98	0.201
Tuolumne	76.2	0.035
Amador	76.93	0.083
San Bernardino	78.27	0.116
Orange	80.87	4.944
Solano	81.7	0.676
Sacramento	81.78	1.727
San Francisco	87.73	25.465
San Joaquin	87.91	0.552
Riverside	90.48	0.274
Monterey	90.62	0.172
Ventura	92.34	0.577
Mendocino	94.37	0.037
San Diego	94.69	0.946
Stanislaus	95.73	0.404
Madera	96.59	0.062
Santa Barbara	98.07	0.217
Merced	98.4	0.147
Fresno	99.79	0.183
Nevada	100.87	0.132
San Benito	105.45	0.042
Shasta	109.22	0.064
Trinity	111.71	0.006
San Luis Obispo	111.99	0.105
Humboldt	116.29	0.053
Del Norte	117.57	0.004
Yolo	122.92	0.221
Tehama	123.98	0.027
Sutter	124.24	0.173
Kern	124.82	0.110
Plumas	128.61	0.012
Tulare	129.65	0.105
Mariposa	129.87	0.016
Colusa	130.05	1.121
Butte	132.53	0.178
Yuba	139.76	0.148
Lake	140.61	0.066
Lassen	142.61	0.010
Sierra	154.42	0.005
Glenn	159.83	0.030
Siskiyou	160.38	0.011
Kings	171.14	0.119
Alpine	193.8	0.003
Mono	217.19	0.005
Imperial	225.14	0.042
Inyo	244.01	0.003
Modoc	334.82	0.004