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Santa Barbara

"The Accessible City:
Employment Opportunities in Time and Space"

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Geography

by

Lauren M. Scott

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August, 1999

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Scott, Lauren. 1996. "Urban Agglomeration, Social Fragmentation." In *Spatial Technologies, Geographic Information, and the City, Technical Report 96-10,* pp. 204-208. Compiled by Helen Couclelis. NCGIA: University of California Santa Barbara.

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Scott, Lauren M. Forthcoming, 1999. "Evaluating Intra-Metropolitan Accessibility in the Information Age: Operational Issues, Objectives, and Implementation." In *Information, Place, and Cyberspace: Issues in Accessibility,* D. Janelle and D. Hodge, Editors. Heidelberg, Berlin: Springer-Verlag.

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ABSTRACT

"The Accessible City:
Employment Opportunities in Time and Space"

by

Lauren M. Scott

Explosive suburban employment growth, broad processes of economic restructuring, and rapid developments in transportation and telecommunications technologies have fundamentally altered the spatial and organizational composition of both where we work and where we live. How have these broad spatial processes impacted intra-metropolitan accessibility? This research presents an analytical framework for evaluating and monitoring intra-metropolitan accessibility to employment opportunities. More specifically, it (1) determines how accessibility has been defined, modeled, measured, and interpreted; (2) presents a new approach for evaluating intra-metropolitan accessibility founded on the Couclelis proximal space construct, the Getis/Ord G_i^* spatial statistic, a level-of-service definition of accessibility, multiple scale analysis, and a multi-dimensional conceptualization of accessibility processes; and (3) applies this analytical framework, implemented within a GIS environment, to employment data for the Greater Los Angeles region in order to demonstrate its effectiveness and potential for addressing a wide variety of empirical research questions, for contributing to urban theory, and for evaluating urban and transportation planning strategies.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

Not so long ago, I was sure I would never have the opportunity to finish even the B.A. degree. It feels *so very* incredible, therefore, to find myself submitting the Ph.D. dissertation! I am most grateful to my husband, Bruce, who by supporting, encouraging, and helping me in *so many ways*, has made it possible for me to pursue my education – my dreams. He has given me an incredible gift! My deepest wish is that he knows, *absolutely*, the depth of both my gratitude and my love. I must also acknowledge our pooch, Abby, (though she would prefer, no doubt, a dog biscuit), for keeping my feet warm while I wrote the dissertation, and for being a constant reminder not to take myself too seriously.

I am very much indebted to my dissertation committee for their guidance, encouragement, and advice. I am thankful to Mike for his feedback and for pushing me to work to the very best of my capabilities. I am thankful to Serge because, while our meetings were few and far between, his advice, ideas, and suggestions were always *exactly* what I needed to move forward. Helen has both inspired me and tortured me. I hope she knows how *truly grateful* I am for the opportunity to work with her, to share ideas but also to share company. So much of my dissertation is a direct reflection of my year in Santa Barbara working with, talking to, and learning from Helen. She is a tremendous teacher, an exceptional advisor, and a remarkable person.

I am most grateful to have had Art as my dissertation chair. I am sure I would not have finished the Ph.D. if it were not for Art's encouragement and guidance. For whatever reasons, he elected to focus on my strengths and potential rather than on my flaws. He believed in me even when I did not believe in myself, and for this I am particularly grateful. Art is without doubt the most effective instructor I have ever known. I have been fortunate in many ways, but *especially* fortunate for the opportunity to study with Art.

I would also like to acknowledge and thank my family (especially my mom), my friends (especially Laura Makey), the SDSU Geography Department (especially Yumiko), the participants at Varenius workshops on accessibility (especially Susan Hanson and Don Janelle), and the faculty at CSUF (especially Bill Lloyd). With so many people rooting for me, encouraging me, praying for me, and helping me, I had no choice but to succeed. I am sincerely and *very* deeply grateful.

CHAPTER 1

INTRODUCTION

Broad urban restructuring processes including globalization, suburbanization, economic restructuring, and rapid developments in telecommunications and transportation technologies, have had dramatic impacts on the urban landscape. During the 1970s, for example, the U.S. housing industry was constructing nearly 2 million units per year (Clark and Kuijpers-Linde, 1994, 467), blanketing the urban periphery with newly built single family homes atop a web of new freeways and transportation corridors. Not coincidentally, more people than ever before were joining the labor force. Between 1980 and 1990, while the total U.S. population grew by less than 10 percent, the number of paid workers increased by more than 19 percent (Hanson, 1995, 20). At the same time, broad economic changes have led to extensive restructuring of the manufacturing sector, massive growth of the service sector, and a generalized dispersion of production processes. Explosive suburban employment growth, declining residential densities, consequent new patterns of cross commuting, and restructuring of economic activities in both time and space, have fundamentally altered the spatial and the organizational composition of both where we work and where we live. How have these broad spatial processes impacted intra-metropolitan accessibility?

1

Research Objectives and Justification

While the concept of accessibility has a long history of geographic research, provides a fundamental component for a large body of formal urban theory, and represents a central theme in urban and transportation planning objectives, it remains a difficult construct to both operationalize and define (Pirie, 1979; Helling, 1996; Couclelis and Getis, 1999). There are outstanding questions, for example, regarding the distinction between potential accessibility and realized access (Couclelis and Getis, 1999); variations in the definition and/or measurement of intra-metropolitan accessibility continue to foster debate among urban researchers (Hughes, 1991); and recent developments in telecommunications technologies increasingly cultivate reservations about the effectiveness of traditional accessibility models and concepts (Giuliano, 1995b; Hanson, 1999). The primary objective of this research, therefore, is to tackle these issues by presenting an effective analytical framework for the evaluation and monitoring of changes in intra-metropolitan accessibility associated with broad urban restructuring processes. The proposed analytical framework is implemented within the *ArcView* (ESRI) GIS environment and is founded on (1) the Couclelis (1997) proximal space construct; (2) the Getis/Ord G_i^* spatial statistic (Getis and Ord, 1992; Ord and Getis, 1995); (3) a level-of-service definition of accessibility; (4) multiple scale analyses; and (5) a multi-dimensional conceptualization of accessibility comprising structural, transportation infrastructure, and functional elements. The framework is applied to 1980 and 1990 employment data in the Greater Los Angeles region in order to demonstrate

2

its effectiveness and potential for addressing a wide variety of empirical research questions, for contributing to urban theory, and for evaluating urban and transportation planning strategies.

This research focuses on employment opportunities because employment represents a fundamental component of urban accessibility and has been directly impacted by broad processes of globalization, suburbanization, economic restructuring, and technological developments. The framework is applied to the Greater Los Angeles study area because restructuring processes here have thoroughly altered the social and economic geography of the region; Los Angeles, in fact, has been referred to as *the* prototype of urban restructuring processes (Soja, Morales, and Wolff, 1983). The GIS environment is a key component of the proposed analytical framework; it provides important tools for visualizing, exploring, analyzing, and displaying spatial data, and is increasingly used in the development of urban policy and for transportation planning (Nyerges, 1995; Arentze, Borgers, and Timmermans, 1994).

Structure of the Dissertation

The dissertation comprises 5 chapters. This introductory chapter outlines the objectives, limitations, and rationale for the dissertation research. Chapter 2 reviews the urban restructuring literature in order to provide a context, scope, and focus for the methodological issues presented in Chapter 3, but also to provide background for the empirical analyses performed in Chapter 4. Having established the scope and context for the dissertation research, Chapter 3 reviews

3

the definitional, representational, and measurement issues that must be addressed in order to effectively evaluate intra-metropolitan accessibility. Using this review as a starting point, the chapter outlines the proposed analytical framework for representing, evaluating and monitoring changes in intra-metropolitan accessibility over time and space. Chapter 4 focuses on application, applying the framework described in Chapter 3 to employment data in the Greater Los Angeles study area for both 1980 and 1990. The issues addressed in this chapter include jobs/housing balance, spatial/skills mismatch, journey-to-work commuting patterns, traffic congestion, and impacts on urban spatial structure and commuting behavior associated with rapid developments in transportation and telecommunications technologies. The final chapter concludes with a discussion of future research directions.

Limitations of the Dissertation Research

Definitional limitations. While it is not yet possible to identify *direct* linkages between changes in the urban landscape and specific urban restructuring processes (globalization, economic restructuring, changing technology), it is possible to begin to investigate *indirect* evidence of these linkages by examining changes in job distributions, resident worker distributions, and commuting patterns over time and space. In theory, urban spatial structure may be defined very broadly to reflect all of the spatial relationships linking a region's urban activities (employment, schools, medical facilities, public services, and/or recreational activities) to the spatial distribution of a region's inhabitants (Pred, 1977, 10;

4

Simpson, 1987, 120). In this research, however, the definition for urban spatial structure is limited to a focus on spatial and functional[1] relationships among employment opportunities and resident workers. Although the emphasis is on relationships among job opportunities and resident workers, the methods and theoretical constructs developed in this research could be adapted for analyses of shopping or recreational opportunities, public service provision, or a variety of other urban spatial activities.

Data limitations. The data used in all of the analyses presented in Chapter 4 are only available for 1980 and 1990. With only two time periods, I am limited in my ability to discuss trends or to make predictions about future spatial distributions, but will instead focus on a discussion of the characteristics of change between 1980 and 1990. In addition, the quality of the data utilized limits empirical analyses to a very general discussion of accessibility in the Greater Los Angeles region. As a consequence, the primary objective of this research is not to provide a full and thorough evaluation of the Los Angeles data set, but to present effective tools, methods, criteria, and procedures for defining, representing, and measuring intra-metropolitan accessibility[2].

Statistical inference. In evaluating the Los Angeles data set, this research focuses on exploratory rather than confirmatory analysis. Maps, charts, diagrams, and mathematical equations (including statistical formulations such as linear

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[1] Functional relationships are based on spatial interaction volumes, and will be described in detail in Chapter 3.
[2] Other limitations imposed by the data are discussed in Chapter 4.

5

regression) are used to present employment data for the study area in a variety of ways. In an inductive manner, these graphical and mathematical representations of the data are utilized to suggest explanation. In some cases explanation provides evidence to support existing urban theories (as, for example, in the analyses of spatial and skills mismatch in Chapter 4); in other cases, explanation suggests hypotheses (as, for example, in the analyses of functional accessibility at the end of Chapter 4). In Chapter 3 regression analysis is utilized to compare the explanatory power of traditional measures of intra-metropolitan accessibility to those for a proposed measure of intra-metropolitan accessibility in which accessibility scores are reported as standard deviations. These statistical indicators and modeling results, however, are best interpreted as descriptive evidence lending support to the inductive relationships that emerge from exploratory analyses. When possible, of course, it is prudent to have a well-recognized benchmark based on statistical theory in which to evaluate results from analyses (rather than to present magnitudes, distributions, or intensities without any such benchmarks). The jury is still out, however, regarding the best way to integrate statistical tools into exploratory analyses (Openshaw, 1996). From my own perspective, since a variety of spatial processes may be at work in shaping any observed spatial pattern, distribution, or structure, results from inductive analyses are most convincing when they can be corroborated by logical, theoretical and/or statistical explanation.

The objectives of exploratory analysis are quite different from those of confirmatory analysis. This dissertation emphasizes exploratory analysis in order

6

to highlight the broad potential and applicability of the proposed analytical framework for addressing a variety of urban research questions; confirmatory analysis of intra-metropolitan accessibility using the techniques presented in Chapters 3 and 4 will be addressed, separately, in future research.

Scope and context. It is important to recognize that many of the specific operational details (definitional, representational, and methodological) associated with measuring intra-metropolitan accessibility will be influenced by the scope and overall objectives of the research study at hand. The analytical framework outlined in Chapter 3 focuses on aggregate-level analysis in order to highlight broad changes in urban spatial structure, rather than focusing on impacts associated with any one individual (disaggregate-level analysis). Applying the analytical framework to longitudinal aggregate-level data (aggregated by census-tract) allows an emphasis on the broad spatial processes shaping urban form and their associated impacts on intra-metropolitan accessibility. Nonetheless, given appropriate data, the analytical framework and many of the procedures described in Chapters 3 and 4 would certainly be effective for disaggregate-level analyses as well.

Contributions of the Dissertation Research

This research contributes to five bodies of literature: (1) methodological literature investigating definitional, representational, and operational issues associated with evaluating intra-metropolitan accessibility, particularly in light of rapid developments in transportation and telecommunications technologies;

7

(2) urban literature addressing the evaluation of changing urban spatial structure, including processes of decentralization/agglomeration, urban efficiency, social equity, and economic restructuring; (3) urban and transportation planning literature concerning jobs/housing balance, spatial/skills mismatch, and transportation issues such as journey-to-work commuting patterns, and traffic congestion; (4) GIS literature concerned with the challenges of integrating spatial analysis, and various conceptualizations of space, spatial relations, and spatial processes within the GIS environment; and (5) spatial analysis literature interested in extending empirical application of recently developed local spatial statistics, specifically G_i^*, originally designed to identify spatial dependency and spatial clustering.

CHAPTER 2

GLOBAL PROCESSES, LOCAL IMPACTS

This chapter reviews the urban restructuring literature in order to provide a context and a focus for the definitions, representational issues, measurements, and analyses of intra-metropolitan accessibility presented in subsequent chapters. Many of the themes developed in this chapter will appear again in empirical analyses presented in Chapter 4. The first section below presents a general overview of urban restructuring processes, including globalization, economic restructuring, suburbanization, and rapid technological developments. This section concludes by discussing concerns regarding societal impacts associated with these broad spatial processes, highlighting specifically, spatial mismatch, skills mismatch, and economic/social polarization. A second section focuses on urban restructuring processes within the Greater Los Angeles study region, emphasizing changing spatial relationships among employment opportunities and resident workers. Summary comments in both sections link discussions of urban spatial restructuring back to the primary focus of this research: defining, modeling, measuring, and evaluating intra-metropolitan accessibility.

Cities and Spatial Restructuring

In an age of information, high-speed computers, and global transactions, one might speculate that cities are becoming less important *places*, that urban agglomeration becomes obsolete as advances in telecommunications and rapid

9

transportation technologies allow ever expanding geographic dispersal of labor, management, and production (Scott, L., 1996). Broad processes of decentralization and globalization *are* clearly evident. CEOs in companies once catering exclusively to domestic markets announce plans and strategies to garner large portions of new sales from international clients. Corporations reorganize firm structure and production processes to cut costs, shorten product cycles, improve efficiency, and maintain maximum flexibility (Golledge and Stimson, 1997). Faced with growing competition, many corporations employ subcontracting practices to transfer the risk of maintaining overhead expenses and wages during periods of reduced labor demand (Law and Wolch, 1993; Scott, 1986), developing complex networks of strategic alliances among inter-dependent firms and individuals for the purposes of design, R&D, supply, production, marketing, and distribution (Golledge and Stimson, 1997).

Increasingly, telematics[3] integrate all stages of the work process (Mitchelson and Wheeler, 1994). Historically, back offices have located near headquarters activities in order to maintain close supervision and rapid turnaround. With rising central city rents and shortages of qualified labor, however, many firms have uncoupled routine functions, relocating them to less expensive areas of the urban periphery in a process referred to as vertical disintegration (Warf, 1995; Scott, 1986). Internationally, this trend takes the form of offshore back-office relocation, undertaken in an effort to cut costs, revive

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[3] The term 'telematics' refers to services and infrastructure that link computer and digital media over telecommunications links (Graham and Marvin, 1996, 3).

profits, and maintain economic competitiveness (Warf, 1995; Graham and Marvin, 1996). The computer networks supporting this geographic dispersion offer corporations scale and scope economies through the sharing of information and resources (Hepworth, 1986), reducing economic uncertainty and lowering marginal costs of production (Warf, 1995).

The ability of labor and capital to participate in the global economy, to move quickly and at low cost, however, is predicated on a foundation of fixed, secure, and largely immobile social and physical infrastructure (Graham and Marvin, 1996). Despite speculations that cities are becoming less important in the global arena, developments in telecommunications may, in fact, serve to synthesize many of the existing advantages of cities: their strategic locations at global transportation nodes, their physical infrastructure (airports, fiber-optic cable networks, and harbors, for example), their concentration of services, suppliers, and consumer markets, their diverse and highly skilled labor pools, their locational prestige, and their social and cultural amenities (Graham and Marvin, 1996). Although there has been considerable dispersal of economic activities, advances in telecommunications and transportation technologies have also spawned a recentralization of the contact-intensive and export-oriented producer services (Golledge and Stimson, 1997). Indeed, the geographic dispersal and complex organizational forms facilitated by recent technological advances may actually serve to promote continuing *concentration* of high-order command and control functions (finance, management, legal services, administration, and production

11

technologies, for example) within select cities such as Los Angeles and New York (Sassen, 1991; Castells, 1996).

Cities, in many ways, represent the very embodiment of spatial interaction and accessibility. By concentrating a wide variety of skilled individuals within a limited, highly interconnected geographic region, cities minimize costly movements of people, goods, and services (Janelle, 1995). Spatial concentration and centralization also give rise to external economies, foster internal markets, and encourage cost advantages associated with economies of scale.

Before electronic networks and automobiles were developed, spatial interaction was accomplished by foot, horse, or river, requiring close physical proximity. The spatial concentration and centralization of urban activities within cities allowed *time* constraints to be overcome by minimizing *space* constraints (see Figure 2.1). With the advent of telecommunications, however, cities increasingly comprise nodes within a broad, and growing network of inter-related firms, institutions, social groups, and individuals operating at multiple scales, within multiple, sometimes global, contexts. Telecommunications technologies transcend time and space, enhancing and extending geographic accessibility by minimizing constraints associated with overcoming distance.

Some researchers have argued that transportation and communications are so highly developed in most U.S. cities, that physical accessibility has become somewhat ubiquitous (Giuliano, 1995b; Chintz, 1991). Transportation and communications technologies develop unevenly over time and space, however, creating a complex patchwork of different spaces associated with disparate,

12
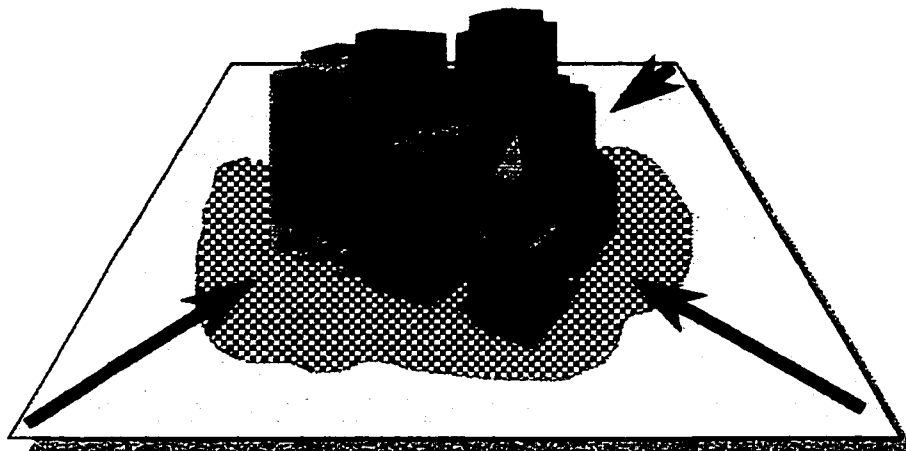
The City

Function: to overcome *time* with space.
Urbanization facilitates spatial interaction by minimizing
space constraints in order to overcome *time* constraints.
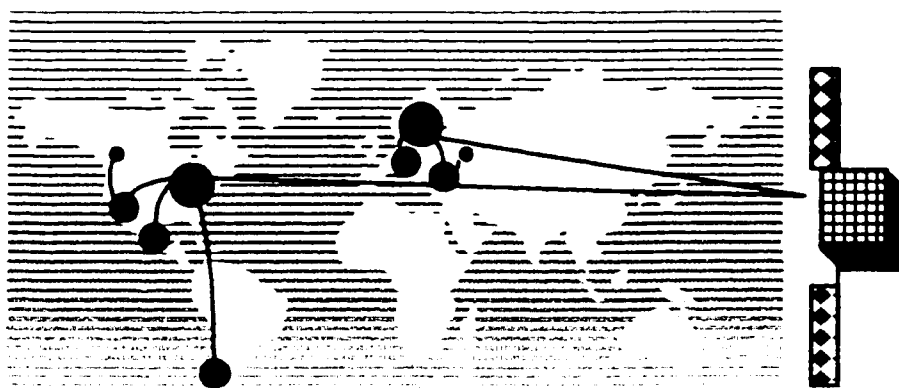
Telecommunications

Function: to overcome *space* with time.
Telecommunications facilitate spatial interaction by minimizing
time constraints in order to overcome *space* constraints.

Figure 2.1 Time, space, and the relationship between cities and telecommunications.

sometimes contradictory, patterns of intra-metropolitan accessibility (Graham and Marvin, 1996). While on the one hand these technologies allow individuals to extend their geographic reach, on the other they facilitate consolidation and dispersion of urban activities. For individuals lacking access to computers, to automobiles, or even to effective public transit, the ever expanding spatial separation facilitated by technological developments may serve to diminish, rather than to enhance, intra-metropolitan accessibility.

Concerns about the societal impacts associated with changing urban spatial structure have been expressed in the spatial mismatch/skills mismatch literature (Hughes, 1991; Holzer, 1991; McLafferty and Preston, 1996; Cooke, 1996; Skinner, 1995; Kasarda, 1990). Theories regarding spatial/skills mismatch contend that global competition, international immigration, and metropolitan decentralization have combined to create structural disparity between inner city residents and employment opportunities (Hughes, 1991). The *spatial* mismatch theory argues that processes of deindustrialization and employment suburbanization have resulted in fewer jobs for central city residents who often do not have access to automobiles to seek employment in outlying suburban areas. The *skills* mismatch theory, on the other hand, contends that not only have well-paid, low-skill manufacturing jobs moved out of the central city, but the new metropolitan jobs being created are of a high-skill, technical nature, inaccessible to a large portion of place-bound, central city residents.

Sassen (1991) argues that urban restructuring is producing job growth at *both* ends of the skill/wage spectrum, resulting in income and occupational polarization. At the top end, growing numbers of highly paid professionals are offered full-time, prestigious opportunities in business, law, finance, and management services. These professionals generate demand for a wide range of low order consumer services at the bottom end of the occupational hierarchy: supporting restaurants, retailing, cleaning, and the entertainment industries, for example (McDowell and Court, 1994; Sassen, 1991). As the multiplier effect would have it, these often casual, part-time, and low-wage jobs generally outnumber the high-skilled professional jobs by a factor of two or three to one (Graham and Marvin, 1996). These compositional changes in urban economic structure have spatial consequences, providing a context for the investigation of intra-metropolitan accessibility to employment opportunities in both time and space.

In the broadest sense, access to employment is a function of a wide range of factors including job skill requirements, worker skill levels, employment information networks, wages offered, wages desired/required, and proximity to available job opportunities (Hughes, 1991). Hughes (1991) argues that many of the Nation's core urban areas have become increasingly isolated from suitable employment opportunities and are exhibiting disturbing levels of poverty. He calls for comprehensive programs providing job training, employment information, and transportation to job opportunities for central-city communities. Before development of effective remedial programs can proceed, however, it is necessary

15

to identify those urban communities and socio-economic groups associated with poor accessibility. This dissertation research presents tools, methods, criteria, and procedures to accomplish this task.

Urban spatial structure is molded and shaped by processes of economic restructuring and changes in telecommunications and transportation technologies (Hodge, Morrill, and Stanilov, 1996). While we may not yet be able to ascertain direct relationships between these broad spatial processes and the refashioning of the urban landscape, we can begin to investigate indirect evidence of their impacts on urban spatial structure (Clark and Kuijpers-Linde, 1994). The next section examines this evidence by reviewing literature relating to the spatial impacts of suburbanization, economic restructuring, and changing technology on employment patterns in the Greater Los Angeles region.

Los Angeles and Changing Employment Patterns

Los Angeles has been called *the* prototypical example of urban restructuring; restructuring processes over the last 30 years have thoroughly modified the social and economic geography of this region (Soja, Morales, and Wolff, 1983). These processes have created a rapidly growing global city of financial management, corporate headquarters, foreign investment, and international trade. During the 1980s, Los Angeles surpassed New York in total industrial production, and replaced San Francisco as the leading West Coast international financial center (Soja, 1989; Ó hUallacháin, 1994). Los Angeles is also home to a large number of corporate headquarters, making it an important

16

center for corporate management, control, and decision-making. Public administration and management functions, in fact, are so centralized within the Los Angeles region, it contains the largest group of government employees outside of Washington, D.C. (Soja, 1989).

Amid indicators of economic growth and prosperity, however, are equally poignant indicators of decline and economic displacement: plant closures, firm relocations, unemployment, deepening poverty, and ethnic/racial segregation (Soja, 1989). Directly related to this economic restructuring, a large influx of immigrants from developing countries have radically altered local labor markets, contributing to a complex mosaic of economic patterns and cultural diversity (Soja, Morales, and Wolff, 1983; Scott and Soja, 1996).

The five county Greater Los Angeles region (Figure 2.2) is commonly viewed as a landscape of endless urban sprawl with widely dispersed population and employment patterns (Giuliano and Small, 1991). This decentralization reflects, in large part, the region's transportation development history (Nelson, 1959; Fogelson, 1967; Wachs, 1996). Early growth was shaped by an extensively developed inter-urban rail network and later by a complex and extended system of freeways (Figure 2.3). While urban growth prior to World War II was primarily confined to Los Angeles County, it is important to keep in mind that very few areas of Los Angeles were ever associated with conventional high urban densities. In the 1960s, the unofficial slogan used to describe Los Angeles was "Sixty Suburbs in Search of a City" (Soja, 1996). By 1965, these residential suburbs extended south well into Orange County and north into the San Fernando Valley (Giuliano

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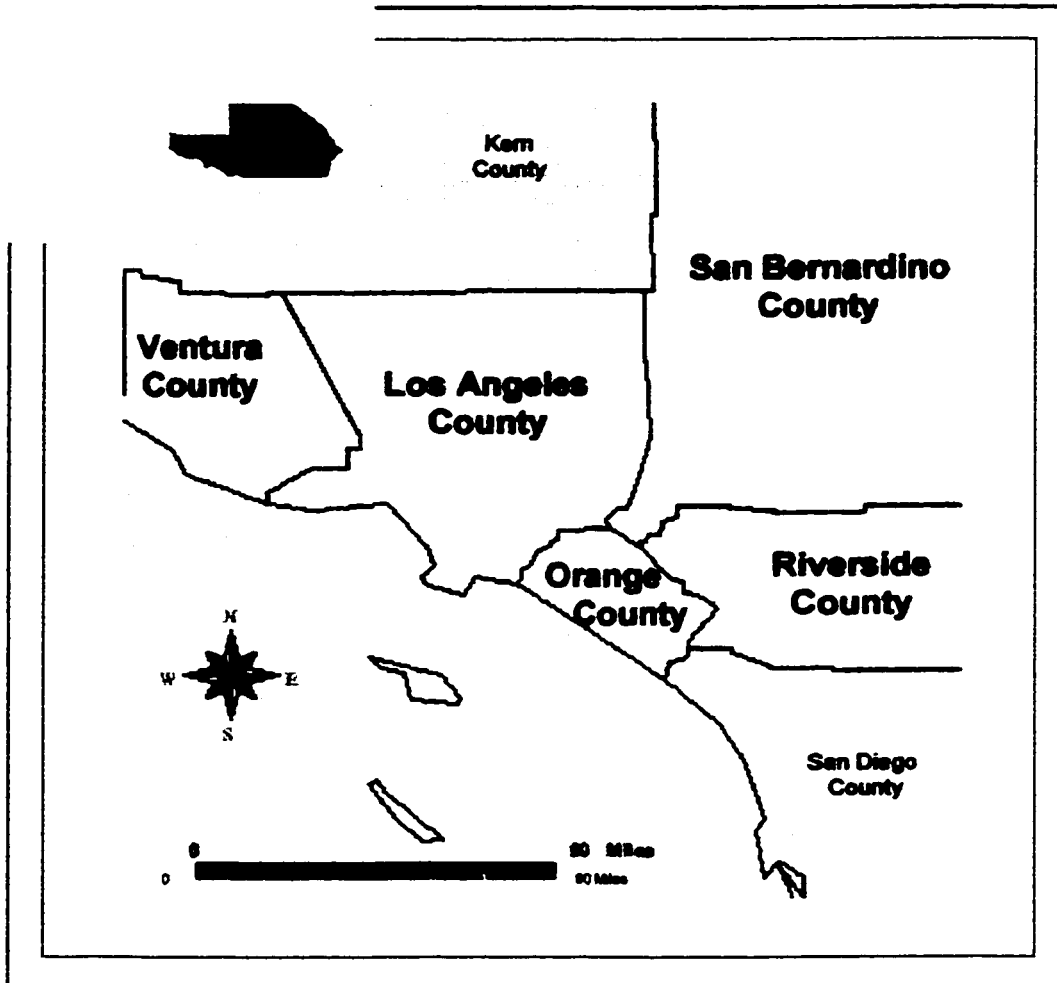
Figure 2.2 The Five County Greater Los Angeles Region.

The Greater Los Angeles Region Study Area
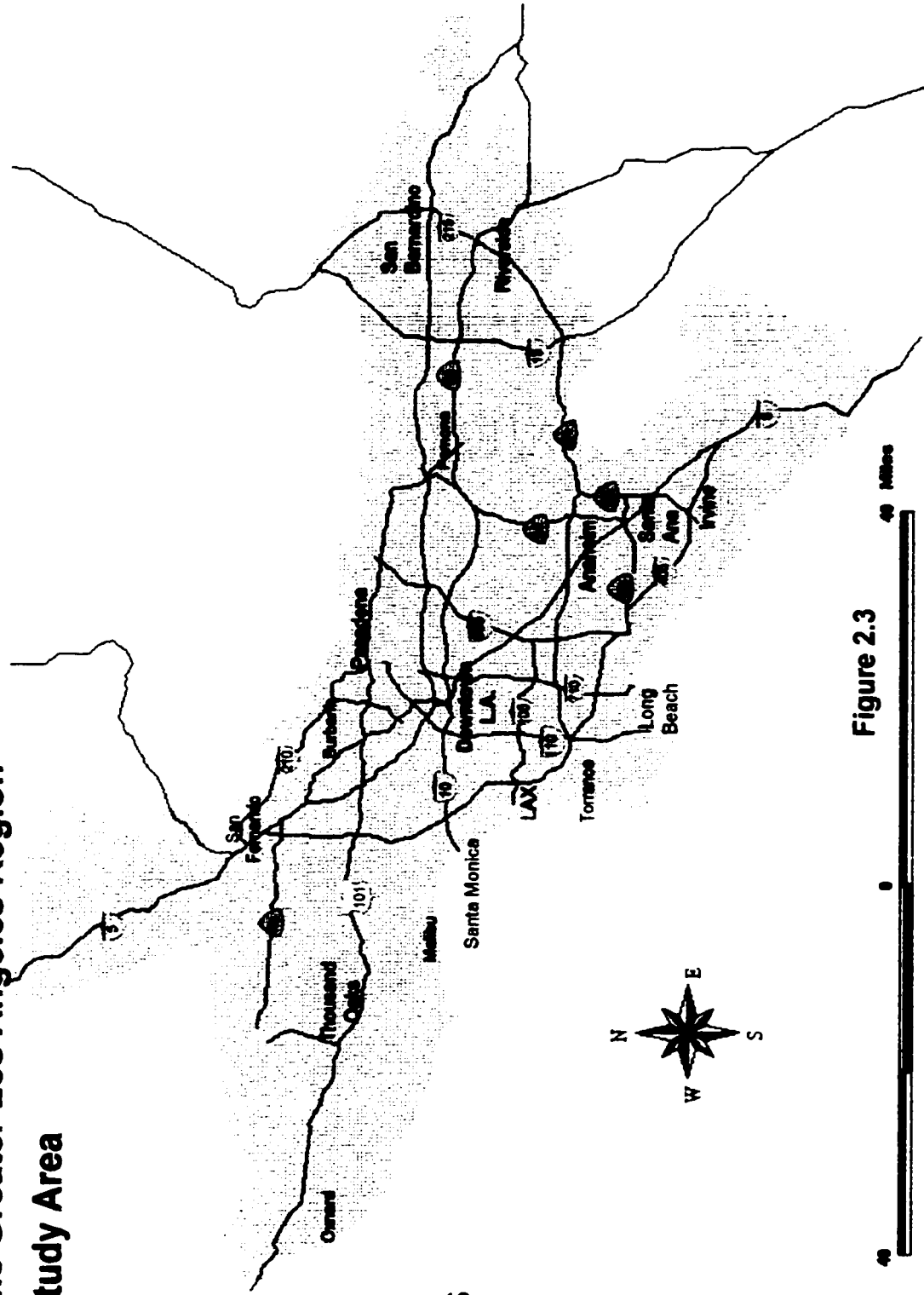
Figure 2.3

and Small, 1991; Scott, A., 1996). As transportation became more efficient, many

firms and industries followed these population trends, drawn to areas offering

lower congestion costs and providing new access to suburban labor markets

(Gordon and Richardson, 1996). By 1980, not only had Orange County and the

San Fernando Valley formed strong employment structures of their own, rapid

residential developments expanded to encompass large tracts of land in the

eastern counties of San Bernardino and Riverside (Giuliano and Small, 1991).

Recent empirical studies aimed at examining L.A.'s decentralized

metropolitan spatial structure (Scott and Getis, 1998; Scott and Lloyd, 1997;

Gordon, Richardson, and Wong, 1986; Gordon and Richardson, 1996; Small and

Song, 1994; Giuliano and Small, 1991), indicate that both population and

employment continue to decentralize, leading Gordon and Richardson (1996), in

fact, to make the claim that Los Angeles is moving beyond polycentrism, toward a

pattern of generalized dispersion. Concluding that urban spatial structure in Los

Angeles is becoming more dispersed, however – while accurate – obscures the

very complex processes of *both* agglomeration and dispersion simultaneously

impacting the region (Scott and Lloyd, 1997).

Greater Los Angeles, representing one of the largest industrial regions in

the world (Soja, 1989), gained approximately 1.4 million new jobs between 1980

and 1990. While the majority of this new job growth took place outside the

region's densest employment clusters, a large proportion of new jobs continued to

migrate to high-density, job-rich areas (Scott and Lloyd, 1997). Employment

patterns (jobs) and the spatial distribution of workers (resident workers) for 1980

are shown in Figures 2.4 and 2.5 below[4]. While jobs are widely decentralized throughout the study area, Downtown Los Angeles retains a dominant influence on the region, exhibiting both high resident worker and high employment densities. Furthermore, a number of other employment centers stand-out. Major job concentrations can be identified extending west from Downtown Los Angeles toward Santa Monica, forming a spine along the 5 freeway, consolidating near the LAX airport, and clustering near Santa Ana at the 5 and 55 freeway interchange. Employment and worker growth between 1980 and 1990 is shown in Figures 2.6 and 2.7. This growth in both employment opportunities and resident workers was accompanied by rather dramatic changes in the industrial composition of the region. Between 1965 and 1994, Los Angeles County, along with the Nation as a whole, experienced sharp decreases in manufacturing activities, offset by strong growth in the service sector (see Figure 2.8).

Evidence of both changing distributional and compositional employment patterns in the Los Angeles region, provides a basis for examining the effects of these changes on intra-metropolitan accessibility. The theoretical outcome, particularly in light of rapid technological developments, is far from clear, however. Some researchers (Black and Conroy, 1977; Gordon, Kumar, and Richardson, 1989; Gordon, Richardson, and Jun, 1991) argue that a dispersed arrangement of

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[4] The study area evaluated in this research, encompasses most of the urbanized portions of the five county Greater Los Angeles region covered by the Southern California Association of Governments (SCAG): Los Angeles, Orange, San Bernardino, Riverside, and Ventura. The sparsely populated San Gabriel and San Bernardino Mountains are not included in the study area.

Greater Los Angeles Region Employment in 1980

Jobs Per Square Mile:

0-10

10-100

100-1000

1000-5000

> 5000
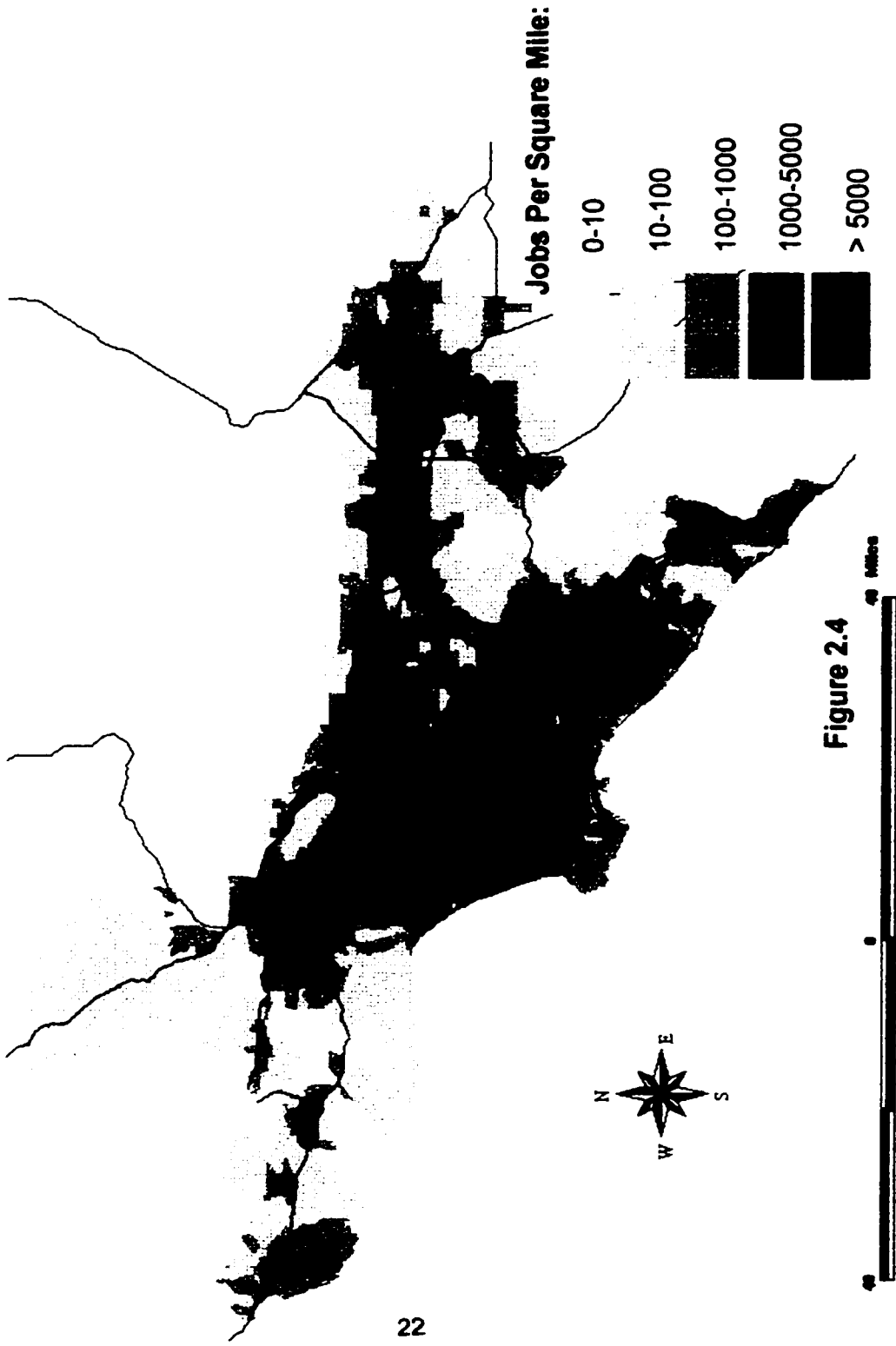
Figure 2.4

Greater Los Angeles Region Workers by Place of Residence, 1980

Workers Per Sq. Mile:

0-10

10-100

100-1000

1000-5000

> 5000

Figure 2.5

60 Miles

23
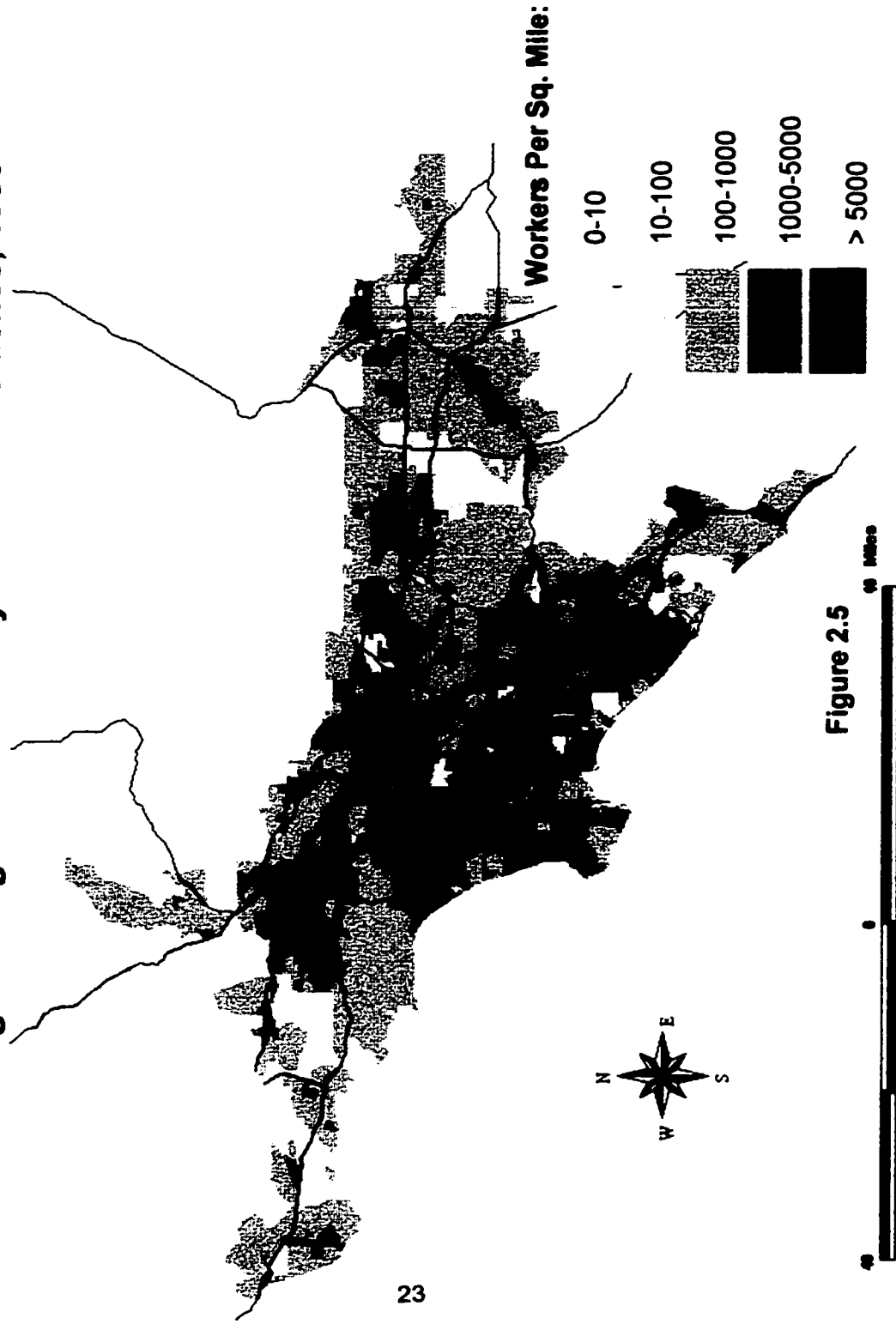
Greater Los Angeles Region Job Growth, 1980 to 1990

Jobs Per Square Mile:

Lost Many   (> 800)

Lost Some   (40-800)

No Change(up to +/-40)

Added Some (40-800)

Added Many (> 800)

Figure 2.6

24
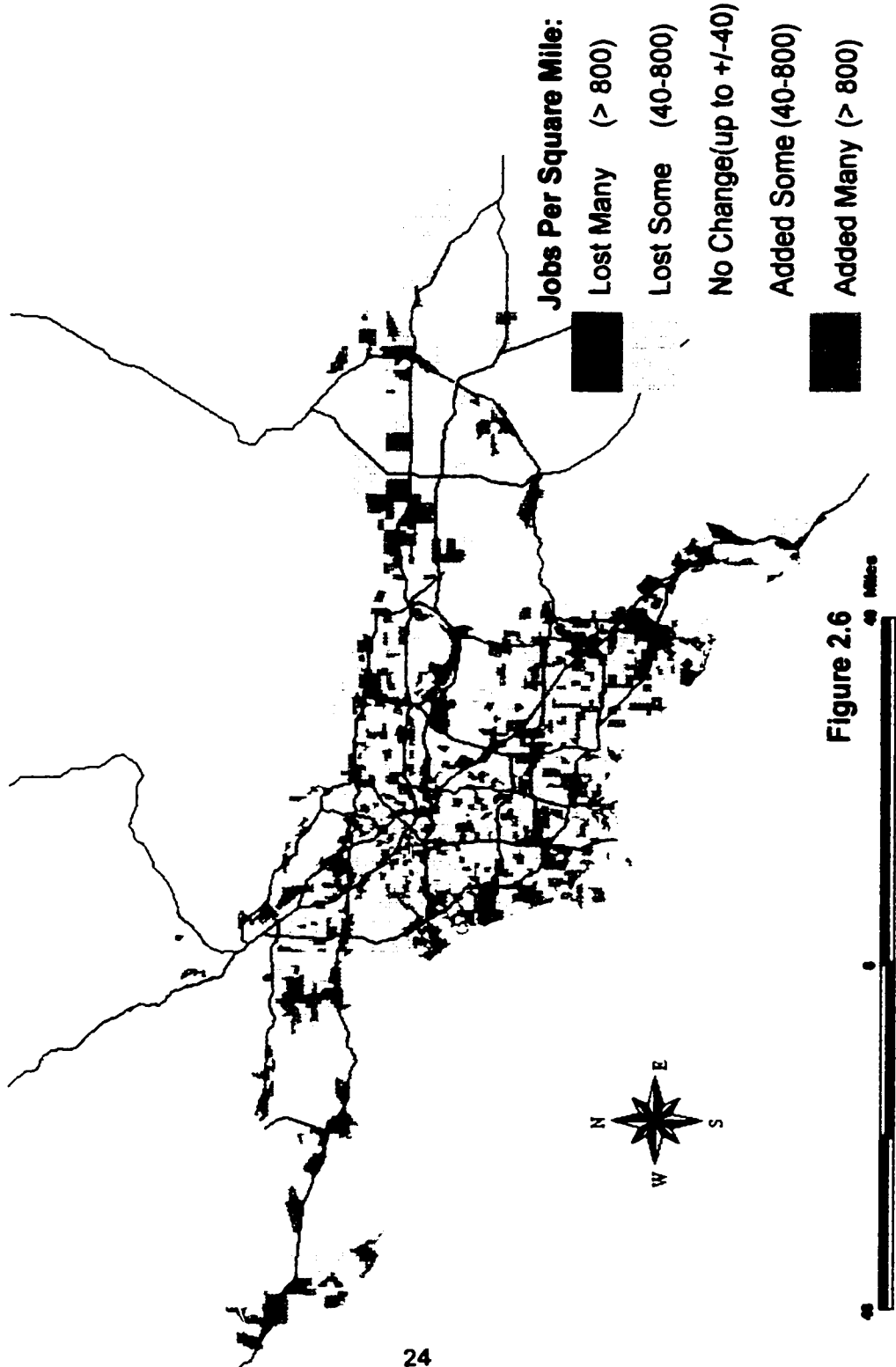
Greater Los Angeles Region Resident Worker Growth, 1980 to 1990

Workers Per Sq. Mile:

Lost Many   (> 800)

Lost Some   (40-800)

No Change(up to +/-40)

Added Some (40-800)

Added Many (> 800)

Figure 2.7

25
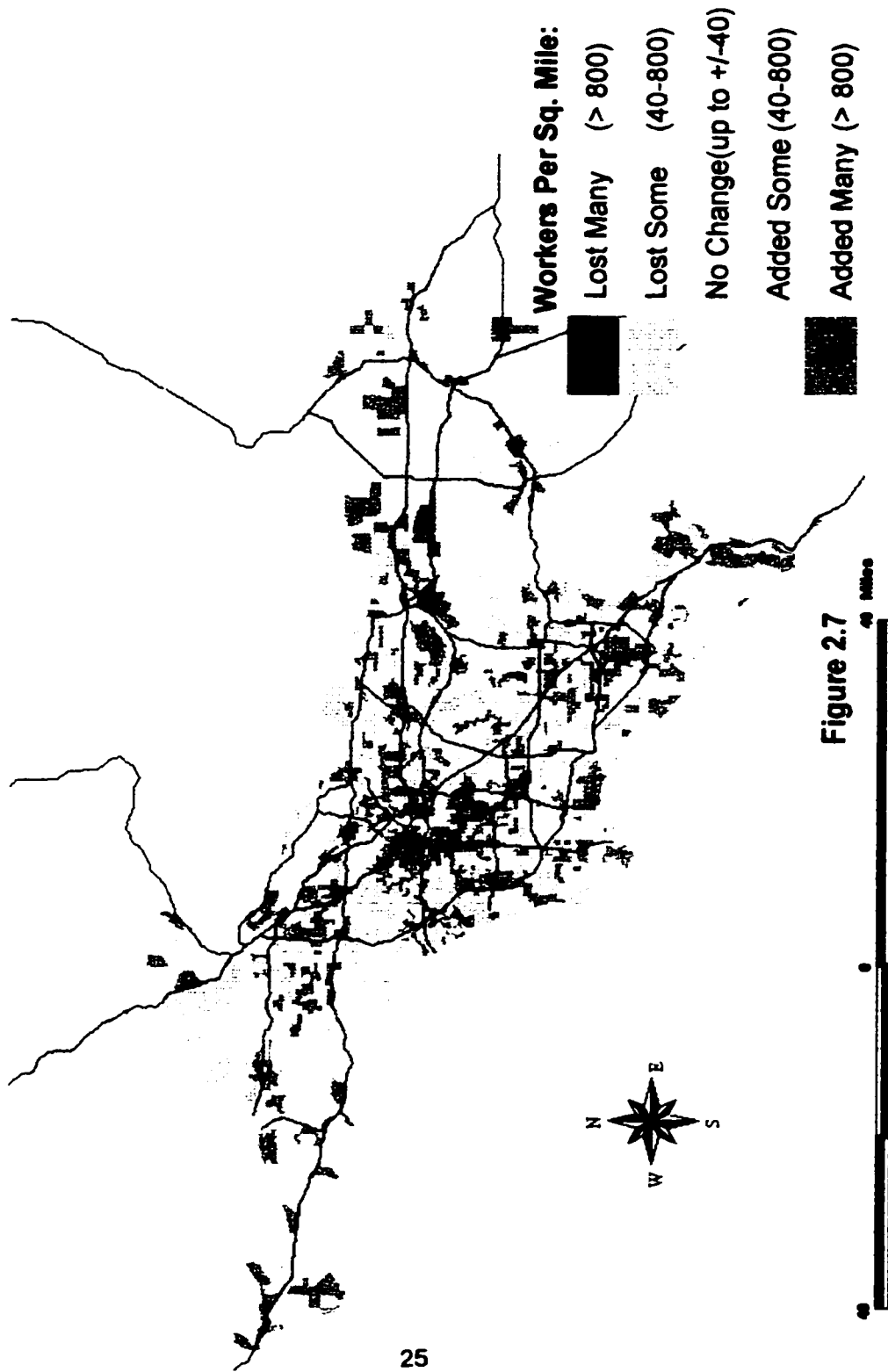
Los Angeles County
Employment by Industry, 1965-1994
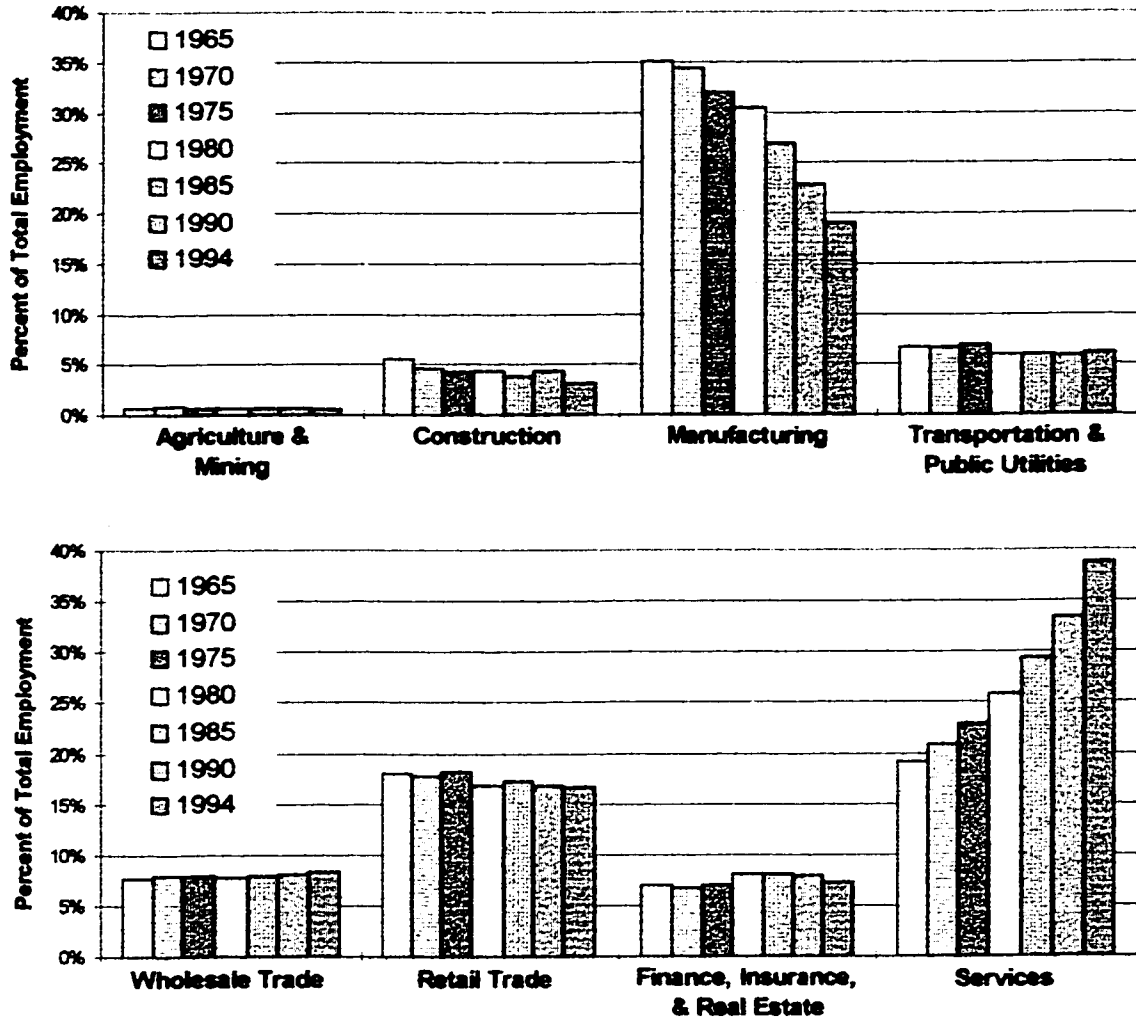
Figure 2.8 Employment by industry in Los Angeles County, 1965-1994. For the most part, the agriculture & mining, construction, transportation and public utilities, wholesale trade, retail trade, and FIRE (finance, insurance and real estate) industries maintained an even share of L.A County's employment base between 1965 and 1994. The construction and retail trade industries, however, show very slight declines. The most significant changes in the composition of jobs in Los Angeles County are associated with the manufacturing and service industries. Manufacturing jobs steadily declined between 1965 and 1994, offset by steady and persistent increases in service jobs.

workplaces improves accessibility to employment opportunities for residents living in the suburbs, especially those with access to private transportation. Simulation studies indicate dispersed polycentric urban spatial patterns are more efficient than compact monocentric patterns because, ultimately, they tend to facilitate greater proximity between work and home (Hodge, Morrill, and Stanilov, 1996). Other researchers (Newman and Kenworthy, 1988; 1992; Cervero and Landis, 1995), however, contend job decentralization unfairly deprives place-bound central-city residents, encourages homogeneity and low densities (associated with environmental and economic inefficiency), and advocates automobile dependence (contributing to congestion, pollution, and decreasing public transportation patronage) (Hodge, Morrill, and Stanilov, 1996). In response, many urban planners along with regional and local government agencies, have endorsed policies promoting jobs/housing balance (Downs, 1992; Livingston, 1992; Sherwood, 1992).

Planning theory suggests balancing jobs and housing may increase intra-metropolitan accessibility to employment opportunities by reducing commuting distances (see Cervero, 1989; Nowlan and Stewart, 1991; for opposing views see Gordon, Richardson, and Jun, 1991; Giuliano, 1991; 1995). Consequently, the concept has gained wide appeal with planners, environmentalists, and policy makers, not only as a way to reduce commuting distances, but also as a possible approach for curtailing transportation-related air pollution, decreasing gasoline consumption, constraining urban sprawl, and minimizing traffic congestion (Livingston, 1992). Cervero, in fact, contends many

27

of the Nation's most pressing and persistent urban problems could be relieved by balancing employment and housing growth (1989).

Achieving balanced jobs/housing ratios in the Los Angeles metropolitan region has been a goal of the Southern California Association of Governments (SCAG) since 1974 (Bookout, 1990). It became a formal component of the Regional Growth Management Plan, however, in 1989 when growth forecasts indicated the region would expand to include 18.3 million people and 9 million jobs by the year 2010. Most of this job growth was projected to occur in the central counties of Los Angeles and Orange, while the majority of new housing was projected to occur in suburban and exurban regions of San Bernardino, Riverside, Orange, and Ventura counties (Sherwood, 1992). With these growth projections, regional transportation models predicted near paralysis by the year 2010 if mitigation measures could not be implemented (Downs, 1992).[5] In response, SCAG put together a comprehensive plan to address the imminent crisis. A primary component of the plan was a jobs/housing balance initiative. By redirecting 12 percent of the new jobs to housing-rich areas and 6 percent of the new housing to job-rich areas, SCAG transportation models concluded traffic congestion could be held to only a 20 percent increase (Sherwood, 1992).

The effectiveness of jobs/housing balance policies has been questioned, however, in a series of articles addressing "wasteful commuting" (Hamilton, 1982;

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[5] Traffic congestion was projected to increase by 50 percent, bringing average highway speeds to a crawl at only 24 miles per hour. Air pollution emissions were projected to continue to exceed standards by as much as 5 times the allowable levels for some pollutants (Sherwood, 1992).

1989; White, 1988; Cropper and Gordon, 1991; Small and Song, 1992; and Giuliano and Small, 1993). The wasteful commuting literature is concerned with two issues: (1) the effectiveness of traditional monocentric urban models (specifically their effectiveness for explaining/predicting journey-to-work commuting patterns), and (2) the relationship between journey-to-work commuting patterns and urban spatial structure (specifically the distribution of jobs in relation to households). In this literature, researchers calculate the "required" commute – the minimum average journey-to-work commute that would occur if residential locational decisions were driven entirely by the desire to minimize commuting costs – and compare this average required commuting distance to actual average journey-to-work commuting distances. Where actual commuting times/distances exceed the minimum ("required") commuting times/distances, commuting behavior is said to be "wasteful" (Hamilton, 1982).

After effectively reviewing the wasteful commuting literature, Giuliano and Small (1993, 1488) conclude it "seems clear" that actual commuting is vastly longer than estimates based on either the monocentric model assumptions or on linear programming methods. "This is true whether commuting cost is measured by time or distance, and whether or not a constraint is placed on the assignment process to represent housing preferences, type of ownership, race or income". Their own analysis, based on 1146 transportation analysis zones (TAZs) in the Greater Los Angeles region, finds large gaps between actual and required region-wide commuting averages. They argue that these findings indicate commuting behavior cannot be explained by urban spatial structure:

29

"... attempts to alter the metropolitan-wide structure of urban land use via policy intervention are likely to have disappointing impacts on commuting patterns, even if successful in changing the degree of jobs-housing balance... Moreover, the standard economic analysis of urban location, which relies upon the tradeoff between land costs and commuting costs as the primary determinant of residential location, also fails to provide adequate explanation for observed location patterns" (Giuliano and Small, 1993, 1498).

While the effectiveness of jobs/housing balance policies, therefore, is certainly an open question, the broader goals of these policies include increasing intra-metropolitan accessibility to employment opportunities by building communities that have sufficient employment and housing to satisfy all of their members – in essence to break down the exclusionary barriers that might force people to live much farther from their place of work than they would like to (Cervero, 1989). Chapter 4 of this research will demonstrate that effective measurement of intra-metropolitan accessibility provides an appropriate method for examining and monitoring a variety of urban relationships (including jobs/housing balance relationships) and for specifically testing relationships between urban spatial structure and journey-to-work travel patterns. Before intra-metropolitan accessibility can be effectively evaluated, however, a number of definitional, representational, and operational issues must be addressed. These issues are discussed in the next chapter.

CHAPTER 3

DEFINING AND REPRESENTING ACCESSIBILITY

"Accessibility... is a slippery notion... one of those common terms that
everyone uses until faced with the problem of defining and measuring it"
(Gould, 1969, 64).

Research on accessibility in geography has a long history, beginning with

Ravenstein's work (1885; 1889) over a century ago. Scholars such as Reilly

(1929), Zipf (1949), Stewart (1947), Warntz (1967), and Wilson (1967) carried the

work significantly further, exploring theories concerning constraints imposed by

distance, time, travel cost, or human effort, and the influence of these constraints

on potential accessibility to work, shopping, recreation, and other spatially

distributed urban activities (Couclelis and Getis, 1999). Application of these

foundational theories can be identified in studies involving retail (Huff, 1964), land

use (Harris, 1954; Hansen, 1959; Stegman, 1969; Black and Conroy, 1977),

public service provision (McLafferty, 1982), migration (Dorigo and Tobler, 1983;

Plane, 1984), information flows (Tornquist, 1968; Murnion, 1999), recreational

travel (Goodchild, 1975), and the assessment of transportation infrastructure

(Garrison, 1960; Linneker and Spence, 1992; Allen, Lui, and Singer, 1993).

Notions about intra-metropolitan accessibility continue to provide the basis for a

variety of urban policy and transportation planning decisions; to represent key

components in urban economic theory relating to land use and urban

development; and to serve as a common focus for a broad body of geographic

31

research concerning economic growth, transportation patterns, metropolitan form, urban efficiency, and social equity.

Despite this long history and the centrality of these ideas to urban research agendas, defining and operationalizing accessibility continues to present challenges (Pirie, 1979; Helling, 1996). There are outstanding questions, for example, regarding the distinction between *accessibility* and *mobility*, and between *potential accessibility* and *realized access* (Couclelis and Getis, 1999; Scott, 1999). The challenges become even more pronounced, however, in the "Information Age" where access to urban activities is no longer necessarily constrained by physical space, but increasingly takes place via electronic telecommunications networks in virtual spaces (Janelle and Hodge, 1999). Further adding to these difficulties are findings suggesting that relationships linking accessibility to urban spatial processes may be diminishing. Giuliano (1995), for example, presents an especially strong argument to this effect. Her argument derives evidence from the "wasteful commuting" literature (Hamilton, 1982; 1989; White, 1988; Hamburg, *et al.*, 1965; Cropper and Gordon, 1991; Small and Song, 1992; Giuliano and Small, 1993; Simpson, 1987). Empirical findings from this body of literature lead to the conclusion that commuting behavior cannot be effectively explained by urban spatial structure (Giuliano and Small, 1993).

This conclusion is disturbing for at least two reasons. (1) It casts doubt on the viability of classic urban economic theory, strongly based on an assumed relationship between accessibility and locational decisions. (2) It reduces confidence in the ability of urban planning to remedy problems associated with

32

urban congestion, sprawl, or automobile-induced air pollution; to explain urban

development; or to predict future urban infrastructure needs.

Alternative explanations for the diminished explanatory power of

accessibility models, however, are possible. The problem may not lie with a

declining significance for accessibility *per se*, but with an inability for existing

measures to adequately *represent* accessibility. That is, there may only be a poor

relationship between urban spatial processes (such as journey-to-work commuting

patterns) and accessibility *indicators* (Leake and Huzayyin, 1979). The most

common accessibility indicators are based almost exclusively on spatial relations

governed by the friction of distance (or time). This limited view of spatial

relationships becomes increasingly insufficient to portray the stretching and the

shrinking of space and time associated with advances in telecommunications and

transportation technologies – technologies that allow, for example, a growing

portion of the workforce to telecommute.

But how can we effectively represent accessibility when existing models

present such inconsistent explanations, and when developments in transportation

and telecommunications technologies require us to completely rethink our

understanding of the space, time, and distance foundations of longstanding

concepts of accessibility? This question sets the objective for this chapter. It is an

important question because so many of the models in regional science, urban

economics, transportation planning, and urban geography include an accessibility

component. If we are able to represent accessibility more effectively, the

possibility exists for developing more effective urban models.

Assessing the effectiveness of any particular representation of intra-metropolitan accessibility, however, is not altogether straightforward. It is one thing to argue from a logical, theoretical, technical, or even aesthetic perspective that one representation of accessibility is more effective than another. It is quite a different issue to demonstrate empirically the superiority of any particular approach. An effective measure and representation of intra-metropolitan accessibility, however, should be able to hold up to empirical analyses by offering improved understanding and explanation of urban spatial processes.

The analytical framework proposed in this chapter incorporates five components: (1) the Couclelis (1997) proximal space construct; (2) the Getis/Ord G_i^* spatial statistic (Getis and Ord, 1992; Ord and Getis, 1995); (3) a "level-of-service" definition of accessibility; (4) multiple scale analyses; and (5) a multi-dimensional representation of accessibility processes. This chapter assesses the effectiveness of the proposed analytical framework by exploring the relationship between the most commonly used aggregate-level measures of accessibility and observed journey-to-work travel patterns, using this relationship as a basis for introducing each component of the proposed framework. It is then demonstrated that the proposed analytical framework provides stronger explanation of journey-to-work commuting distances than existing accessibility measures. Certainly other spatial relationships could have been selected for evaluation purposes (predicting income distributions, median rents, or population densities, for example). The relationship between journey-to-work commuting costs and intra-metropolitan accessibility was selected for a number of reasons.

34

(1) Epitomized by the "wasteful commuting" literature, researchers have typically found a weak relationship between commuting costs and urban accessibility (Giuliano and Small, 1993). (2) Commuting behavior has been used in the literature as a surrogate for urban efficiency (Pooler, 1993). And (3) the externalities associated with long-distance commuting have provided central themes in urban and transportation planning literature dealing with jobs/housing balance, spatial/skills mismatch, traffic congestion, and emerging transportation technologies (Hodge, Morrill, and Stanilov, 1996) – themes explored in Chapter 4 of the dissertation.

Accessibility and the Journey-to-Work

A large body of formal urban theory contends that accessibility is at the very core of processes shaping urban spatial structure: people choose residential locations to satisfy both housing needs and workplace access, and employers choose work locations that are accessible to employees, urban infrastructure, and consumer markets (Giuliano, 1995b). Consequently, many researchers insist that the concept of accessibility is fundamental to definitions and explanations of urban form, function, and efficiency, arguing that a site's accessibility to economic and social opportunities largely determines its value, development intensity, and economic, social, and political uses (Wachs and Kumagai, 1973; Knox, 1980; Koenig, 1980). The basis for these assertions derives from standard urban economic theory, initially developed to respond to the challenges of effectively explaining observed regularities in the spatial structure of cities. The key to this

35

body of theory, in all of its various formulations and extensions, is the observation

that commuting cost differences within an urban area *must* be balanced by

differences in other cost-of-living prices or locational amenities. If consumers living

far from the city center are not compensated in some fashion for their long

commutes, they are not going to voluntarily live at the urban periphery (Brueckner,

1987). These models (e.g., Alonso, 1964; Mills, 1972; and Muth, 1969), therefore,

are founded on principles of profit and utility maximization. They assert that the

spatial distribution of various land uses is a function of the prices for all of the

factors associated with either production or consumption, including transportation

costs. The concept of accessibility is implicit in these models since the value of a

particular location relative to all urban opportunities is reflected in the price for land

(Giuliano, 1995a).

Using standard urban economic theory as a foundation, then, one would

expect to find a relationship between urban accessibility and journey-to-work

commuting costs. To test this relationship, intra-metropolitan accessibility is

measured (at the census tract level) for the 5 county Greater Los Angeles region

(Figure 2.3) using the most common aggregate-level accessibility measures:

spatial interaction indicators[6], isochronic measures[7], and network models[8]. (The

software developed to perform these analyses is presented in Appendix E,

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[6] For examples of spatial interaction accessibility indicators, see Cervero, Rood, and
Appleyard (1997), Dalvi and Martin (1976), Geertman and Ritsema Van Eck (1995), Knox
(1980) or Shen (1998).
[7] For examples of the isochronic approach, see Black and Conroy (1977) or Wachs and
Kumagai (1973).
[8] For examples of network models of accessibility, refer to Ingram (1971), Irwin and
Hughes (1992) or Muraco (1972).

ACCESS92). These measures were selected because they are representative of the variety of aggregate-level approaches utilized in the current literature. Each measure, however, is represented in its simplest form. Detailed technical comparisons are bypassed here since these types of analyses are already well represented (e.g., Breheny, 1979; Kwan, 1998; Leake and Huzayyin, 1979; Jones, 1981; Koenig, 1980; Linneker and Spence, 1992; Morris, Dumble, and Wigan, 1979; Pirie, 1979; Talen and Anselin, 1996; and Scott, 1998).

The spatial interaction model of accessibility may be presented most simply as:

$$A_i = \sum_j E_j \, d_{ij}^{-b}$$

where:

A_i = the accessibility index representing how accessible tract i is to employment opportunities
E_j = a count of the employment opportunities at tract j
d_{ij} = the distance between tracts i and j
b = an exponent to reflect friction of distance, calibrated for the study area to be *1.49*

With spatial interaction measures, accessibility for each tract i is represented as the sum of all jobs for all tracts within the study area, where the number of jobs for each tract j is discounted by an impedance function[9]. For the Greater Los Angeles study area the calibrated impedance function for 1990 is $1/d_{ij}^{1.49}$.

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[9] The impedance parameter (a *friction of distance* or *beta* value) is calculated for the study area using a doubly constrained gravity model and a convergence algorithm similar to that suggested by Fotheringham and O'Kelly (1989, see page 53). The calibration procedure is diagramed in the first part of the flowchart (Figure AD1) in Appendix D. Since this calibration procedure is also used in estimating *functional* travel times (discussed in detail later in this chapter), calibrating the doubly constrained gravity model using a sample of all journey-to-work flows was not appropriate (since this could have biased some of the functional time estimates). Instead, a convergence algorithm is used to find the beta value that will best reproduce a frequency curve of estimated journey-to-work distances to match a frequency curve for all actual observed journey-to-work distances.

The isochronic accessibility measure may be written most simply as:

$$A_i = \Sigma_j E_j \, w_{ij} \, (d)$$

where:

A_i = the accessibility index representing how accessible tract i is to employment opportunities

E_j = a count of the employment opportunities at tract j

w_{ij} = 1 if the distance between tract i and tract j is less than or equal to d, 0 otherwise

d = a critical distance, 17 miles for these analyses

Isochronic measures represent accessibility as a simple count of the number of opportunities within distance (or travel time) d of each tract i. A difficulty with isochronic measures is determining an appropriate value for the critical isochrone, d. For comparison purposes in this chapter, a d value of 17 miles was selected since this integer produces the largest R^2 value for the regression analysis described below.

Network accessibility measures take a variety of forms (Jones, 1981). This chapter utilizes a measure suggested by Ingram (1971). It may be written as follows:

$$A_i = \Sigma_j 100 \, d_{ij}^{-b}$$

where:

A_i = the accessibility index associated with tract i

d_{ij} = the distance between tracts i and j

b = an exponent to reflect the friction of distance, calibrated for the study area to be 1.49 (see footnote[9])

Network accessibility measures focus exclusively on transportation infrastructure rather than opportunity distributions, representing accessibility as the total cost to travel from each tract i to every other tract j in the study area, where distance is discounted by a calibrated impedance factor. This type of network accessibility indicator is a measure of transportation network centrality.

Comparative analysis: Once a set of indicators has been calculated for each of the accessibility measures presented above, OLS regression may be performed to test the relationship between these indicators and commuting costs. In representing commuting costs, the average journey-to-work commuting distance is calculated for each tract i as the average distance associated with all journey-to-work flows either originating or terminating at tract i. (The source code used to calculate commuting costs is presented in Appendix E, GETCOMM). By calculating commuting averages to include both out-going and in-coming flows, both resident worker accessibility to job opportunities and employer accessibility to labor market resources is represented (see "Level-of-Service Definition", presented later in this chapter).

Note that all of the regression models presented throughout this and the next chapter are highly significant at the 0.001 level; all use the spatial filtering technique outlined by Getis (1995) to handle spatial autocorrelation; all of the coefficients for these regression models produce expected signs; and the multivariate models presented in this research are free from multicollinearity effects[10].

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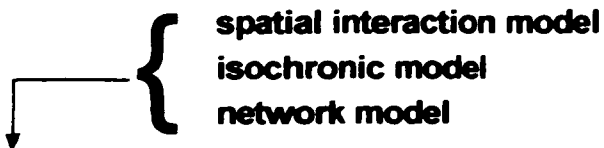
[10] Multicollinearity implies near-linear dependence among the independent variables in a regression analysis (Montgomery and Peck, 1992, 189). To test for multicollinearity, a *Variance Inflation Factor* (*VIF*) was calculated for each independent regression variable, x. The *VIF* for the jth regression coefficient, for example, may be written as:

$$VIF_j = 1 / (1 - R^2_j)$$

where R^2_j is the coefficient of multiple determination obtained from regressing x_j against all other independent regression variables. If x_j is nearly linearly dependent on one or more of the other independent regression variables, VIF_j will be large. Variance inflation factors larger than 10 imply serious problems with multicollinearity (Montgomery and Peck, 1992, 192). For this research, independent variables were not used if they were associated with a *VIF* equal to or greater than 5.

39

The results of the initial OLS regression are summarized in Table 3.1

below. It is interesting to find that the isochronic accessibility measure performs

best, as these measures have been criticized (Kwan, 1998; Helling, 1998) for

giving equal weighting to all opportunities within a fixed critical distance or

isochrone. Intuitively, however, this finding makes sense. Few of us would worry

about the length of our commute in selecting between one job 5 miles away and

another job 8 miles away. It is only when some options are more distant that we

begin to question whether or not we want to spend so much time out of each

workday commuting. In fact, representing spatial relationships among jobs and

residential locations in terms of a zone of indifference combined with an

impedance function for distances beyond this fixed critical zone (Getis, 1969),

improves model explanation. Using a zone of indifference (ZOI) of 17 miles with a

$[1/(d_{ij} - ZOI+1)^{1.49}]$ impedance for distances (d_{ij}) larger than 17 miles increases

explanation to 30 percent of the variation in average commuting distances.

The results in Table 3.1 indicate a definite, though rather weak, relationship

between existing accessibility indicators and average journey-to-work commuting

distances. An important observation, however, is that each of these measures of

accessibility conceptualizes spatial relationships among jobs and residential

locations in a different manner. With spatial interaction models, this relationship is

based on frictional distance (Figure 3.1a). Isochronic measures present this same

relationship as a binary function for a given critical distance band (Figure 3.1b). In

contrast, network models of accessibility measure the centrality of an origin on the

transportation network. Central locations receive the highest accessibility scores

40

{ spatial interaction model
  isochronic model
  network model

$$D_i = \beta_0 + \beta_1 A_i + \varepsilon$$

Accessibility Model	Formulation	Spatial Relation	R^2
Spatial Interaction	$A_i = \sum_j E_j \, d_{ij}^{-b}$	Calibrated friction of distance: $1/d_{ij}^{1.49}$	.23
Isochronic	$A_i = \sum_j E_j \, w_{ij}(d)$	Critical isochrone: $d = 17$ miles	.29
Network	$A_i = \sum_j 100 \, d_{ij}^{-b}$	Total cost with impedance: $100 * 1/d_{ij}^{1.49}$	.24

Table 3.1 Commuting Distance (D_i) as a Function of Common
Accessibility Indicators: Spatial Interaction, Isochronic, and
Network Models
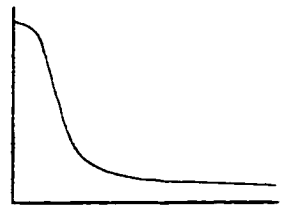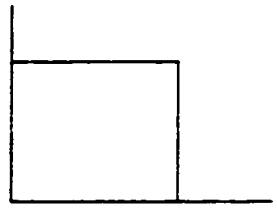
(a) Frictional Distance   (b) Binary Contiguity
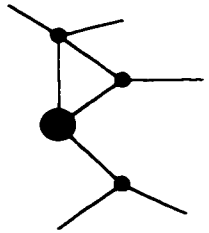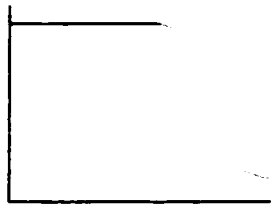
(c) Network Centrality   (d) Zone of Indifference

Figure 3.1 A Variety of Conceptualizations of the Spatial Relations Among Employment Opportunities and Census Tract Residential Locations Used in Evaluating Intra-Metropolitan Accessibility.

42

(Figure 3.1c). Representing spatial relations in terms of a zone of indifference with an impedance factor for distances beyond this zone, combines the isochronic approach with the spatial interaction approach (Figure 3.1d). It is certainly not difficult to think of many other possibilities as well. Gatrell (1983), in fact, reminds us that there are an almost infinite number of relations that may be defined for any given set of spatial objects. This reminder introduces the first component of the proposed analytical framework for evaluating and representing intra-metropolitan accessibility: the Couclelis (1997) proximal space construct.

Proximal Space

A number of researchers have suggested using GIS to model intra-metropolitan accessibility (Kwan, 1998; Miller, 1991; Arentze, Borgers, and Timmermans, 1994; Geertman and Ritsema Van Eck, 1995). Couclelis cautions, however, that the GIS environment presents a very specific representation of space (1991). GIS are geared toward spatial objects and an absolute or "container" view of space; they emphasize *site* characteristics over *situation* characteristics[11]. Consequently, the end result of any combination of GIS operations will typically involve information relating to specific locations or to specific spatial objects (points, lines, areas, or volumes). GIS are limited in their ability to represent non-localized spatial processes inherent in spatial organization,

[11] Where site characteristics reflect the attributes and qualities of particular locations or spatial objects, situation characteristics reflect each location's embeddedness within a broader spatial structure of relations or interactions involving other locations and other spatial objects.

43

configuration, pattern, spatial dynamics, restructuring, transformation, or change (Couclelis, 1991).

At a more general level, Sheppard (1996) discusses the concepts of site and situation in relation to "local context". He notes that the concept of local context is critical for explaining why seemingly similar processes may lead to very different outcomes in different places. Unfortunately, when places are modeled as discrete containers, and the concept of "local context" is narrowly defined in terms of site characteristics and the geometrical distances among site characteristics, the possibility for "action at a distance" – the possibility for objects or phenomena, such as information flows, to affect local context – is ignored. Sheppard (1996) suggests a broadening of the concept of local context to incorporate both site and situation characteristics.

The merging of both site and situation characteristics within a GIS environment, however, is not a straightforward undertaking. At issue is the fundamental conflict between two very different conceptualizations of space: absolute space and relative space[12]. Couclelis (1991; 1997) has developed the notion of *proximal space* as a way to bridge these two concepts. Where absolute space emphasizes the locational coordinates and attribute characteristics of site,

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[12] From the absolute or Newtonian perspective, space is represented as a distinct entity with characteristics similar to a system of pigeonholes or containers (Lawton, 1983, 197). It is conceptualized as emptiness – an entity with existence independent of matter, possessing the structure to hold or to individuate phenomena – a universal receptacle in which objects exist and events occur (Smith, 1984; Harvey, 1973). From the relative or Liebnitz perspective, on the other hand, space is an abstract concept reflecting the spatial relationships between perceived objects, endowed with structure and properties that are intimately tied to process (Lawton, 1983, 197; Couclelis, 1992, 221).

and relative space emphasizes the spatial relations associated with situation, the key notion in proximal space is the neighborhood (Couclelis, 1997). This notion of neighborhood – neither static nor restricted to physical contiguity – reflects Sheppard's extended concept of "local context"[13].

While many accessibility measures incorporate both a site and a situation component (typically a spatial attributes variable and a distance constraint or impedance variable), most are firmly grounded in physical spatial relations, such as travel time or distance. Gatrell (1983) notes, however, that despite a proliferation of urban models with a time or a distance component, time or distance themselves have never had causal properties. Instead, it is the *implications* of time and distance that have consequences, and it is precisely these implications that are being modified by rapid developments in transportation and telecommunications technologies. He notes the broad range of alternative relations that may be defined for any given set of spatial objects, making a distinction between "attribute proximities" and "interaction proximities" (Gatrell, 1983). Attribute proximities define relations between two or more locations based on attribute profiles (income, racial, or occupational profiles, for example). Defining relations using attribute proximities, location itself and the distances separating different locations are immaterial. In contrast, interaction proximities define relations between two or more locations on the basis of spatial interaction volumes

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[13] A related concept in spatial econometrics can be seen with the use of spatial lag variables in some autoregressive modeling. See, for example, Paelinck and Klaassen (1979).

(social networks, journey-to-work trips, commodity flows, for example). Here, location and distance are central components of the relations defined for a set of spatial objects.

Similarly, the notion of proximal space (Couclelis, 1997) emphasizes spatial relations in the form of interactions *centered on specific localities*, interactions that may be relevant from a variety of different formal perspectives: spatial proximity, functional proximity, and statistical spatial dependency. Spatial proximity reflects the physical spatial relationships associated with a local site and its neighbors. Functional proximity reflects a local site within the context of relationships based on influence or interaction. Statistical spatial dependence reflects the cohesion and homogeneity of a site and its neighbors. Within the proximal space construct, relations may be operationalized as a series of functions, heuristics, or other symbols linking each location to every other location under study, encouraging exploration of different conceptualizations of spatial/temporal context and the variety of relationships that may exist for any given set of spatial objects. Keep in mind, however, that the proximal space construct is not simply recognition that a variety of spatial relations exist and may be creatively modeled, but that these relations are a fundamental component of the spatial objects being examined. From this perspective, accessibility is considered a structure (rather than a static score), whose form and magnitude is a function of intrinsic spatial/temporal relations (see "A simple example", presented later in this chapter).

Takeyama and Couclelis (1997) describe the variety of relations that may be defined for a set of spatial objects in terms of a "relational map". This concept

46

of a relational map may be represented quite efficiently using a "spatial weights matrix". A spatial weights matrix contains row and column entries for each pair of i and j locations under study, where each w_{ij} entry defines the relationship that exists between locations i and j. A number of spatial statistics and models in geography and econometrics, in fact, utilize a spatial weights component. In practice these matrices often reflect binary contiguity relationships. In most cases, however, they are not limited to this representation (see Florax and Rey, 1995, however, for a discussion of spatial weights matrix misspecification impacts in relation to statistical inference). This observation leads to the second component of the proposed analytical framework for evaluating and representing intra-metropolitan accessibility: the Getis/Ord G_i^* spatial statistic (Getis and Ord, 1992; Ord and Getis, 1995).

Getis/Ord G_i^* Spatial Statistic

Anselin (1990) argues that two general effects make 'spatial data special': spatial dependence and spatial heterogeneity. Spatial dependence refers to the almost inescapable presence of autocorrelation in spatially referenced data (Goodchild, 1997). With geographic data we expect to find stronger relationships among nearby variables than among spatially distant variables (Anselin and Getis, 1992). Spatial heterogeneity refers to the tendency for parameters and other characteristics of models describing spatial data to vary from place to place (Goodchild, 1997). The implication of both of these spatial effects is that they must be taken into account whenever we deal with spatial data (Anselin and Getis,

47

1992). Consequently, a number of researchers have developed pattern analysis techniques explicitly designed to identify spatial dependence and spatial heterogeneity (e.g., the spatial statistics of Moran and Geary; Getis and Ord, 1992; 1995; and Anselin, 1995). The "local statistics" of Getis/Ord and Anselin consider each location or event in a study region within the context of neighboring locations/events, where the "neighborhood" is defined at a variety of different spatial scales. The analytical framework proposed in this research, extends the application of these statistics by utilizing the Getis/Ord G_i^* local statistic to evaluate intra-metropolitan accessibility.

The Getis/Ord G_i^* statistic (Getis and Ord, 1992; Ord and Getis, 1995), which is used to test hypotheses based on randomly distributed spatial data[14], can also be used (as done in this dissertation) to measure the degree of association or spatial clustering associated with a single variable (E) distributed over a spatial surface. Consider an urban landscape divided into n regions, $i = 1, 2, ..., n$, where each region is identified with a location whose Cartesian coordinates are known. Each location i has associated with it a value e_i of the variable E. Each value, e_i, is affiliated with a set of neighbors – a set of e_j values – where the "neighborhood" is defined by a spatial weights matrix. The spatial weights matrix is square, with row and column entries for each pair of locations i and j. As one example, a binary spatial weights matrix may define local interactions – the neighborhood – in terms of physical distance: a 2 mile distance radius, for example. Each row, then, would

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[14] See Ord and Getis (1995) for a detailed discussion regarding the use of the G_i^* statistic for statistical inference.

be associated with column entries of either one or zero: values of one would reflect

membership in the neighborhood, and would be associated with all locations j

within a 2 mile distance radius of location i, including the diagonal where $j=i$

(footnote[15]).

The 1992 formulation of the G_i^* statistic, however, has many similarities

with spatial interaction models (Getis, 1991), and may be rewritten using a format

consistent to the previously presented accessibility indicators (see also Appendix

B, Figure AB1):

$$A_i = [\ \Sigma_j\ w_{ij}(d)\ E_j\ ]\ /\ \Sigma_j\ E_j$$

where:

A_i = the intensity of employment opportunities associated with tract i
E_j = a count of the employment opportunities at tract j; j may equal i
$w_{ij}(d)$ = a spatial weights matrix representing the relations between each
tract i and every tract j under study; j may equal i

As an accessibility indicator, the 1992 G_i^* statistic measures accessibility as a

proportion. The numerator is a summation of the product of the w_{ij} spatial weights

matrix entry (representing the relationship between locations i and j) and the

number of employment opportunities at location j. The denominator is the sum of

all employment opportunities in the study area. By varying the way the spatial

weights matrix component is defined, however, the 1992 G_i^* statistic will reproduce

the spatial interaction, isochronic, and network accessibility scores precisely, with

only one difference: these scores are represented as a proportion of the total

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[15] The G_i^* and G_i formulations differ in the way the neighborhood is defined. With G_i^* j may equal i; for the G_i formulation, however, the spatial weights matrix has a zero for each diagonal entry. This distinction results in slight differences in the way the G_i^* and G_i formulations are calculated (see Ord and Getis, 1995).

49

employment opportunities in the study area. To reproduce the spatial interaction accessibility scores, for example, $w_{ij}(d)$ is defined as $1/d_{ij}^{1.49}$. To reproduce the isochronic accessibility scores, $w_{ij}(d) = 1$ for all j within 17 miles (the selected critical distance) of each location i, and 0 otherwise. In order to reproduce the network model accessibility scores[16], $w_{ij}(d) = 100 * 1/d_{ij}^{1.49}$ and $E_j = 1$ for all j. The proportions obtained from the G_i^* formulation, of course, produce the precise same R^2 values as the spatial interaction, isochronic, and network measures.

If the objective, then, is to predict journey-to-work commuting distances, the G_i^* statistic in combination with the proximal space construct presents a powerful tool for exploring various spatial relations and variable combinations (see "GIS Implementation" in Chapter 4). One could certainly use this framework to examine additional models involving, for example, variables reflecting occupational differences, race/ethnicity, neighborhood characteristics, housing preferences, or gender. The objective in this research, however, is not to predict journey-to-work commuting distances, but instead to find an effective *representation* of intra-metropolitan accessibility.

In order to effectively *represent* intra-metropolitan accessibility, it is impossible to avoid the chore of defining, very precisely, what it is we *mean* by "accessibility". In other words, one must move from a strictly predictive model, to more of a normative model, allowing evaluation of observed spatial distributions in relation to some *idealized* distribution – a distribution reflecting our notion of

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[16] The network model does not use employment distributions, so the denominator is the number of tracts in the study area.

50

effective accessibility. To help with this task, begin by considering how existing

models of accessibility might serve to inform urban planning. In the spatial

interaction and isochronic models, accessibility is defined in terms of proximity to

employment opportunities (this is typical). Regardless of how these models are

implemented, locations with a large number of jobs will receive the highest

accessibility scores; operationally, these measures define the notion of *effective*

accessibility in relation to job counts. For the Los Angeles study area, the highest

accessibility scores will be associated with Downtown Los Angeles since it

contains the largest clustering of employment opportunities in the region. Does

this mean that all communities should be encouraged to replicate the Downtown

employment patterns? Few urban planners would find these conclusions very

useful.

The 1992 G_i^* statistic (Getis and Ord, 1992) has a second form, however,

which allows an alternative definition of this notion of effective accessibility.

Generally G_i^* scores are not presented as proportions but as statistical significance

levels (Z scores). In the 1992 formulation the proportions and significance levels

are calculated in two separate steps (see Appendix B, Figures AB1 and AB2).

The 1995 formulation of the statistic (Ord and Getis, 1995) combines these two

steps, presenting only the significance levels. This formulation may be written as

follows (see also Appendix B, Figure AB4):

$$A_i = \frac{\sum_j w_{ij}(d)\ E_j\ -\ W_i \bar{E}}{s\ \{\ [\ (\ ns_{1i}\ )\ -\ W_i^2\ ]\ /\ (n - 1)\ \}^{\frac{1}{2}}}$$

where:

51

A_i = the G_i^* accessibility score for location i

$w_{ij}(d)$ = a spatial weights matrix (with row entries for each location i and column entries for each location j) reflecting the proximal space relations between each i and j (j may equal i)

E_j = the number of employment opportunities at zone j

W_i = the sum of column entries for row i of the spatial weights matrix

$\bar{E}$ = the mean for all E_j observations

s = the square root of the variance for all E_j observations

n = the total number of observations

S_{1i} = the sum of squared column entries for row i of the spatial weights matrix

While the 1995 formulation of G_i^* appears much more complex than the 1992 formulation, in fact the two are equivalent: calculating the Z scores as indicated in Appendix B (Figure AB2) will produce the precise same values as those derived from the 1995 equation above. The more complicated 1995 formulation simply incorporates conversion of the 1992 G_i^* scores, from proportions to their equivalent representation as standard deviations. Since the 1995 formulation is less intuitive than the 1992 formulation, it is helpful to remember that the theoretical form of the 1995 G_i^* statistic is still a proportion; this makes it easier to visualize, for example, how the G_i^* scores will behave with changes in employment distributions or with changes in study area boundaries.

The 1995 G_i^* scores are represented, however, as standard normal deviations where the expectation is zero and the variance is one (Ord and Getis, 1995); this implies that all values for the employment variable, E, are independent and randomly distributed in space. Thus, the 1995 G_i^* statistic may be used as a measure of deviation in standard normal units from an *idealized random distribution*. The magnitudes of these deviations (the accessibility scores) are

determined through an evaluation of the spatial autocorrelation and spatial

heterogeneity effects associated with the specified spatial weights matrix, $w_{ij}(d)$.

As discussed in the next section, evaluation of spatial autocorrelation presents a

useful descriptive indication of intra-metropolitan accessibility.

But is a random distribution of employment patterns an appropriate model

of *effective accessibility*? To answer this question one may borrow the "required

commute" concept from the wasteful commuting literature. The required

commute, most often calculated using linear programming techniques, represents

the minimum journey-to-work commute that would occur if residential locational

decisions were determined entirely by the desire to minimize commuting costs.

That is, given observed distributions of both jobs and workers, linear programming

techniques allocate workers to jobs in such a way that overall commuting costs

are minimized. The total commuting cost for the observed distributions represents

the required commute.

Now imagine a simulation run many, many times in which jobs and workers

are *randomly* allocated to census tracts within some study area. After all

simulations are run, a probability surface is constructed by dividing the total

number of workers and jobs allocated to each tract by the number of simulations

performed. As the number of simulations approaches infinity, the theoretical

distribution that emerges is one in which jobs and workers are evenly distributed

throughout the study area. Consequently, the required commute for this

theoretical distribution becomes a function of intra-tract commuting distances

alone. If, for example, intra-tract commuting distances are defined to be zero (and

this is not uncommon), the required commute for this theoretical distribution is also zero. Note that this theoretical distribution reflects *maximum* dispersion of jobs and workers.

This type of thought experiment (or actual simulation) leads to the conclusion that dispersed urban spatial structure provides a better *potential* or *lower bounds* for shorter journey-to-work commuting, than monocentric or polycentric urban forms (Helling, 1998; Gordon, Kumar, and Richardson, 1989; Giuliano and Small, 1993; Hodge, Morrill, and Stanilov, 1996). Nonetheless, while an idealized random distribution of employment opportunities may provide one vision of urban efficiency, it is highly unlikely that urban planners would find recommendations to promote randomly distributed employment patterns any more useful than the suggestion that all communities be modeled after Downtown Los Angeles. To effectively represent accessibility, therefore, we need to consider more than just the distribution of employment opportunities. This introduces the third component of the analytical framework for evaluating and representing intra-metropolitan accessibility: a level-of-service definition.

Level-of-service Definition

In its most basic form, the concept of accessibility can be defined as the potential, or opportunity, for spatial interaction (Hansen, 1959). Spatial interaction may involve exchange among people, or it may comprise the movement of materials and information (Helling, 1996). Accessibility to employment opportunities is, therefore, a function of 1) the number, spatial distribution, and

54

characteristics of employment opportunities, 2) the number, spatial distribution, and characteristics of resident workers, and 3) the transportation and communications networks connecting resident workers to employment opportunities. Review of the research literature on accessibility measurement, however, reveals a number of unsettled definitional and operational issues:

(1) Mobility vs. accessibility. Handy (1994a) notes that accessibility has only recently become a focus in transportation planning. Traditionally, transportation planners have emphasized mobility and infrastructure performance over concerns about accessibility. Mobility refers to the ease of movement or the physical ability to transcend space (facilitated travel), and encompasses monitoring the infrastructure for travel (road capacities, speed limits, and congestion, for example). Accessibility, on the other hand, extends this concept of mobility, to include examination of the *context* for travel (Helling, 1998). Travel is rarely undertaken for the sake of movement alone, but instead takes place within specific contexts, motivated by the desire or need to satisfy a variety of economic, social, or psychological objectives (Wachs and Kumagai, 1973). The concept of accessibility fully encompasses this notion of *context*, extending the scope of concern associated with mobility to include the spatial/temporal opportunities provided at destinations and the social, economic, political, and psychological capability to reach destinations (Handy, 1994a). As a planning goal, then, a focus on accessibility reflects a broader, more inclusive concept, which has advantages over an exclusive focus on mobility (see "Accessibility and Transportation Infrastructure" in Chapter 4). Addressing the issue of accessibility in transportation

55

planning, Handy (1994a) summarizes three broad goals: (1) a greater precision in our definitions of accessibility; (2) an emphasis on enhanced accessibility, rather than just improved mobility; and (3) the development of effective accessibility performance measures to monitor progress toward meeting planning objectives.

(2) Potential vs. outcome. At a very broad level, measures of accessibility may be grouped into one of two definitional categories (Breheny, 1978): "potential" measures and "outcome" measures. "Potential" measures consider accessibility to be a property, or attribute, of specific locations or individuals, and may involve counting spatial opportunities and/or measuring distances between origins and destinations, but they do not incorporate actual travel behavior, or use observed travel flows to calibrate or to simulate measure components. Isochronic accessibility measures, for example, define accessibility in terms of the total number of spatial opportunities within a specified distance or time cost of a particular location i, regardless of whether or not individuals at location i actually utilize these spatial opportunities. These "potential" measures define accessibility in terms of the *potential* for spatial interaction.

"Outcome" measures, on the other hand, define accessibility in terms of realized accessibility, as expressed through observed travel behavior. These "outcome" approaches consider proof of accessibility to be a function of the actual use of services or actual participation in activities surrounding specific origins (Morris, Dumble, and Wigan, 1979). Some network models of accessibility relying on actual travel flows to identify highly accessible nodes, for example, reflect this "outcome" definition of accessibility.

56

Spatial interaction models – the most commonly used accessibility measures – incorporate elements of both the "potential" and the "outcome" definitional categories. While these accessibility measures generally define accessibility in terms of the "potential" for spatial interaction, they calibrate model parameters using actual travel behavior (the "outcome" measure strategy).

Whenever accessibility models rely on actual travel behavior, either directly or for model calibration, it becomes somewhat troublesome to disentangle structure from agency. Suppose, for example, we find that journey-to-work distances have increased. Using an "outcome" definition of accessibility (*i.e.*, using actual travel flows), it is difficult to determine whether the longer commutes are the result of improved accessibility (an improved transportation system, for example, may provide access to better jobs or to better homes at a farther distance away) or whether the longer commutes are the result of diminished accessibility (workers may be required to travel farther because suitable employment or housing is just not available nearby) (Knox, 1980).

Measures based on the "outcome" definition of accessibility may also lead to "self-fulfilling" predictions (Erlander and Stewart, 1990). Examination of actual travel patterns, for example, may reveal that senior citizens do not travel much in a particular region. As a result, the planning process may set a low priority on development of transportation options to support senior communities. If, however, the reason for low travel rates among seniors is due to limited transportation options (low car ownership and/or poor public transit, for example), the "outcome" definition of accessibility will be misleading (Wachs and Kumagai, 1973).

57

Breheny (1978) opposes the "outcome" definition of accessibility because, he argues, observed travel behavior is so heavily constrained by the transportation and land use systems in which spatial interactions are embedded. Observed travel behavior does not necessarily reflect preferred, ideal, or even adequate travel patterns. Further, if the purpose for developing accessibility measures is to help improve levels of accessibility through transportation and land use planning, "it seems illogical to use measures which may have built into them the inefficiencies and inequalities of the existing system" (Breheny, 1978, 466). These models may, in fact, serve to propagate rather than to alleviate accessibility problems (Wachs and Kumagai, 1973, 441).

Difficulty in separating structure from agency when accessibility is measured using actual travel behavior has led a number of researchers to give preference to the "potential" type accessibility measures (Breheny, 1978; Wachs and Kumagai, 1973; Helling, 1998). Defining accessibility in relation to potential opportunities, however, creates difficulties once we begin to consider *all* of the various opportunities *potentially* accessible using telecommunications technologies. The problem is especially troublesome when accessibility is defined to be a characteristic, or attribute, of place.

(3) Accessibility and social equity. Whenever we model the concept of accessibility, we are implicitly asking three questions: "Accessibility to what?", "By whom?", and "How?". Destination choices, access costs for different groups of individuals, and transportation infrastructure, each represent important components of accessibility (Handy, 1994a). Most models of accessibility,

58

however, do not integrate this full range of accessibility components. Consider the spatial interaction, isochronic, and network models presented earlier. With the spatial interaction and isochronic models, accessibility scores increase as job counts increase, regardless of variations in the number of workers competing for jobs. Suppose, for example, a study area comprises 3 isolated communities, each with 100 jobs. Even if the first community has no workers, the second has 100 workers, and the last has 1000 workers, the scores for all three communities will be equal. Variations in jobs or workers have no effect at all on the network model of accessibility, which only considers variations in transportation infrastructure.

Proposed definition. Rather than defining accessibility narrowly in terms of transportation infrastructure and/or job count magnitudes alone, it seems more appropriate to define accessibility in terms of "level-of-service" – in terms of how well a given location serves surrounding populations. In the case of accessibility to employment, for example, if the jobs provided in a given region effectively match worker demand, and the linkages connecting them have sufficient capacity, a high accessibility score is appropriate. From this perspective, the concept of accessibility involves both supply and demand. From the employers' point of view, demand is reflected by a need for workers to fill particular jobs, and the number of workers available represents supply. From the workers' point of view, demand reflects a need for jobs, while the number of jobs available represents supply.

59

Suppose we redefine a spatial opportunities variable (L) to reflect both jobs and

workers[17], by letting:

e_j = the number of jobs (employment opportunities) in a region j
E = the total number of jobs in the entire study area
o_j = the number of workers, by residence, in a region j
O = the total number of workers in the entire study area.

Now define each L_j as follows:

$$L_j = (e_j / E) - (o_j / O)$$

Notice that if region j contains 10 percent of study area jobs and 10 percent of

study area workers, L_j will equal 0. If, however, region j contains a larger

proportion of jobs than workers, L_j will be positive. Positive L_j values reflect

regions where employers have less than "perfect" accessibility to potential

employees. Similarly, negative L_j values reflect regions offering workers less than

"perfect" accessibility to potential employment opportunities[18]. By defining

accessibility in terms of how well a particular region serves surrounding

populations, both the employers' and the workers' perspectives on accessibility

are represented. A theoretical distribution of both jobs and workers in which all L_j

tend toward zero, then, reflects a notion of "perfect" accessibility defined in terms

of social equity; each worker in the study area has similar potential accessibility to

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[17] This "level-of-service" definition for accessibility is appropriate because the relationship between jobs and resident workers is represented as a simple one-to-one correspondence. Measuring accessibility to other types of services (retail or medical facilities, for example) would require modified formulations to reflect qualitative differences among these facilities.

[18] Notice that this "level-of-service" definition does not include information regarding actual commuting patterns, nor does it consider (or constrain) intra-regional spatial variations (employment/residential densities and/or intra-regional heterogeneity of job/worker spatial distributions). As a consequence, scale of analysis (discussed in the next section) is a critical aspect of analysis.

employment opportunities. In addition, the required commute for this theoretical distribution is the same as that obtained from the simulation described earlier: as intra-regional commute distances approach zero, the required commute for this distribution also approaches zero.

Notice too, that a level-of-service definition of accessibility requires no assumptions regarding metropolitan form. The study area may range from complete monocentricity to complete dispersion and the summation of all L_j will equal zero as long as the number of jobs match the number of workers at each region j. This is an important point because many urban models incorporating an accessibility component require researchers to pre-specify a discrete set of employment centers before beginning analyses (e.g., Heikkila, et al.; Giuliano and Small, 1993; McMillen and McDonald, 1997). In metropolitan areas where these centers are easily discernible, this may not pose a problem. In the Los Angeles region, however, researchers have identified anywhere from 6 to 54 different centers (Giuliano and Small, 1991) using a variety of methods and often rather arbitrary criteria. Moving to a level-of-service definition of accessibility may eliminate the need to make a priori assumptions regarding urban form.

Real urban landscapes, of course, are unlikely to reflect this perfect level-of-service definition of accessibility. Instead, they are typically structured into a mosaic of residential and industrial land uses. Where agglomeration forces are strong, job opportunities will typically cluster into one or more distinct, well-defined employment centers; where agglomeration forces are weak, employment opportunities will tend to be more dispersed (Giuliano and Small, 1991). Some

firms are highly dependent on local labor markets and will favor locations offering good access to potential employees. Other firms are less sensitive to labor market proximity and will favor locations offering other local advantages.

The spatial distributions emerging as a result of the interweaving of these complex spatial processes, however, will certainly have consequential impacts on intra-metropolitan accessibility. Where job-rich (worker-poor) sites intermingle with worker-rich (job-poor) sites, worker shortages at one location may balance job shortages at locations nearby, so that accessibility for the region as a whole is maintained. Where job-rich sites cluster together, however, worker shortages are additive. Similarly, where worker-rich sites cluster, job shortages are additive, increasing the overall spatial separation among workers and jobs.

Notice that the discussion above makes reference to "balance", "job-rich", and "job-poor". Clearly, **scale** is critical to analysis! This brings us to the forth component of the analytical framework for evaluating and representing intra-metropolitan accessibility: multiple scale analysis.

Multiple Scale Analysis

Just as the proximal space construct encourages exploration of various spatial relationships, the G_i^* statistic encourages exploration at multiple spatial scales. The G_i^* statistic considers each tract i within the context of its neighboring tracts j, where the neighborhood is defined by the spatial weights matrix, reflecting this notion of proximal space. The G_i^* statistical framework determines the degree of spatial clustering associated with either job-rich or worker-rich urban spatial

62

patterns (reflected by the spatial opportunities variable, L, defined above), at

multiple scales of analysis. Because the G_i^* statistic considers each location *i*

within the context of its neighbors, influence from the boundary configurations of

the spatial units used in analysis (census tract boundaries in this case), is

minimized.

It may be that urban planning objectives guide selection of a spatial

weights matrix. For example, a regional agency may set as an objective balancing

communities so that all households are within 8 miles of potential employment

opportunities. There are good reasons, however, for representing and exploring

accessibility using multiple scale analysis. Exploring accessibility at multiple spatial

scales portrays the idea that individuals may trade off time and distance, or may

utilize different transportation modes (bicycles, public transportation, private

automobiles, or telecommunications), in order to gain access to spatial

opportunities at a distance. While most accessibility indicators present

intra-metropolitan accessibility as a single score or index for each location under

study, the concept of accessibility is more realistically represented as a process or

function of space, time, and available technology.

A simple example: In Figure 3.2a, the 1995 G_i^* statistic has been applied to

the level-of-service spatial opportunities variable (L) using a spatial weights matrix

based on a selected 15 mile critical distance radius. Each census tract is

evaluated within the context of its neighbors, where the "neighborhood" is defined

as those census tracts within 15 miles. Tracts with positive G_i^* scores are

associated with job-rich regions. Job-rich regions, while they may offer good

Scale = 15 Miles

(a)

Accessibility:

- Very Poor for Workers
- Poor for Workers
- **Effective**
- Poor for Employers
- Very Poor for Employers

(b)
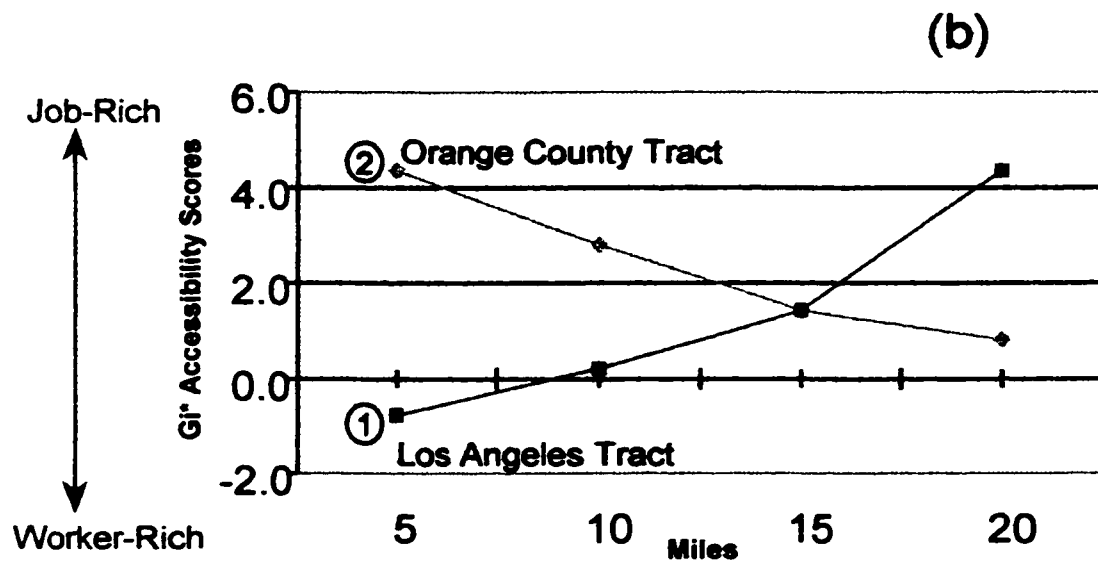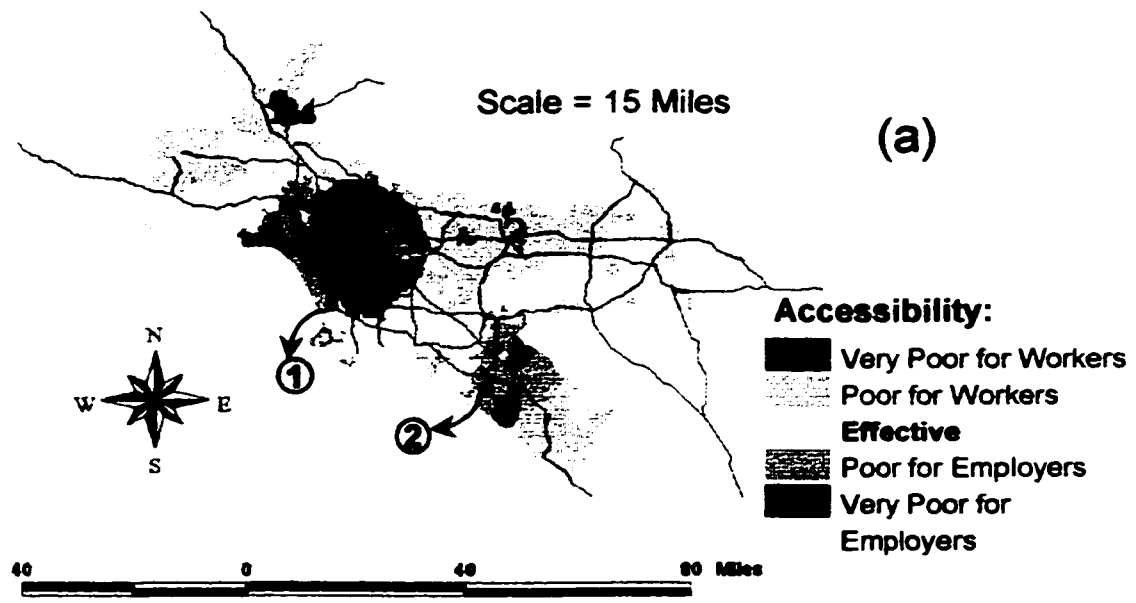
Figure 3.2 G_i^* Level-of-Service Accessibility Scores and Multiple Scale Analysis

access to job opportunities for local workers, provide poor access to employers

needing to fill those jobs. Tracts associated with negative G_i^* scores reflect

job-poor regions providing insufficient access to employment opportunities for local

workers. Tracts with scores near zero represent regions offering effective

level-of-service accessibility to both employers and workers[19]. The map identifies

two census tracts, one in Los Angeles County (labeled "1") and the other in

Orange County (labeled "2"). Both tracts are associated with similar accessibility

scores when evaluated within the context of a 15 mile distance radius.

Considering only this one score, however, obscures important details about

variations in accessibility with changes in scale and with changes in spatial

context. Figure 3.2b graphs the G_i^* scores for these two locations at 5, 10, 15, and

20 miles. For the Los Angeles County tract (labeled "1"), accessibility to

employment opportunities increases rapidly if one is willing and able to travel 15 or

20 miles. For the job-rich Orange County tract (labeled "2"), however, increased

travel offers diminishing returns to *additional* employment opportunities.

Performing analyses at multiple spatial scales highlights the spatial dynamics of

intra-metropolitan accessibility. It captures the idea that accessibility is not a fixed

score, but a structure in which form and magnitude are tied to spatial context.

Consistent with the proximal space construct, this structure reflects neither *site* nor

situation, but an interface between the two (see also Getis, 1994).

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[19] In Figure 3.2a, accessibility designations of "very poor" are associated with G_i^* scores greater than +2, or less than -2, standard deviations; designations of "poor" are associated with G_i^* scores ranging from +1 to +2 or from -1 to -2. "Effective" accessibility is associated with G_i^* scores between -1 and +1.

Representing Accessibility as a Multi-Dimensional Construct

We have progressed significantly from the simple spatial interaction, isochronic, and network models presented at the beginning of the chapter. Nonetheless, the model of accessibility depicted in Figure 3.2 is still limited in its ability to effectively represent intra-metropolitan accessibility: so far, only physical distance spatial relationships have been considered. The final component of the analytical framework for evaluating and representing intra-metropolitan accessibility recognizes the multi-dimensional nature of the accessibility concept.

To demonstrate this multi-dimensional component, imagine that you commute 45 minutes to and from work each day in rush-hour traffic. For most of us it would not take very long before this commute became a tremendous chore. If your company offers flextime-working arrangements, you may elect to take advantage of these in order to reduce time spent commuting in heavy traffic. If some of your work can be accomplished from home, you may discuss with your employer the possibility for telecommuting. If neither flextime nor telecommuting is available to you, perhaps you will consult associates at work regarding residential options closer to your place of work, or consult friends and family regarding other employment opportunities. Another possibility, of course, is that you continue to put up with the onerous commute.

Evaluating intra-metropolitan accessibility from the perspective of physical distances allows us to focus on spatial distributions of origins and destinations, and to address a variety of research questions involving, for example, jobs/housing balance or spatial mismatch issues (see "Structural Accessibility" in

Chapter 4). The brief scenario presented above, however, demonstrates the limitations of representing accessibility solely from this perspective. A second important perspective in evaluating intra-metropolitan accessibility involves transportation infrastructure and traffic congestion.

Consider, for example, the difference between commuting 45 minutes in congested traffic and commuting 45 minutes on an open highway. While the issue of traffic congestion certainly influences the commuting *experience*, it also plays an important role in shaping the geography of spatial opportunities and the degree to which individuals have access to urban activities. Transportation and communications networks develop unevenly over time and space. Connections among some locations may involve efficient highway corridors, public transit, or information networks. Connections among other locations may involve overcoming physical barriers or be associated with congestion or otherwise inefficient transportation and communications networks. Within this complex mosaic of urban land uses and transportation infrastructure, individuals may trade time or other resources (income, for example) to gain access to opportunities at a distance. Overcoming distance, however, always involves some form of opportunity costs. There are costs, for example, associated with operating a vehicle or using public transportation. The time needed to transcend space (walking to work, for example) may also represent a cost. Even when telecommunications technologies are employed, there are costs associated with gaining access to appropriate equipment, education, and authority to use these technologies. In addition, many employees who choose to telecommute to the

workplace may pay for this convenience in the form of reduced opportunities for promotion or salary increases as a result of spending large amounts of time off-site. Opportunity costs will be smallest where residential neighborhoods and employment centers are efficiently connected via transportation or telecommunications networks; opportunity costs will be large, however, if there are physical or *functional* barriers restricting movement or communications.

The G_i^* spatial weights matrix, w_{ij} *(d)*, reflecting the proximal space construct, provides a key element for modeling a variety of opportunity costs imposed by the complex physical and functional connections (proximities) among the sites of a particular study region. Comparing intra-metropolitan accessibility measured in relation to physical distance against analyses based on journey-to-work travel time costs, for example, allows evaluation and isolation of the impacts on intra-metropolitan accessibility imposed by transportation infrastructure and traffic congestion (see "Accessibility and Transportation Infrastructure" in Chapter 4).

These structural components of intra-metropolitan accessibility, however, do not yet incorporate *functional* components of accessibility – the idea that, quite often, we make our own accessibility (by arranging our schedules to miss traffic or by taking advantage of telecommuting opportunities, for example). In fact, if we were to consider all of the complex individual characteristics and behavioral factors potentially influencing locational decisions and travel patterns (e.g., worker or firm preferences, motivations, aspirations, objectives, social networks, search strategies, even dumb luck) it would quickly become clear that modeling all of

these various factors would be difficult at best. One approach to understanding

how these complex individual factors play out in the aggregate, however, is to

examine observed travel behavior. At the most general level, we can state that if

an individual at residential location i is employed at job location j, location j *must* be

accessible to location i at some level. The difficulty with using observed travel

behavior to measure intra-metropolitan accessibility is that it becomes difficult to

disentangle structure from agency. Is location j accessible to location i because

the individuals at location i are particularly insensitive to long commutes (perhaps

these individuals telecommute, or have financial means to facilitate travel)? Or is

location j accessible to location i because of efficient urban infrastructure? To

effectively utilize observed travel behavior for evaluating intra-metropolitan

accessibility, we must be able to separate the structural components, from the

non-structural (functional) components of accessibility.

Using the proposed analytical framework, we may take advantage of the

G_i^* statistic's flexibility for defining "neighborhood" and, consequently, for defining

the scope of local interactions in order to incorporate functional components of

accessibility into our model. This is accomplished by using actual travel behavior

to construct a set of *functional* travel costs, adapting a method developed by

Tobler and Wineburg (1971). The adapted method (see Appendix D for a

flowchart of these procedures) involves inverting a doubly constrained gravity

model with known journey-to-work flows and then solving for functional travel

distances[20]. The doubly constrained gravity model may be written as:

$$f_{ij} = A_i B_j \frac{O_i D_j}{c_{ij}\beta}$$

and may be interpreted as follows:

f_{ij} = the estimated number of journey-to-work flows from site i to site j
O_i = the number of workers at site i (origins)
D_j = the number of jobs at site j (destinations)
c_{ij} = the travel cost from site i to site j
β = an exponent reflecting the concept of a "distance decay"
A_i = a vector of scaling factors to ensure $\sum_j F_{ij} = O_i$, for every O_i
B_j = a vector of scaling factors to ensure $\sum_i F_{ij} = D_j$, for every D_j.

The first step in calculating functional travel costs is to calibrate the doubly

constrained gravity model above using standard calibration procedures (see, for

example, Fotheringham and O'Kelly, 1989, and Appendix D). The second step

involves inverting the above model and then replacing estimated flow volumes (f_{ij})

with known flow volumes (F_{ij}) to obtain functional travel costs (c_{ij}):

$$c_{ij} = \left(A_i B_j \frac{O_i D_j}{F_{ij}} \right)^{1/b}$$

The effect of this procedure is a stretching and a pulling of conceptual

space to reflect observed travel behavior. Locations with higher than expected

volumes of spatial interaction move "closer" together in conceptual space, while

locations with very little spatial interaction are pushed farther apart. The functional

distance (or time) spatial relationships that emerge (c_{ij}) may then be compared to

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[20] This method has also been applied by Plane (1984) in the evaluation of inter-state
migration patterns.

actual travel costs to identify the sensitivity of each location in the study area to the

structural constraints of accessibility imposed by urban spatial structure (see

"Functional Accessibility" in Chapter 4). Interestingly, results from this type of

analysis reveal that spatial relations among some locations are very similar in both

physical and functional space, while other locations seem to reflect almost no

functional ties to physically proximal neighborhoods at all. Comparing physical

relations to functional relations in this manner provides a glimpse at the degree to

which human agency challenges the constraints imposed by distance and by

urban spatial structure.

Summarizing the analytical framework: The final form of the analytical

framework proposed in this research is a model in which intra-metropolitan

accessibility is conceptualized as a multi-dimensional construct comprising a

structural, transportation, and functional component. Each of these dimensions is

evaluated using the 1995 Getis/Ord G_i^* spatial statistic[21], structuring the spatial

weights matrix to represent a variety of proximal space relations at multiple scales

of analysis. The model may be summarized as follows:

$$A_i = \frac{\sum_j w_{ij}(d) \ L_j \ - \ W_i \ \bar{L}}{s \{[(ns_{1i}) - W_i^2] / (n-1) \}^{\frac{1}{2}}}$$

---

[21] The G_i^* statistic will distinguish job-rich and worker-rich regions (where the spatial configuration of a region is determined by the spatial weights matrix), but does not provide information regarding heterogeneity within regions. An interesting direction for future research will utilize the G_i^* statistic in conjunction with the Moran's I local statistic (Anselin, 1995) in order to distinguish among regions with uniform distributions of both jobs and workers, from those reflecting a heterogeneous mix of employment/worker sources/sinks.

where:

A_i = the G_i^* accessibility score associated with location i

$w_{ij}(d)$ = a specified spatial weights matrix (with row entries for each location i and column entries for each location j) defining proximal space relations between each i and j; j may equal i

L_j = $(e_j / E) - (o_j / O)$; a level-of-service spatial opportunities variable reflecting the spatial distribution of employment opportunities in relation to the spatial distribution resident workers at each location j:

e_j = the number of jobs at location j
E = the total number of jobs in the study area
o_j = the number of resident workers at location j
O = the total number of workers in the study area

W_i = the sum of column entries for row i of the spatial weights matrix
$\bar{L}$ = the mean for all L_j observations
s = the square root of the variance for all L_j observations
n = the total number of observations (*i.e.*, 2381 tracts in 1990)
S_{1i} = the sum of squared column entries for row i of the spatial weights matrix

This model is normative, rather than predictive. Its purpose is to evaluate observed relationships among jobs and resident workers against an idealized distribution of these same relationships, where the idealized distribution is founded on a social equity, level-of-service conceptualization of "perfect" accessibility in which all L_j tend toward zero. The G_i^* scores produced using this model provide descriptive indication of intra-metropolitan accessibility to employment opportunities and to labor market resources for each location i relative to all other locations j within the study area. The actual application of this analytical framework to real-world data will be the focus of the next chapter. There is one more question, however, that remains to be answered.

72

Representing Intra-Metropolitan Accessibility

Still outstanding for the purposes of this chapter is the thorny question of whether or not the components of the analytical framework presented above provide an improved *representation* of intra-metropolitan accessibility. This chapter has argued that an effective representation of accessibility will comprise structural, transportation, and functional elements, and has noted (Table 3.1) that the best explanation of journey-to-work commuting distances using existing measures of intra-metropolitan accessibility is 29 percent. Can the proposed framework improve on this?

A theoretical model of the relationship between journey-to-work commuting distances and existing measures of intra-metropolitan accessibility may be written as follows:

$$D = \beta_0 + b_1 A + \varepsilon$$

where:

D = average journey-to-work commuting distances, calculated to include all commutes either originating or terminating in each tract i (see Appendix E, GETCOMM).

A = accessibility indices, calculated using the spatial interaction, isochronic, or network accessibility formulations (see Appendix E, ACCESS92).

β_n = OLS regression coefficients.

ε = an error term.

Note, however, that the accessibility scores in the model above are spatially autocorrelated and consequently produce spatially autocorrelated regression residuals. Spatial autocorrelation among regression residuals (ε) is a problem that cannot be ignored since it may lead to inefficient estimates of regression

coefficients and unreliable regression diagnostics (Ying and Getis, 1996; Anselin and Griffith, 1988).

Fortunately, a number of methods exist for resolving these problems. Cliff and Ord (1981, 184) identify two general approaches to resolution: (1) filtering spatially autocorrelated data to remove spatial autocorrelation, or (2) modifying statistical models to accommodate spatial autocorrelation. Elements of both of these approaches are evident in the "spatial filtering" method (Getis, 1995) utilized by this dissertation research.

To help illustrate the spatial filtering method, consider first, commonly used data resampling procedures. Data resampling is one example of a filtering approach: resampling of spatially autocorrelated data is performed at farther and farther distance intervals until data values with similar magnitudes are no longer spatially clustered. In geographic models, however, these spatial patterns will often be inextricably linked to those very spatial processes we are trying to understand in the first place; space, itself, frequently has important explanatory value. By removing the spatial components of a data set, researchers risk misspecification and diminish model explanatory power if, indeed, space is relevant to the relationships being examined. Note too that resolving spatial autocorrelation by using resampling methods has the effect of changing the resolution of our analyses and may potentially limit our ability to examine local variations (the identification of "hot spots", for example).

When we approach the problem of spatially autocorrelated regression residuals by resampling, we implicitly consider spatial autocorrelation to be a

74

nuisance (a reflection of data redundancy or over-sampling), and there may be situations where this is appropriate. An alternative viewpoint, however, considers spatial autocorrelation to be a fundamental component of spatial data. From this perspective, finding spatial autocorrelation among regression residuals is an indication that important spatial variables have been excluded from our model (Haining, 1994). Remediation does not involve removing all evidence of space, but rather involves seeking the appropriate spatial component variables lacking in our regression models (spatially lagged, trend surface, or dummy spatial variables, for example).

This alternative viewpoint is the one emphasized in the spatial filtering technique suggested by Getis (1995) for use with OLS regression analysis. The Getis spatial filtering technique incorporates spatial component variables into OLS regression analysis in order to remedy misspecification and the problem of spatially autocorrelated residuals. These spatial component variables are obtained from a theoretical OLS regression model directly, by utilizing information derived from running the 1992 G_i^* statistic in conjunction with the Moran's I statistic (see Appendix A). First, spatial dependency within each dependent and independent variable in the theoretical regression model is removed using a filtering procedure (see Appendix B, Figure AB3). Next, the filtered spatial components derived from the filtering procedure are reintroduced into the regression model in order to avoid misspecification. With spatial dependence accounted for by the new spatial component variable(s), regression residuals are no longer spatially autocorrelated and, as the final step, ordinary least squares

75

methods may be utilized to perform model estimation (see Getis, 1995). An example of the spatial filtering technique is presented in Appendix B, Figure AB3 and the software used to carry out spatial filtering is provided in Appendix A.

Now let us return to our theoretical model:

$$D = \beta_0 + \beta_1 A + \varepsilon$$

In order to test the relationship between existing accessibility indicators and journey-to-work commuting distances, we must first address the problem of spatial autocorrelation among the regression residuals. To accomplish this, the accessibility variable (A) is transformed from a spatially dependent variable into a "filtered" spatially *independent* variable with an associated spatial component. The spatial component is then reintroduced into the regression equation as a new independent variable, yielding:

$$D = \beta_0 + \beta_1 A^f + \beta_2 A^{sp} + \varepsilon$$

where:

D = the average journey-to-work commuting distances, calculated to include all commutes either originating or terminating in each tract i (see Appendix E, GETCOMM).
A^f = the filtered component of the accessibility variable A.
A^{sp} = the spatial component of the accessibility variable A.
β_n = the OLS regression coefficients.
ε = an error term.

The best explanatory power for the model above using the spatial interaction, isochronic, and network measures of intra-metropolitan accessibility (applying these measures to employment data for the five county Greater Los Angeles study area) is 29 percent, as shown in Table 3.1.

We may now compare these results to the explanatory power provided by the analytical framework outlined in this chapter. Representing accessibility as a multi-dimensional construct, the following alternative model is proposed:

$$D = \beta_0 + \beta_1 S + \beta_2 T + \beta_3 F + \varepsilon$$

In the proposed model, the accessibility variable (A) has been replaced by a structural variable (S), a transportation component variable (T), and a functional component variable (F), defined as follows:

S = a level-of-service structural accessibility variable obtained by taking the absolute value of the 1995 $G_i^*(d)$ scores calculated using the level-of-service opportunities variable, L The best explanatory power is obtained using d equal to 1 mile.

T = a transportation component variable reflecting mobility/congestion; T is derived by comparing (for each census tract) total distance travel costs to total time travel costs, given a specific travel distance and equivalent/ associated travel time. The degree to which normalized *distance* travel costs are larger than normalized *time* travel costs, reflects a tract's traffic mobility score. The best explanatory power is obtained using a travel distance equal to 10 miles vs. a travel time equal to 20 minutes[22]. (A flowchart showing the procedures used to calculate T is provided in Appendix F, Figure AF1).

F = a functional component variable reflecting the similarity of job and worker distributions in both physical and functional space. The highest multiple R^2 value uses d equal to 29 minutes. (Appendix F includes a flowchart, Figure AF2, detailing the procedures used to derive this variable).

Large values for the structural variable (S) reflect deviation from perfect level-of-service accessibility. These tracts are either job-poor or worker-poor.

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[22] The median travel time for all 10 mile journey-to-work commutes in the study area is 20 minutes. Travel costs are normalized by dividing distances/times by the study area average travel distance/time. To normalize distance travel costs for example, let m equal the distance to travel from tract i to tract j, and k equal the average journey-to-work commuting distance for the study area. Dividing m by k, then, produces a normalized cost for travel between tracts i and j.

Small values for the structural variable (S) reflect tracts with effective level-of-service accessibility, and are expected to be associated with small average journey-to-work commuting distances. The transportation component variable (T) models traffic congestion and mobility. Negative values reflect tracts associated with congested transportation routes; congestion limits the extent to which commuters in these tracts can travel within a fixed period of time (20 minutes). Tracts with good mobility – positive values for the transportation variable (T) – should be associated with the largest tract average journey-to-work commuting distances.

Modeling the functional component of accessibility for this predictive model was somewhat difficult because actual journey-to-work travel flows were utilized in constructing the functional travel cost values. It was necessary, therefore, to avoid using the functional cost values directly. Instead, the functional accessibility component is calculated as the absolute difference between job/worker proportions found in physical space to those found based on functional proximity[23]. Large values for this functional variable (F) indicate a large discrepancy between functional space and physical space job/worker distributions, suggesting longer commutes.

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[23] While functional travel costs have the effect of distorting conceptual space (pulling locations with heavy interaction closer, and pushing those with little interaction farther apart), total costs within the entire study area remain stable.

After performing spatial filtering procedures to handle spatial

autocorrelation (see Getis, 1995, Appendix B, Figure AB3, and Appendix A), the

proposed model may be written as:

$$D = \beta_0 + \beta_1 S^f + \beta_2 S^{sp} + \beta_3 T^f + \beta_4 T^{sp} + \beta_5 F^f + \beta_6 F^{sp} + \varepsilon$$

where:

S^f = the filtered component of the structural variable S.
S^{sp}= the spatial component of the structural variable S.
T^f = the filtered component of the transportation variable T.
T^{sp}= the spatial component of the transportation variable T.
F^f = the filtered component of the functional variable F.
F^{sp}= the spatial component of the functional variable F.

Results from this regression are shown in Table 3.2. Notice that the coefficient on

the structural explanatory variable (S) is positive, indicating that the shortest

average journey-to-work commuting distances are associated with effective

level-of-service accessibility, as expected. The coefficient on the transportation

variable (T) indicates a positive relationship between effective mobility and

commuting distances, suggesting individuals minimize commuting distances when

the journey-to-work involves bumper-to-bumper traffic (or, alternately, individuals

are willing to commute longer distances when the commute involves open

highways and fast speeds). The functional component of the model (F) has a

positive coefficient, as expected. Where actual proximal locations in physical

space have a very different composition of jobs and workers in functional space,

commuting distances are longer. This final regression model explains 52 percent

of the variation in commuting distances (adjusted R^2), providing a significant

improvement over existing measures of accessibility, and providing evidence that

N=2381

Coefficients:

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	8.0908	0.1538	52.6197	0.0000
S^f	0.3796	0.0485	7.8298	0.0000
S^{sp}	0.3547	0.0548	6.4744	0.0000
T^f	0.1451	0.0069	21.1137	0.0000
T^{sp}	0.0966	0.0047	20.7481	0.0000
F^f	27.4267	1.5148	18.1062	0.0000
F^{sp}	42.3340	1.7302	24.4677	0.0000

Multiple R-Squared: 0.5214

Table 3.2 Results from Multivariate Regression Analysis to Predict Journey-to-Work Commuting Distances.

the proposed analytical framework offers an improved representation of intra-metropolitan accessibility. This increase in explanatory power is especially significant given that the proposed multivariate model still only considers spatial relationships among jobs and resident workers. We would expect journey-to-work commuting distances to also be a function of many other variables (not included in the model), such as neighborhood characteristics, individual preferences, social networks, and accessibility to recreational opportunities, friends, and family, for example. Application of the proposed analytical framework is addressed next.

CHAPTER 4

APPLICATION

Accessibility measures summarize a great deal of information about household locations in relation to spatially distributed urban activities within the context of transportation and communications infrastructure. They present us with important descriptive indicators of urban form, efficiency, growth, economic health, and social equity (Black and Conroy, 1977; Knox, 1980). Consequently, the ability to effectively measure intra-metropolitan accessibility offers important applications for urban planning. Effective evaluation of intra-metropolitan accessibility, for example, is a first step in identifying and prescribing remedial solutions in regions, or for groups of individuals, where societal goals of accessibility may not be met (Morris, Dumble, and Wigan, 1979). In addition, the ability to effectively monitor changes in accessibility allows assessment of the differential consequences of urban planning policy decisions (either actual or hypothetical) (Wachs and Kumagai, 1973).

This chapter focuses on application, developing the concepts and measures outlined in Chapter 3 further by utilizing them to explore broad changes in intra-metropolitan accessibility within the 5 county Greater Los Angeles study area (Figure 2.3). The chapter begins with an overview of the GIS implementation of the proposed analytical framework, and with a description of the data used for analyses. The primary objective of the chapter, however, is to demonstrate that the analytical framework, implemented within an ArcView 3.1 GIS environment,

provides an effective research and planning tool for exploring and monitoring changes in intra-metropolitan accessibility relating to urban growth, urban efficiency, and the re-distribution of urban activities. The issues addressed include job/worker balance, spatial/skills mismatch, journey-to-work commuting patterns, traffic congestion, and impacts of changing technology on urban spatial structure and commuting behavior. Using a variety of cartographic, graphical, and statistical techniques, the chapter emphasizes the potential and the practical effectiveness of the proposed analytical framework for addressing a variety of urban research questions.

GIS Implementation

While Geographic Information Systems (GIS) contain powerful tools for entering, storing, and displaying spatially indexed information, they have been criticized for lacking equally strong spatial analytic capabilities (Anselin, Dodson, and Hudak, 1993; Bailey and Gatrell, 1995; Burrough, 1990; Fotheringham, 1993). PC-based GIS packages, in particular, have provided only limited analytic functionality in the past. As a consequence, a number of researchers have explored a variety of approaches for integrating spatial analysis, or statistical analysis, within the GIS framework. At the same time, however, GIS vendors have been extending the spatial analytic capabilities of commercial GIS products. As an example, ArcView 3.1 (ESRI), a PC-based GIS product, has just recently been released with network, grid handling, and 3D modeling analytical modules.

83

Spatial data analysis can be defined as a set of techniques for analyzing

geographically referenced data (Goodchild, et. al, 1992). These techniques range

from simple descriptive measures to complex statistical inference (Anselin and

Getis, 1992). In all cases, however, the spatial arrangement of the events or

objects being studied – location, area, distance, interaction – forms a key

component of analysis (Anselin, Dodson, and Hudak, 1993). Haining (1994)

describes the aim of spatial analysis in terms of three broad elements:

(1) Description: The careful and accurate portrayal of spatial patterns associated
    with events or objects in geographic space.

(2) Understanding: The systematic exploration of spatial relationships in order to
    gain understanding of the processes shaping observed distributions.

(3) Prediction: The development of models and methods for the prediction and
    control of events or objects in geographic space.

The case for linking spatial data analysis techniques to GIS is grounded in

the idea that additional explanation, understanding, and insight can be gleaned

when data is viewed and examined from multiple perspectives (Goodchild, et al.,

1992). The integration of multiple perspectives in an environment that supports

flexible methods for data retrieval, manipulation, and display, is argued to yield

more than the sum of the component parts (Anselin, Dodson, and Hudak, 1993).

Currently, several analytical tools are available in commercial GIS software

for dealing with relative or absolute distances. These tools include buffer

operations and shortest path analyses. Tools to provide an overview of

intra-metropolitan accessibility, however, are not yet available in commercial GIS

software (Geertman and Ritsema van Eck, 1995).

A number of researchers, however, have explored different approaches for integrating spatial analysis, or statistical analysis, within GIS. (For a review of these applications, see Anselin and Getis, 1992; Bailey and Gatrell, 1995, Chapter 2; Anselin, Dodson, and Hudak, 1993; and Scott, 1993). In general, these approaches can be classified into three broad categories: tight, close, and loose coupling. Tight coupling approaches involve developing software modules to perform spatial analysis techniques, and directly integrating those modules within commercial GIS software products. Ding and Fotheringham (1991), for example, use the ArcInfo AML programming language to develop spatial autocorrelation and spatial association statistical measures within ArcInfo. Tight coupling strategies provide an effective means for extending GIS spatial analytic capabilities, but involve intensive programming efforts, and have been criticized for poor performance and limited analytical functionality (Anselin and Bao, 1996; Anselin and Getis, 1992). Tight coupling strategies are particularly appropriate, however, for performing very specialized analyses not offered by existing GIS or other analytic software.

Loose coupling approaches, on the other hand, involve developing data links between commercial GIS software packages and commercial spatial analysis or statistical software packages (Goodchild, et. al, 1992). Researchers might use a statistical package to run a regression analysis, for example, and then map the residuals using a GIS software package. The main weakness associated with loose coupling is clumsiness in data transfer procedures (Ding and Fotheringham, 1991). The greatest strengths of loose coupling strategies, however, are that they

85

involve a minimum level of programming, combine the functionality of multiple software products, and allow the researcher to use the most appropriate software for the task at hand: for statistical analysis, for example, the researcher uses a statistical package; for GIS operations, commercial GIS software is utilized (Goodchild, et al., 1992).

Close coupling strategies are based on the loose coupling structure, but involve efficient links and often elaborate user interfaces so that the user may not even realize they are operating within multiple stand-alone software packages (Bailey and Gatrell, 1995). An example of close coupling is provided by Anselin and Bao (1996) who link the SpaceStat spatial analytic software to the *ArcView 2.0* GIS environment[24]. These strategies offer the flexibility of loose coupling while minimizing awkward data transfer procedures. Close coupling solutions offer tremendous flexibility and power for extending the spatial analytic capabilities of GIS, but require an adaptable and reliable mix of software packages.

In this research, the G_i^* statistic and proximal space construct are implemented using a series of both FORTRAN and *Avenue*[25] programs directly integrated within the *ArcView 3.1* GIS environment. While the programming effort is not trivial, the result is an effective and easy to use utility for performing intra-metropolitan accessibility analyses. The G_i^* statistic runs with the click of a menu option embedded in the standard *ArcView* interface. The user is then

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[24] Current versions of the *SpaceStat* software package include tools to work with *ArcView* version 3.1.
[25] *Avenue* is the programming language provided with the *ArcView* GIS software, used to extend, customize, or automate *ArcView's* functions and functionality.

presented with a dialog box and prompted to identify from a list of options, a base theme, an evaluation variable, a proximal space cost matrix and other parameters needed for analysis (Figure 4.1). With these specifications, the *Avenue* dialog box launches appropriate FORTRAN utilities to perform statistical analysis and to generate a series of output tables for import back to the *ArcView* application. These output tables are converted to new themes by *Avenue* and automatically added to the application project using appropriate legend titles and classification schemes (Figure 4.2). The user may then utilize display capabilities within the GIS environment to develop maps, charts, and reports of the accessibility results. (See Appendix G for sample *Avenue* scripts and FORTRAN source code).

This close coupling approach was utilized rather than programming all of the statistical calculations within *Avenue* in order to maximize performance. To evaluate intra-metropolitan accessibility for the 5 County Greater Los Angeles region, statistical software must manipulate cost matrices with over 5 million elements. Simply reading this cost matrix into the *ArcView* environment takes much more time than is reasonable[26]. Consequently, performing the statistical calculations within FORTRAN (or another programming language) allows the

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[26] After an hour of intensive disk activity, I finally killed the Avenue procedure that was attempting to read the cost matrix into memory. Clearly, Avenue was not the appropriate tool for the task at hand. I considered manipulating the cost matrices as GRID coverages. GRID coverages, however, are stored as disk files. Retrieving the cost values stored in each individual GRID cell would therefore slow performance significantly, particularly when multiple iterations were needed (the user may elect to run the G_i^* statistic with the distance radius set to 5, 10, and 15 miles, for example). In contrast, the FORTRAN utility developed to perform accessibility calculations can read the cost matrices into memory very quickly (15 seconds on my 166mhz PC) when they are stored in binary format.
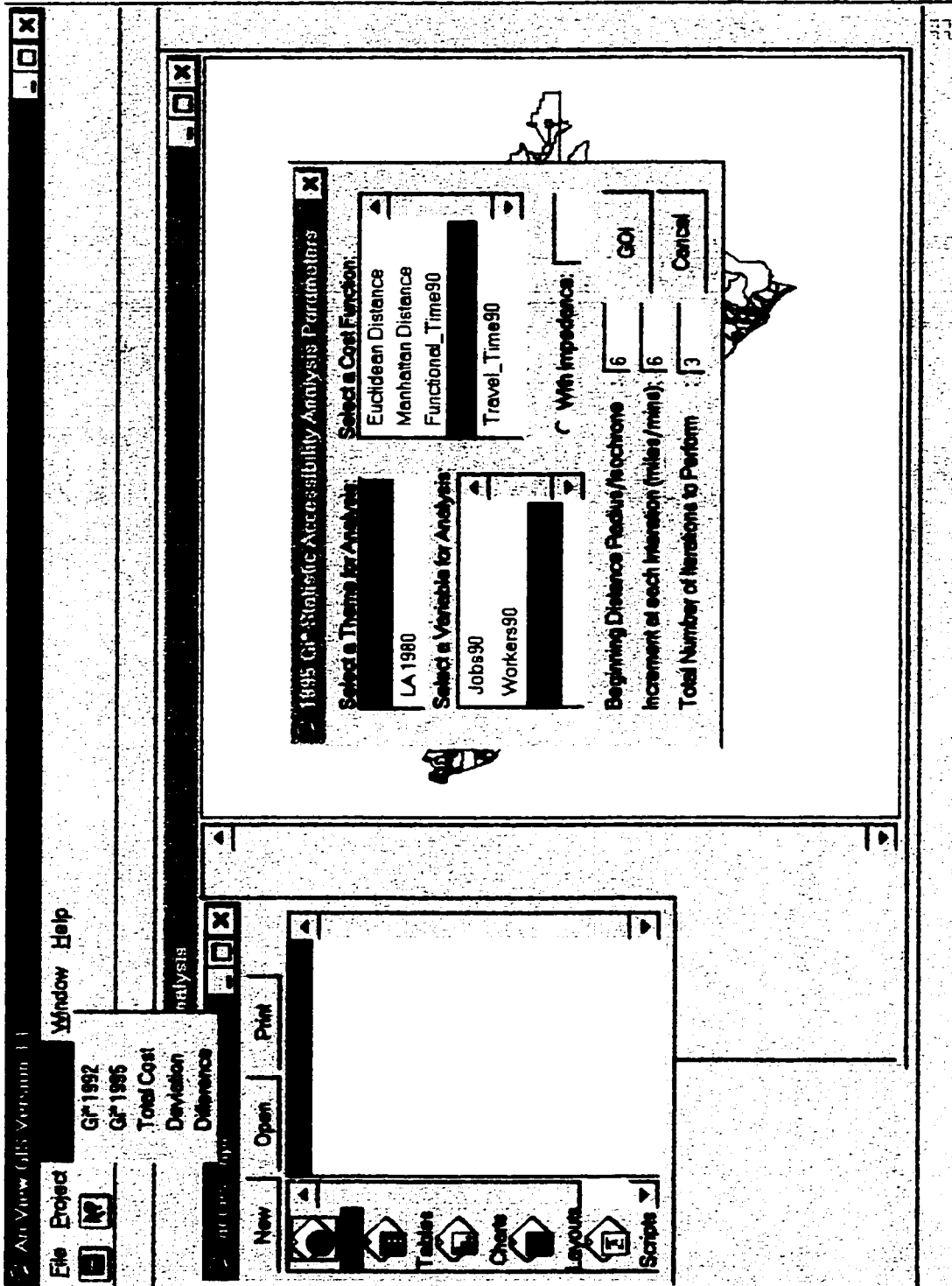
Figure 4.1 ArcView GIS environment interface for performing accessibility analysis.
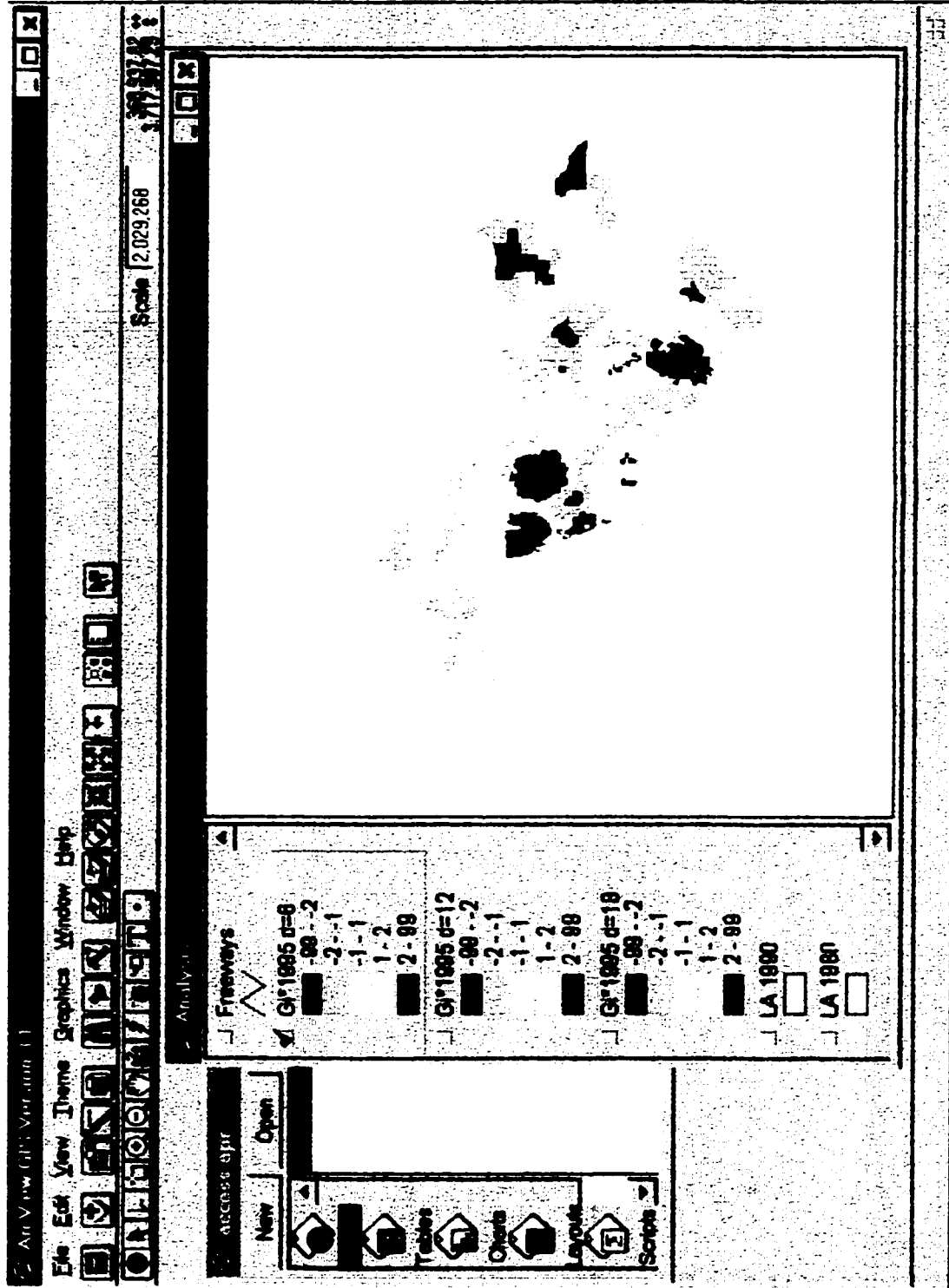
Figure 4.2 ArcView GIS environment displaying results of the G_i^* statistic accessibility analysis.

developer greater flexibility for maximizing software performance. The user

interface and all of the functions to manipulate the graphical output, however, are

programmed using *Avenue*, which offers an effective development environment

for these types of tasks. Because the user interacts with the *ArcView* interface

exclusively, these implementation details are completely invisible. Appropriate

error checking is performed in *Avenue* to ensure that all critical resources needed

to complete the accessibility analyses are in place before each FORTRAN

application is launched. The result is a seamless, efficient, and user-friendly

environment for performing a variety of accessibility analyses.

Data

The study area evaluated in this research encompasses most of the

urbanized portions of the five county Greater Los Angeles region: Los Angeles,

Orange, San Bernardino, Riverside, and Ventura Counties. Sparsely populated

tracts in these counties, such as those associated with the San Gabriel and San

Bernardino Mountains, are excluded. The data used for analyses include the

Urban Transportation Planning Package (UTPP 1980), the Census Transportation

Planning Package (CTPP 1990), and DYNAMAP 2000 road coverages[27].

The DYNAMAP 2000 data set and *ArcView GIS Network Analyst* software are

used to estimate shortest path tract-to-tract journey-to-work distances. The UTPP

and CTPP data sets provide journey-to-work flow data, by census tract, with

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[27] The U.S. Department of Transportation, Bureau of Transportation Statistics (BTS) provided the CTPP data free of charge. A NSF Dissertation Improvement Grant has provided funding for the UTPP and DYNAMAP 2000 data sets.

additional aggregate-level characteristics for workers both by tract of residence and by tract of work. Very few data sets provide worker information by tract of work or provide origin/destination flow data at an acceptable level of spatial resolution. The tract of work refers to the geographic location at which workers, age 16 years and older, carried out employment activities during the reference week preceding the census (Fulton, 1983). This data includes only people who actually worked during the reference week, however; it excludes people on vacation, sick, on strike, or otherwise away from the work place. In addition, individuals holding two or more jobs are counted only once in reference to their "principal" place of employment (Forstall and Greene, 1997).

The UTPP 1980 and CTPP 1990 data sets, derived from census long-form questionnaires, are subject to the usual census data accuracy problems: sampling, imputation, and undercount issues (see Myers, 1992). The place of work information included with these data, however, present additional accuracy issues due to difficulties in coding place of work responses to precise geographic locations, and to a large incidence of incomplete or uncodable survey data (Forstall and Greene, 1997). Responses that could not be assigned accurately to a census tract were subject to allocation procedures. Allocation was performed, however, only if a major share of workers with similar socioeconomic and residential profiles could be coded to specific at-work tracts. As a consequence, while virtually all of the highly urbanized portions of the study area permitted allocation, peripheral and low-density portions of the study area, often did not.

In addition, the allocation procedures used by the Census Bureau changed between 1980 and 1990[28]. Both the 1980 and 1990 allocation schemes, however, were designed to maintain tract proportions and labor force socioeconomic profiles (see Fulton, 1983). Nonetheless, in 1980, at-work coding was a manual procedure, and due to budget restrictions, only half of the long-form responses were coded (resulting in a 1 in 12 sample). In 1990, this coding was automated (a 1 in 6 sample), increasing the number of people "at-risk" for place of work coding, but still excluding low incidence commuting flows. In 1990, for example, no attempt was made to code workers matching the following profiles to a work-place census tract (personal correspondence with Phillip A. Salopek, Chief of the Journey-to-Work and Migration Statistics Branch of the Census Bureau's Population Division):

1) Commuting between Ventura and Orange Counties
2) Commuting between Riverside and Ventura Counties
3) Commuting between San Bernardino and Ventura Counties
4) Living in Orange County, working in Riverside County
5) Living in Orange County, working in San Bernardino County

While the UTPP and CTPP data sets contain median and average journey-to-work travel times, unfortunately, this data is of a very poor quality. Not only must a large number of missing tract-to-tract travel time costs be estimated, approximately 10 percent of the travel time values provided with this data are clearly erroneous (indicating individuals driving alone in a car can travel

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[28] I did not attempt to rectify the 1980 allocation results to the 1990 allocation results. These data were used as provided by the Census.

approximately 90 miles in 15 minutes, or require 99 minutes to travel

approximately 0.5 miles). As a consequence, this research utilizes an algorithm

(see Appendix C) to estimate travel time costs based on the calculated shortest

path journey-to-work distances, and the travel time costs provided with the CTPP

and UTPP data sets. For each origin/destination travel time matrix entry, the

algorithm identifies similar commuting profiles (similar shortest path distances,

proximal origins, and proximal destinations). Where the CTPP/UTPP travel times

are missing, or deviate significantly from the median travel times associated with

all similar commutes, travel times are estimated.

The accuracy issues discussed above limit confidence in the results of the

empirical analyses presented in this chapter. Nonetheless, the UTPP and CTPP

data are still effective in demonstrating the primary objective of these analyses: to

illustrate the analytical framework's potential (given accurate data) to address a

broad range of urban research questions.

Evaluating Intra-Metropolitan Accessibility

An analytical framework for evaluating and monitoring intra-metropolitan

accessibility was outlined in Chapter 3. A GIS environment for implementing the

proposed framework was presented above. All that remains is to demonstrate the

utility of the proposed analytical framework for urban planning, and to link the

discussion of intra-metropolitan accessibility back to the themes developed in

Chapter 2. In the remainder of this chapter, therefore, the analytical framework will

be utilized to examine structural, transportation infrastructure, and functional

93

accessibility using 1980 and 1990 employment data for the 5 county Greater Los Angeles region. Structural intra-metropolitan accessibility is evaluated in order to elucidate broad changes in urban spatial structure between 1980 and 1990, and to assess the equity of these changes for different income groups and occupational categories. Traffic congestion and the impacts of the transportation network on intra-metropolitan accessibility are explored in order to illustrate how urban restructuring processes have modified journey-to-work commuting patterns and to assess the implications of these changes for transportation planning. Finally, functional components of intra-metropolitan accessibility are explored to help discern how broad changes in transportation and telecommunications technologies are reshaping the urban landscape.

Each of the themes developed in the analyses that follow – job/worker balance, spatial/skills mismatch, journey-to-work commuting patterns, traffic congestion, and impacts of changing technology on urban spatial structure and commuting behavior – could easily constitute a full and detailed research project. A full treatment of these themes, however, is beyond the scope and objectives of the dissertation. Instead, the samples of analyses presented in this chapter serve as a starting point, and catalyst, for future research projects.

Structural Accessibility

Technology is enabling firms and resident populations to increasingly disperse both to lower-cost urban areas and to suburban and exurban locations at the urban periphery. These broad changes have prompted a variety of research questions regarding transportation patterns, social equity, and urban spatial

efficiency. Using the proposed analytical framework to evaluate intra-metropolitan accessibility from the perspective of physical spatial relationships allows examination of the impacts of these changes in urban spatial structure on local and regional accessibility.

Scale: In the sample analyses that follow, the term "neighborhood" is used in describing the scale of analysis employed to evaluate intra-metropolitan accessibility. This term is a bit misleading, as most of us will think of "neighborhood" in terms of short distances (1 or 2 miles), and strictly in relation to residential communities, rather than encompassing a mix of both employment districts and residential tracts. Within the context of evaluating relationships among employment opportunities and resident workers, however, this term takes on a broader meaning, representing more the concept of commuter sheds than residential communities. The average commuting distance in 1990 for the 5 county region is 12.9 miles. Many of the analyses presented, therefore, utilize a 12 mile distance radius. Analyses are also performed at 6 and 18 miles to bookend the 12 mile evaluations. In many ways, the scale selected for the analyses presented in this chapter has been rather arbitrary, and in a fuller development of the themes presented below analysis at multiple spatial scales or at a scale reflecting urban planning objectives would be most appropriate. In order to demonstrate the broader potential of the analytical framework, however, decisions regarding scale of analysis were needed. Much of the analysis of structural spatial relationships, for example, is performed at 3 or 6 miles in order to encompass individuals who may not have access to private vehicles and who may

rely on public transportation. The 3 mile distance radius is also selected because for most of the Los Angeles data (including the employment variable E), the critical distance where spatial dependency among data points is minimized occurs at approximately 3.0 miles (for some variables it is 2.9 miles, for others 3.2 miles, etc.). This critical distance is identified using the spatial filtering software described in Appendix A. Using a trial and error approach, the software performs spatial filtering procedures for $d=1.0$ miles, 1.1 miles, 1.2 miles, etc., seeking the distance radius where spatial dependency is effectively removed. The critical distance identified reflects the scale of analysis where redundancy among data values is minimized (the spatial dependency associated with a filtered variable is measured using the Moran's I statistic).

Analysis of travel times and transportation infrastructure is performed using a 30 minute isochrone to encompass broad commuting patterns in the region, and because broader distances were more effective than shorter distances in explaining commuting behavior for the model presented in Chapter 3 (Table 3.2). Evaluation of functional spatial relations is also performed using the 30 minute isochrone to allow comparison to analyses based on actual travel times. For several analyses (including the analysis described next), a variety of spatial scales are employed to emphasize the dynamic nature of accessibility with changes in scale and with changes in spatial context.

In Figures 4.3, 4.4, and 4.5, structural accessibility in the 5 county Greater Los Angeles region for 1980 is computed at multiple spatial scales: 6, 12, and 18 miles. In Figure 4.3, each census tract (centroid) is evaluated within the context of

Structural Accessibility in Greater Los Angeles, 1980
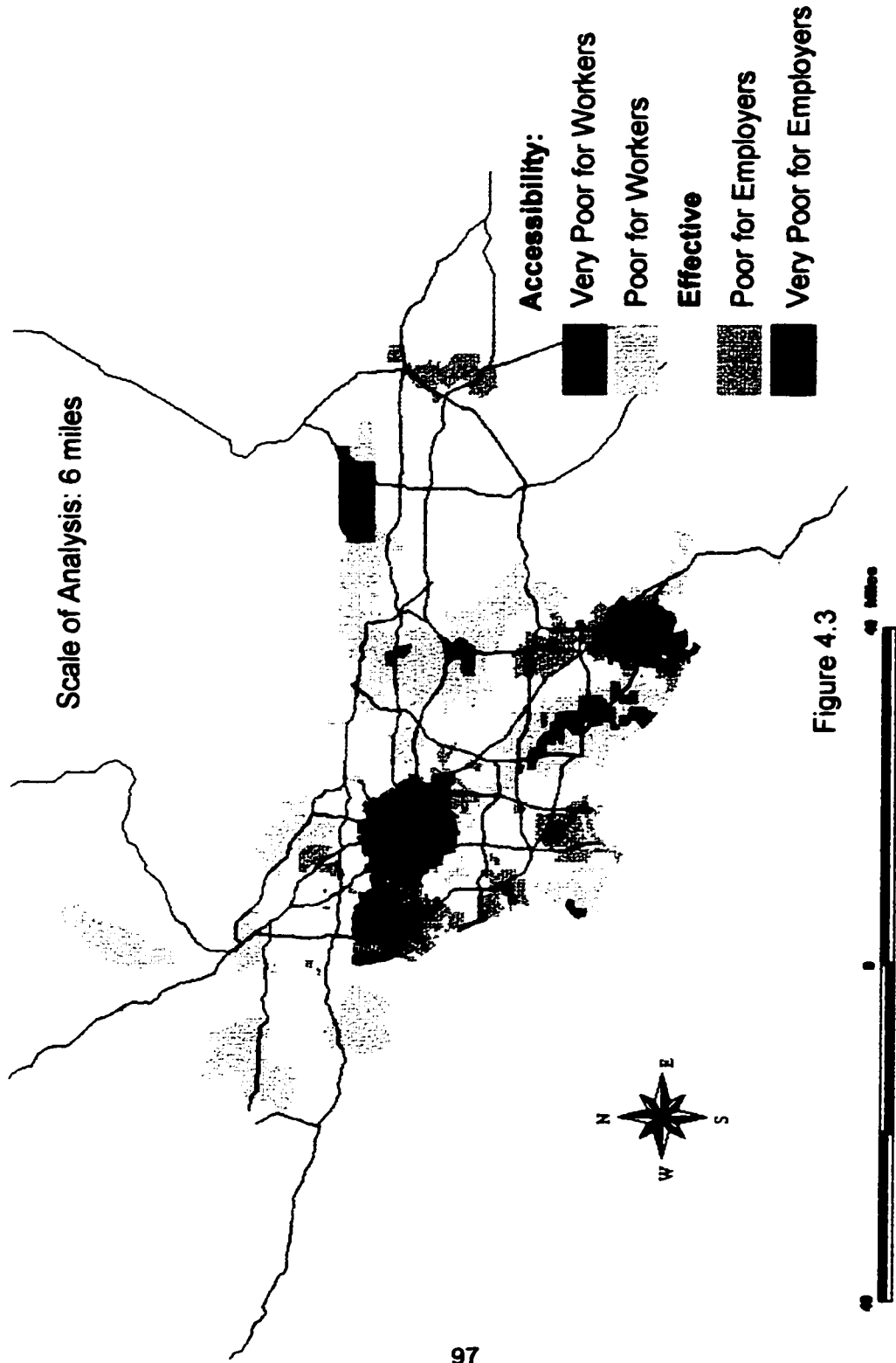
Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure 4.3

40 Miles

Structural Accessibility in Greater Los Angeles, 1980

Scale of Analysis: 12 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure 4.4

Structural Accessibility in Greater Los Angeles, 1980

Scale of Analysis: 18 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers
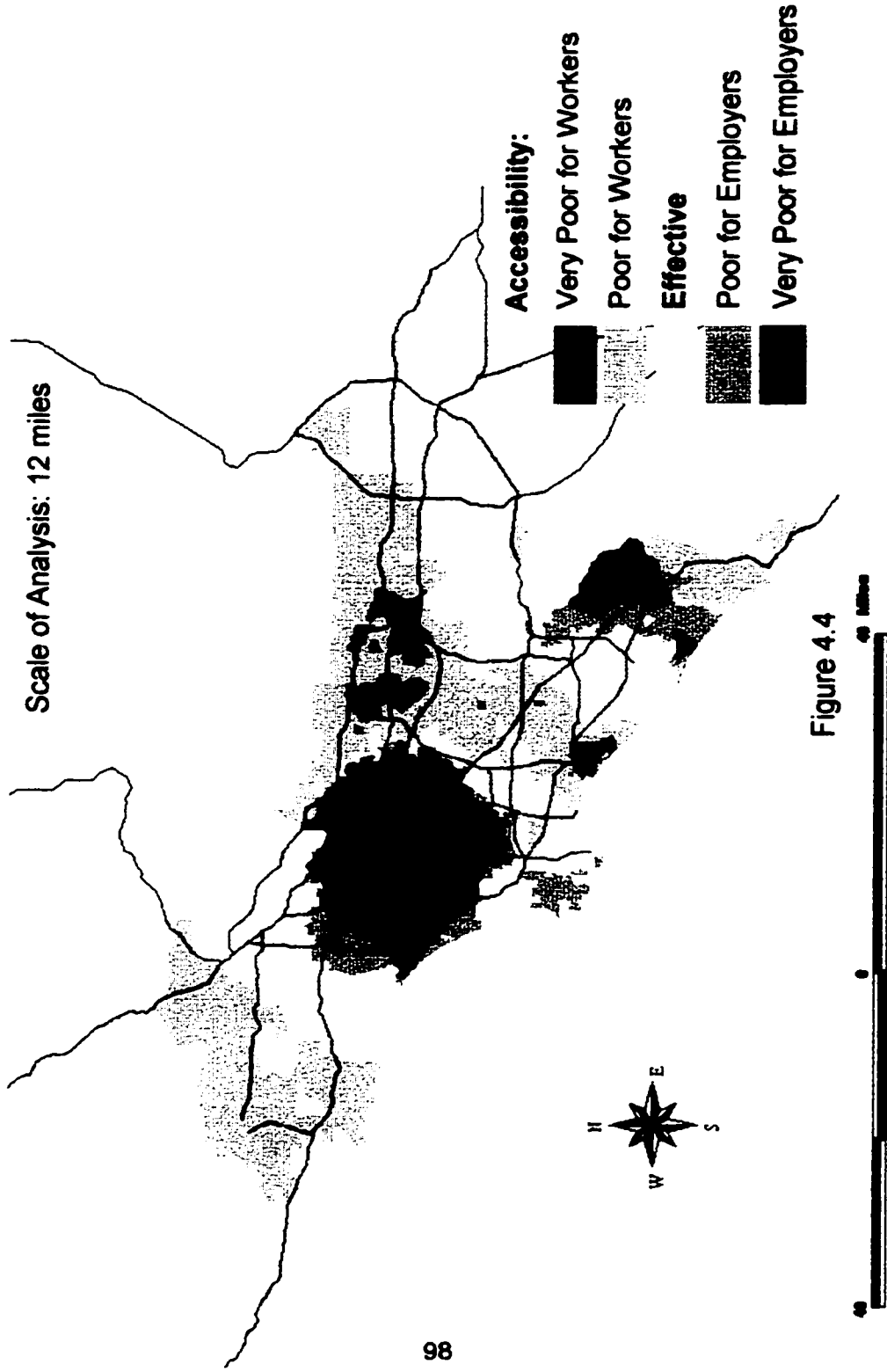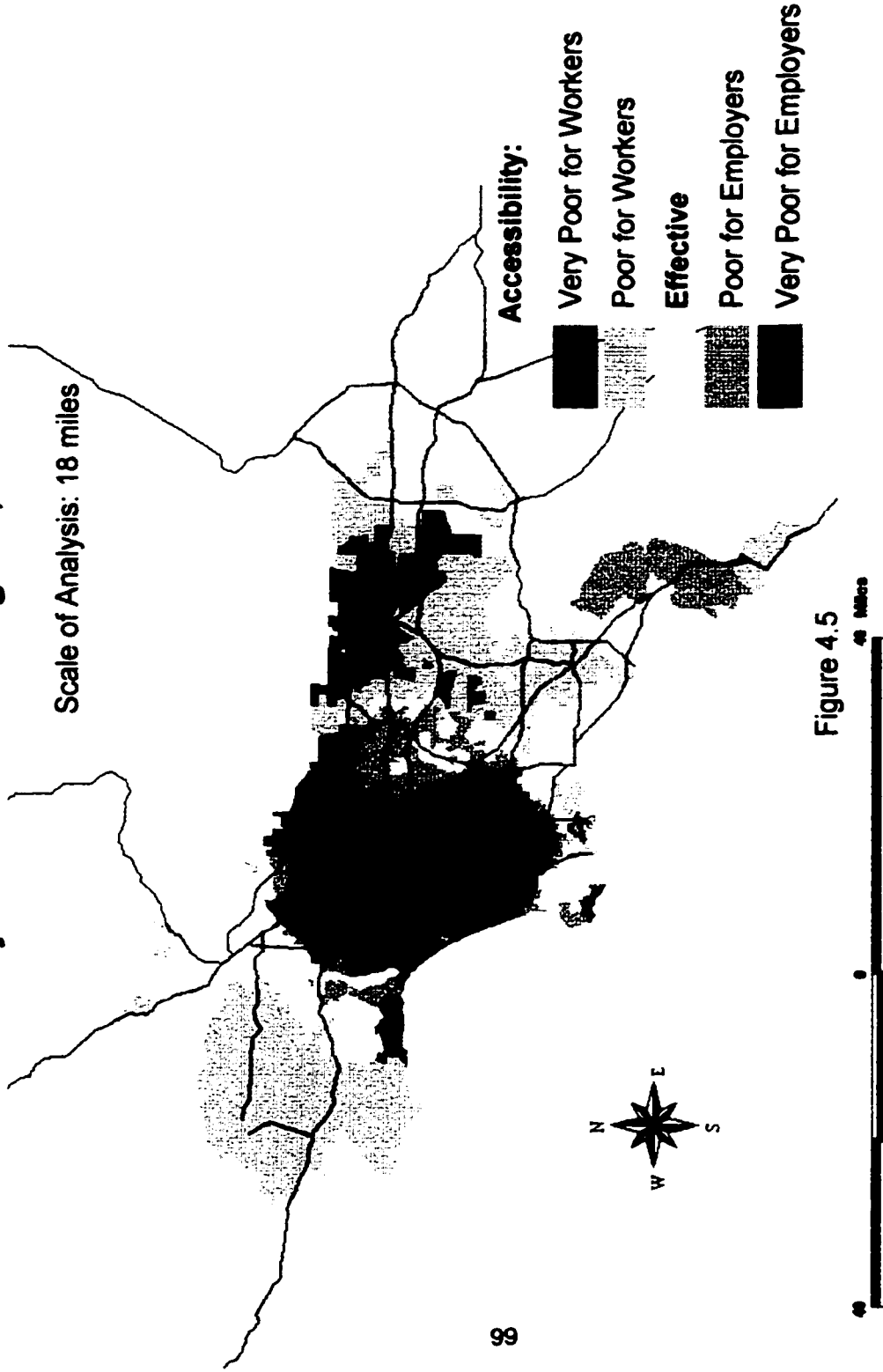
Figure 4.5

its neighbors, where the neighborhood is defined as those census tracts within a 6

mile distance radius of each tract being evaluated. In Figure 4.4, the

neighborhood is extended to encompass neighboring tracts within a 12 mile

distance radius. Similarly, the context for analysis in Figure 4.4 is defined using an

18 mile distance radius. The G_i^* statistic measures the statistical spatial

dependence of the level-of-service opportunity scores associated with each

proximal space neighborhood. Tracts with positive G_i^* accessibility scores reflect

job-rich regions providing employers with poor accessibility to labor. Similarly,

tracts associated with negative G_i^* scores reflect job-poor regions offering

insufficient accessibility to employment opportunities for local workers. Tracts

shaded in neutral tones represent regions providing effective accessibility to both

employers and workers[29].

In Figure 4.3, using a distance radius of 6 miles, 5 significant job-rich

(worker-poor) clusters are apparent: the Downtown Los Angeles area extending

west along Wilshire Blvd through Century City and Westwood toward Santa

Monica, the LAX area south to Redondo Beach, the Long Beach area extending

north to Lakewood, the Santa Ana area in Orange County encompassing Irvine

and Anaheim, and the San Bernardino/Riverside cluster inland. A number of

worker-rich (job-poor) clusters are also discernible including a swath of residential

---

[29] Throughout this chapter, accessibility designations of "very poor" are associated with G_i^* accessibility scores greater than +2 or less than -2 standard deviations; designations of "poor" are associated with G_i^* scores ranging from +1 to +2 or from -1 to -2 standard deviations. "Effective" accessibility is reserved for G_i^* accessibility scores between -1 and +1 standard deviations.

communities beginning northwest of San Bernardino in Rancho Cucamonga and extending west and south to Yorba Linda just east of Anaheim. A second corridor begins southeast of Downtown Los Angeles in Norwalk and extends south to the coastal city of Huntington Beach. A smaller cluster of coastal job-poor residential neighborhoods can be identified south of Torrance in Palos Verdes.

When the scale of analysis is increased to 12 miles (Figure 4.4), these spatial patterns become more consolidated. Two primary job-rich (worker-poor) regions stand out: a cluster surrounding Downtown Los Angeles and a cluster associated with the cities of Santa Ana and Anaheim in Orange County. Dominant worker-rich (job-poor) regions are diffuse to the northwest, east, and south of Downtown, with intense clustering south of Long Beach extending northeast toward Pomona.

Evaluation of structural accessibility using an 18 mile scale of analysis (Figure 4.5) highlights broad regional trends in 1980, indicating jobs are concentrated most heavily in Downtown Los Angeles and surrounding areas, and resident workers are concentrated in suburban communities both west and east of the Downtown cluster. Notice that the residential communities at the tip of the Long Beach peninsula, while worker-rich at the 6 mile scale of analysis, are job-rich when evaluated at the 18 mile scale of analysis. Residents living in these Palos Verdes estates, if willing and able to commute 15 to 20 miles, have accessibility to a tremendous number of job opportunities. Similarly, those workers living southwest of Anaheim who have good access to transportation in 1980 are

well situated to take advantage of job opportunities both to the north in Los Angeles, and to the south in Orange County.

It is important to remember that Figures 4.3, 4.4, and 4.5 do not map jobs or workers directly, but *accessibility to jobs and workers*, which is a function of scale. In Figure 4.6, census tracts with at least 2 jobs for every worker are mapped on top of the accessibility scores for 1990 at the 18 mile scale of analysis. While San Bernardino contains several job-rich tracts, for example, the number of jobs available does not match the large number of resident workers in surrounding communities, and overall these tracts are associated with worker-rich accessibility scores. In Figure 4.7, striping is applied to census tracts with at least two workers for every job in 1990. While the Downtown regional job-rich cluster engulfs a number of census tracts with many more workers than jobs, the jobs surrounding these residential communities far outnumber the workers available to fill them; overall, these tracts receive job-rich accessibility scores.

Analysis is performed at multiple spatial scales to emphasize the idea that accessibility is not a static score, but a function of space, time, and available technology. Individuals may trade off the time and expense associated with commuting (or telecommuting) in order to overcome space, gaining access to spatial opportunities at a distance. Getis (1994) suggests capturing scale-related variations in G_i^* scores as a function or series of slope gradients (see Figure 3.2b for a graphical example). Slope gradients, for example, could reveal additional information regarding potential benefits derived from the commuting trade off (see "Multiple Scale Analysis" in Chapter 3 and Figure 3.2).

102

Structural Accessibility in Relation to Job/Worker Ratios*, 1990:

Scale of Analysis: 18 miles

* Striping identifies tracts with more jobs than workers.
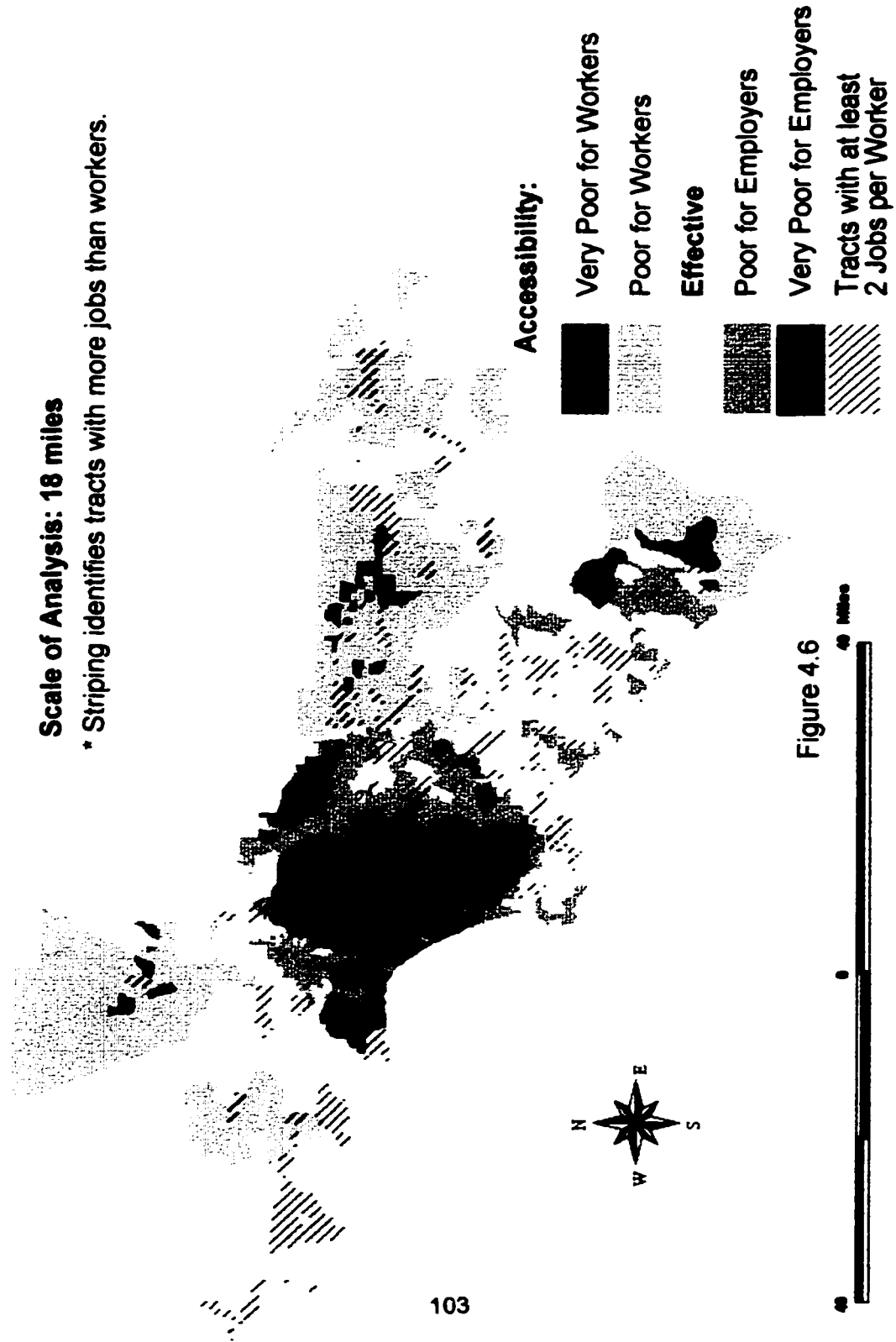
Accessibility:

- Very Poor for Workers
- Poor for Workers
- Effective
- Poor for Employers
- Very Poor for Employers
- Tracts with at least 2 Jobs per Worker

Figure 4.6

103

Structural Accessibility in Relation to Job/Worker Ratios*, 1990:

Scale of Analysis: 18 miles

* Striping identifies tracts with more workers than jobs.

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Tracts with at least
2 Workers per Job

Figure 4.7

104
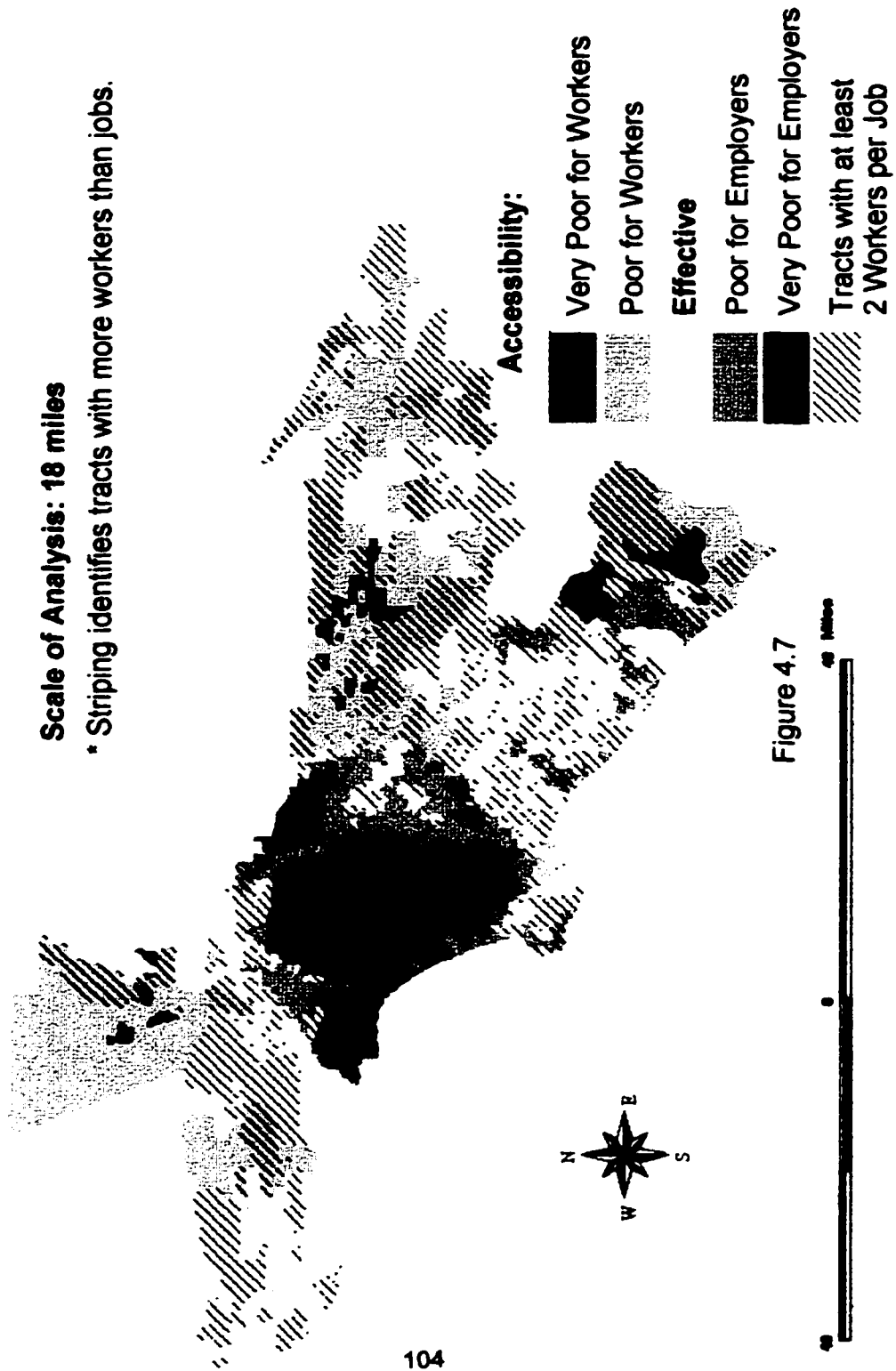
Mode of transportation and the ability to commute, however, are certainly not universal. For individuals with access to a private automobile, commuting 10 to 15 miles may be a viable option. In most cases, however, this will not be a viable option for individuals relying on public transportation in Southern California. In this research, accessibility scores are based on road network infrastructure. Adding public transportation infrastructure or environmental characteristics to reflect route safety or bike pathways, for example, would allow evaluation of structural accessibility for other transportation modes. Performing analyses at multiple spatial scales, however, offers a first pass evaluation of structural accessibility for a variety of transportation modes. Mapping structural accessibility at a small spatial scale of analysis (a 2 mile distance radius, for example) will capture the broadest range of transportation modes, providing applicability for walkers, bicyclists, bus riders, and automobile drivers. In this way, specific planning objectives or particular research agendas play an important role in dictating the scale used to evaluate structural accessibility.

Change: Chapter 2 outlined the broad urban restructuring processes both affecting cities in general and affecting Greater Los Angeles in particular. These changes include explosive suburban employment growth, declining residential densities, complex new patterns of commuting, and a restructuring of economic activities – production processes, organization, and configuration – in both time and space. Figures 4.3, 4.4, and 4.5 present structural accessibility at multiple spatial scales for 1980. Figures 4.6 and 4.7 portray structural accessibility in *1990* at an 18 mile scale of analysis. Comparing the 1980 to the1990 structural

accessibility scores reveals the dispersion of both jobs and resident workers

discussed in Chapter 2. Job concentrations surrounding Downtown Los Angeles

are less intense in 1990 than in 1980, and the worker-rich regions of the study

area are more diffuse while extending further north, east, and south to the study

area boundary. From a regional perspective, Figure 4.8 indicates that these

changes are leading to an increasing number of balanced tracts associated with

effective structural accessibility, and to fewer tracts exhibiting either extreme job or

worker concentrations. These changes in structural accessibility are mapped in

Figures 4.9, 4.10, and 4.11. Large improvements in structural accessibility (at

both the 6 and 12 mile scales of analysis) can be seen in the Downtown Los

Angeles region, indicating a move toward more balanced distributions of jobs and

workers. The changes portrayed in these maps, however, reflect a variety of

processes. The job-rich Downtown core experienced improved accessibility

because these tracts gained workers faster than jobs. Tracts at the north end of

the study area also gained workers faster than jobs, but for these worker-rich

(job-poor) tracts, this had a negative impact on level-of-service accessibility.

Figure 4.10 maps the relationship between job growth and changing structural

accessibility. Job-growth near worker-rich Thousand Oaks, for example, resulted

in improved structural accessibility, while job growth in Orange County near Irvine

served to increase job intensities and poor accessibility for local employers.

Figure 4.11 shows the relationship between structural accessibility change and

increasing worker supplies. Note, however, that the improved structural

accessibility associated with the Downtown region is not simply a reflection of

106
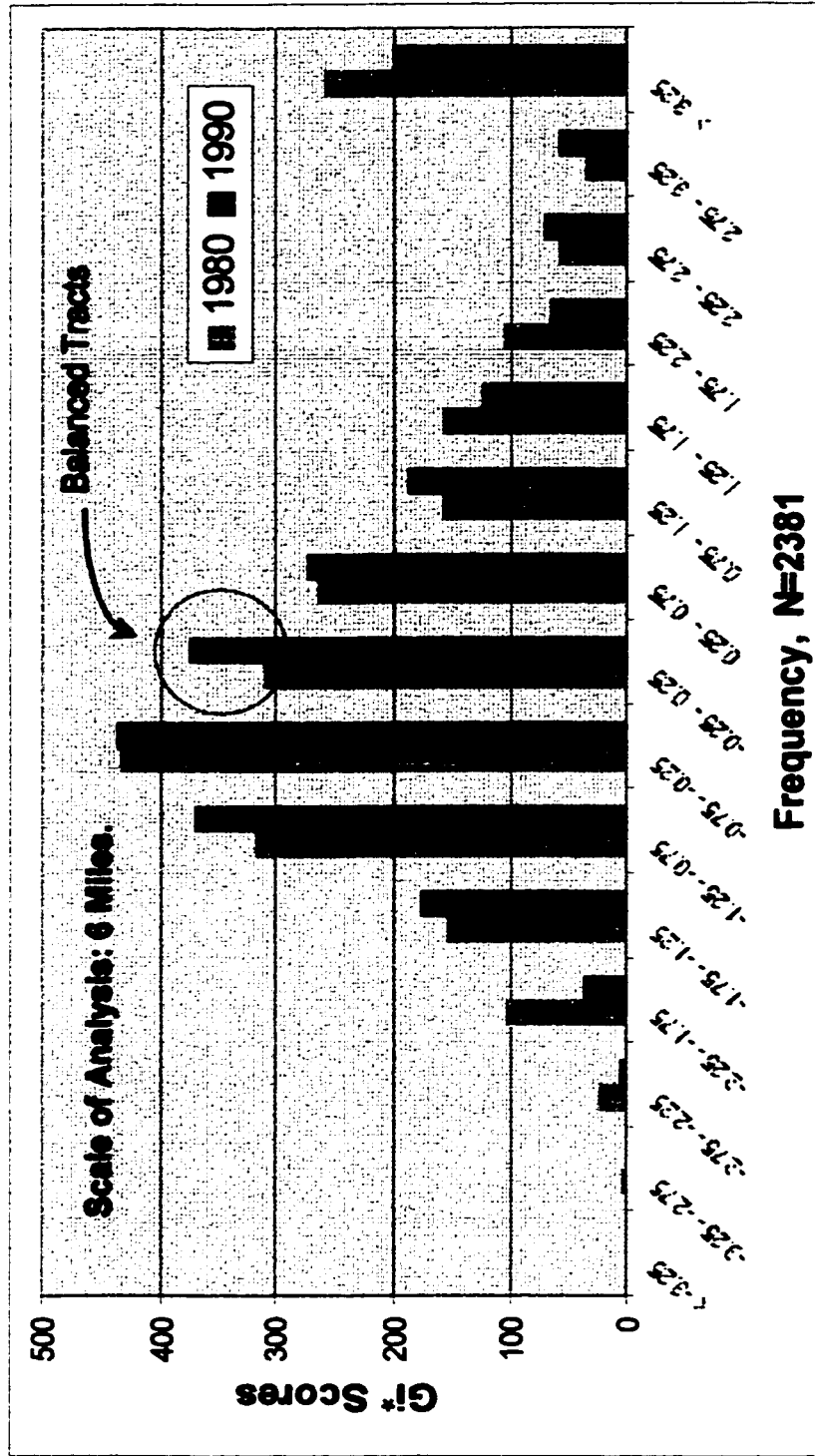
Figure 4.8 A greater number of tracts (evaluated within the context of all neighboring tracts within 6 miles) are balanced with regard to jobs and resident workers in 1990 than in 1980. Fewer tracts in 1990 exhibit either extreme job concentrations or extreme resident worker concentrations, reflecting processes of job dispersion between 1980 and 1990.

Changes in Structural Accessibility, 1980 to 1990

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

No Change

Better in 1990

Much Better in 1990

Figure 4.9

0   40   80 Miles
40
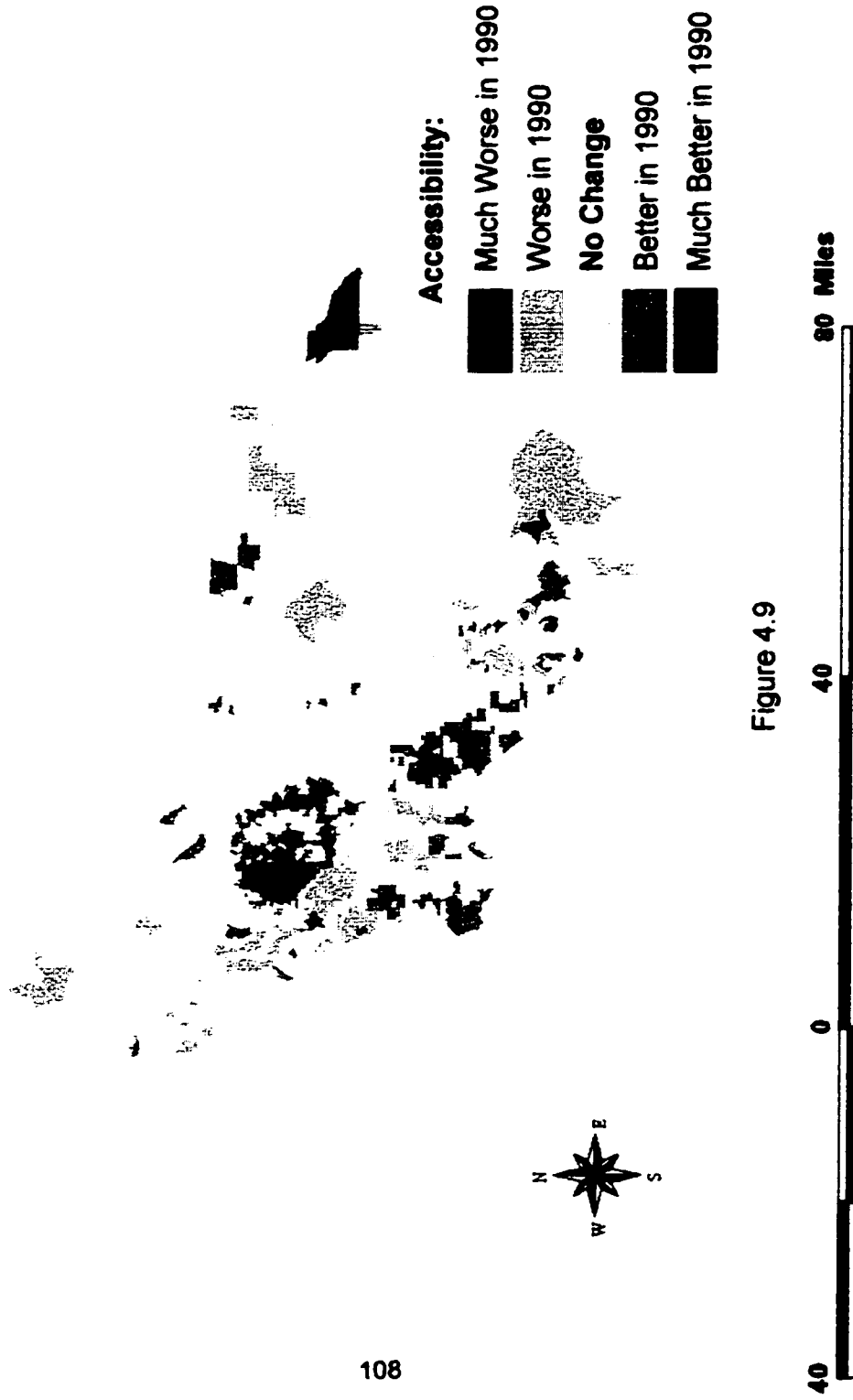
Changes in Structural Accessibility and Job Growth*, 1980 to 1990

Scale of Analysis: 12 miles

* Striping identifies job growth.

Accessibility:

Much Worse in 1990

Worse in 1990

No Change

Better in 1990

Much Better in 1990

Change associated
with Job Growth

Figure 4.10
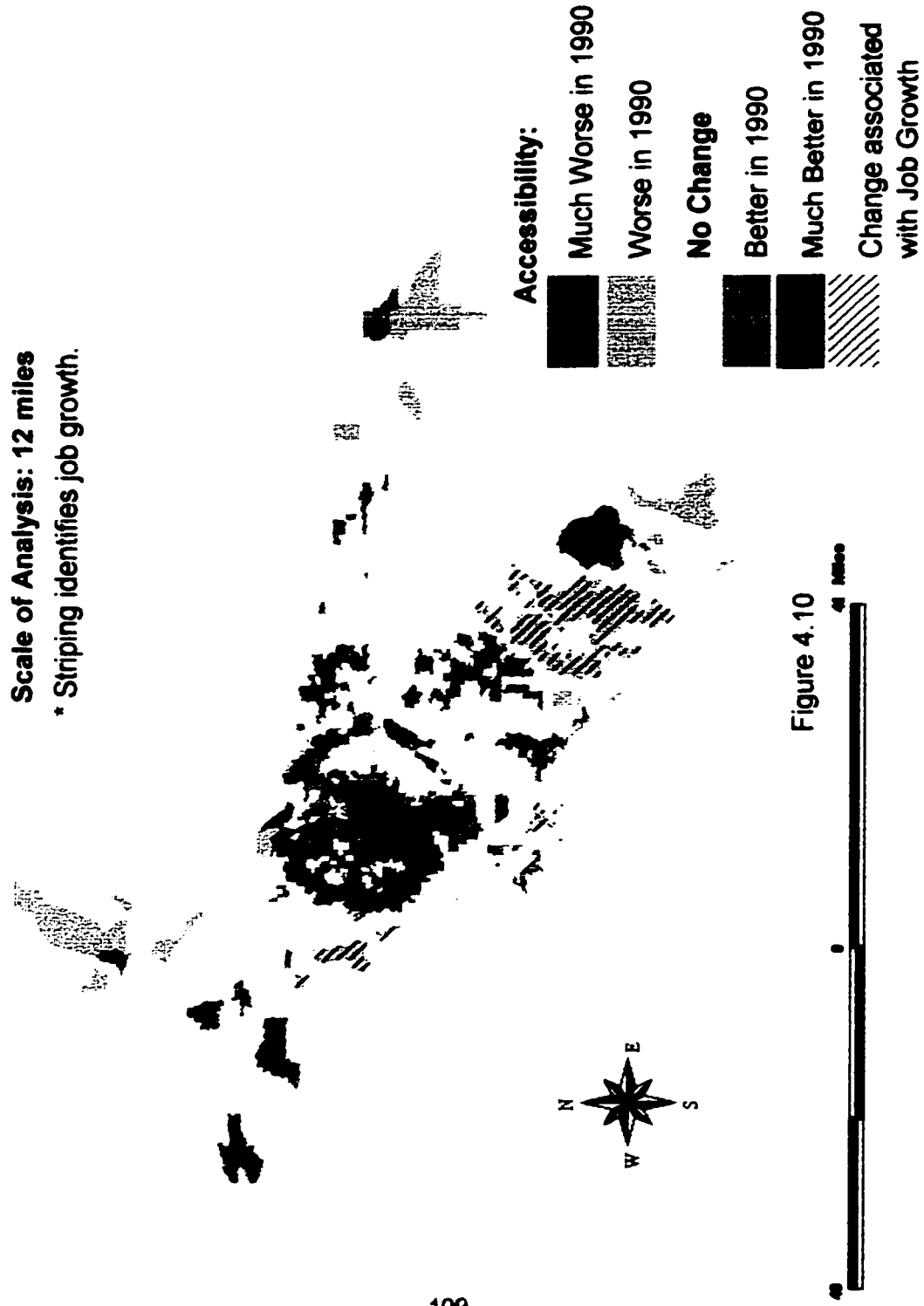
Changes in Structural Accessibility and Worker Distributions*, 1980 to 1990

Scale of Analysis: 12 miles

* Striping identifies changes associated with increasing numbers of resident workers.

Accessibility:

Much Worse in 1990

Worse in 1990

No Change

Better in 1990

Much Better in 1990

Change associated
with Worker Growth

Figure 4.11

110
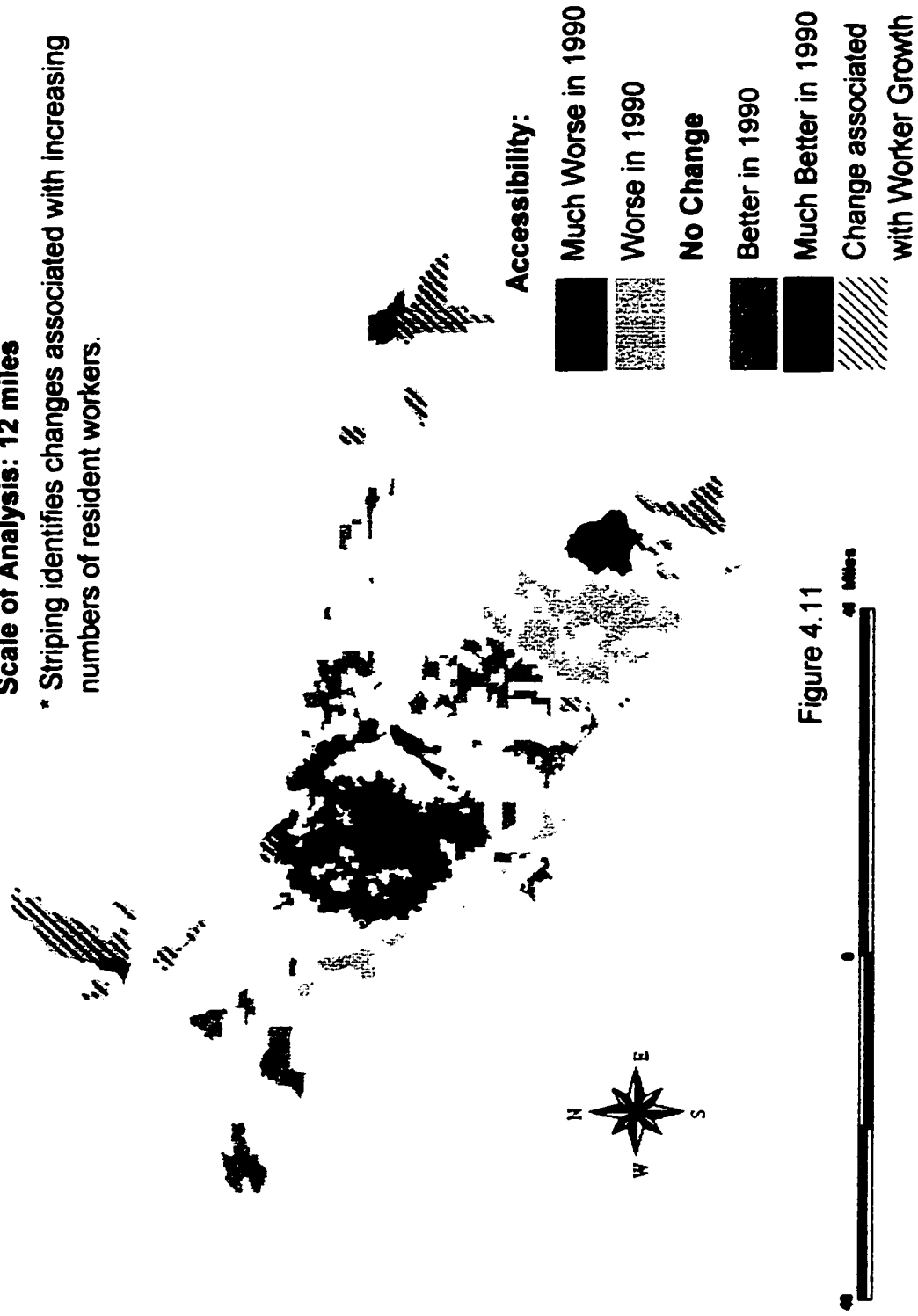
increasing numbers of workers. It also reflects the higher job growth rates occurring in other parts of the study area, and in some cases, job losses. Figures 4.3 through 4.11 confirm continued decentralization of both resident populations and employment, and portray the differential spatial impacts of these processes. How have these processes impacted different groups of individuals within Greater Los Angeles?

Spatial mismatch. Urban restructuring during the 1980s has instigated continued debate regarding the spatial mismatch, skills mismatch, and social polarization hypotheses, yielding little resolution (Hodge, 1996). The spatial mismatch hypothesis contends that global competition, immigration, industrial restructuring, and metropolitan decentralization have put inner-city low-income and minority residents at a disadvantage with respect to accessibility to employment opportunities (see "Cities and Spatial Restructuring" in Chapter 2). One of the most contentious issues regarding the spatial mismatch debate concerns the definition and measurement of job accessibility (Hughes, 1991). Examining changes in structural accessibility using the analytical framework proposed in this research, in fact, provides some clues for why spatial mismatch research findings may be producing conflicting results.

Figures 4.12 and 4.13 map median income levels for 1980 and 1990. Low-income tracts reflect tract median incomes less than 75 percent of the study area average median income ($19,328 in 1980; $40,937 in 1990). High-income tracts are assigned when tract median incomes are at least 125 percent of the study area average median income. Interestingly, many of the low-income tracts

111

at the periphery of the study area in 1980 are classified as high-income tracts in 1990, reflecting the rapid suburbanization occurring throughout the Greater Los Angeles region. Many of these low-income tracts devoted to agricultural activities in 1980, today reflect a sea of new single family homes and multi-complex condominiums.

Figure 4.14 indicates that all three income classes – low, middle, and high – improved their level-of-service accessibility between 1980 and 1990: all became more balanced (see Appendix F, Figure AF3 for a flowchart depicting the methods used to produce Figure 4.14). Figure 4.14 indicates that low-income tracts were associated with higher job intensities in 1980 than in 1990, but also that low-income tracts continue to be associated with job-rich accessibility scores, providing exposure to a larger number of employment opportunities than either the middle- or high-income tracts. Figure 4.15 maps high and low-income classes on top of the structural accessibility changes. While the job-rich, low-income tracts near Downtown Los Angeles experienced improved structural accessibility between 1980 and 1990 (they became more balanced), this improvement was primarily the result of diminishing job-rich intensities.

Skills mismatch. Similar analyses can be performed for different occupational categories. While the previous analyses indicate low-income tracts are exposed to a large number of employment opportunities, it does not indicate whether or not physically proximal opportunities match occupational skills. Figures 4.16, 4.17, and 4.18 depict change in average accessibility scores between 1980 and 1990 for 6 occupational categories by income class. (A flowchart depicting

112

Tract Median Incomes in Greater Los Angeles, 1980

Scale of Analysis: by Census Tract

Income Level:

Low

Middle

High
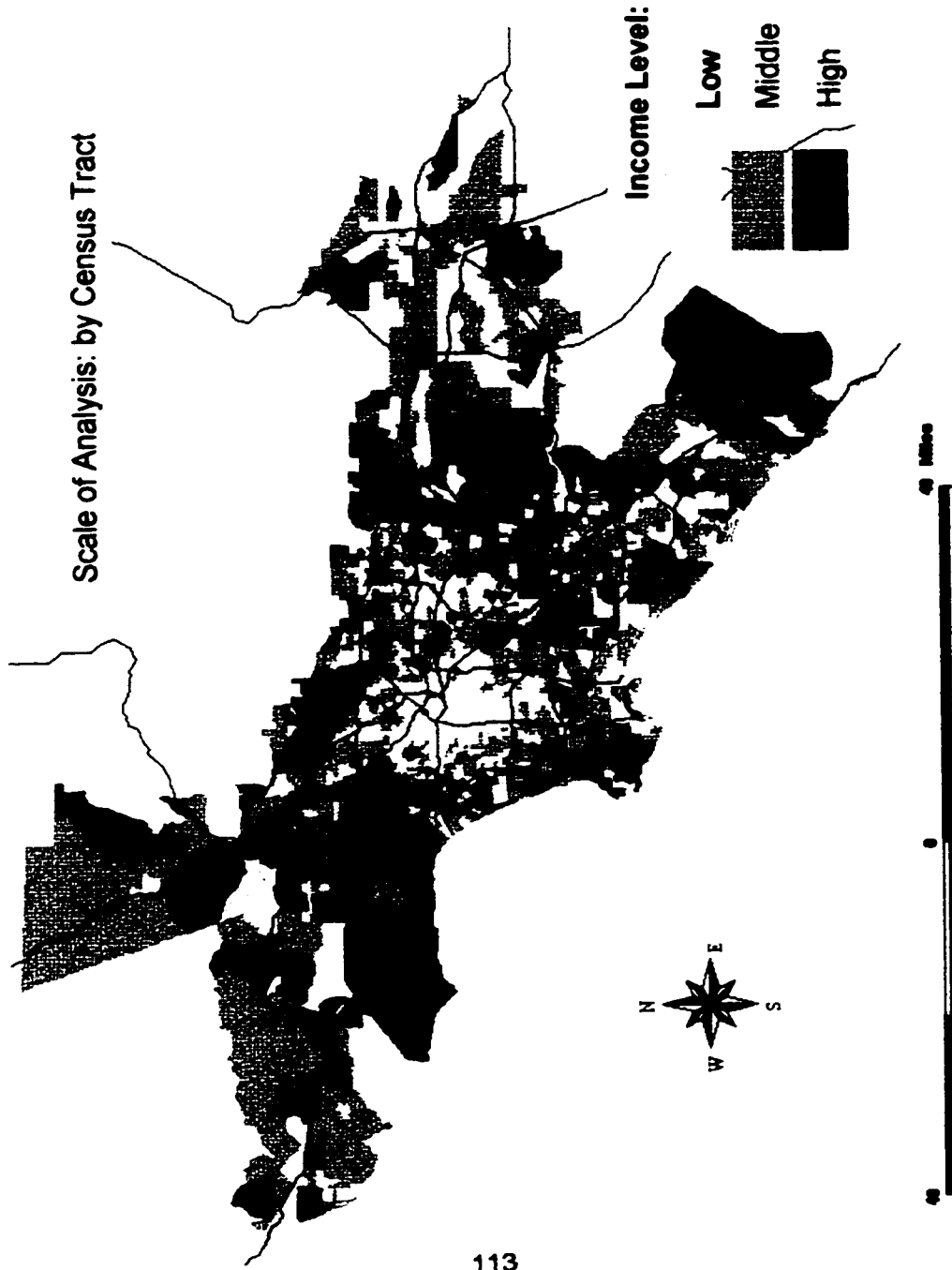
Figure 4.12 Tract income levels in relation to the regional median of $19328.

113

Tract Median Incomes in Greater Los Angeles, 1990

Scale of Analysis: by Census Tract

Income Level:

Low

Middle
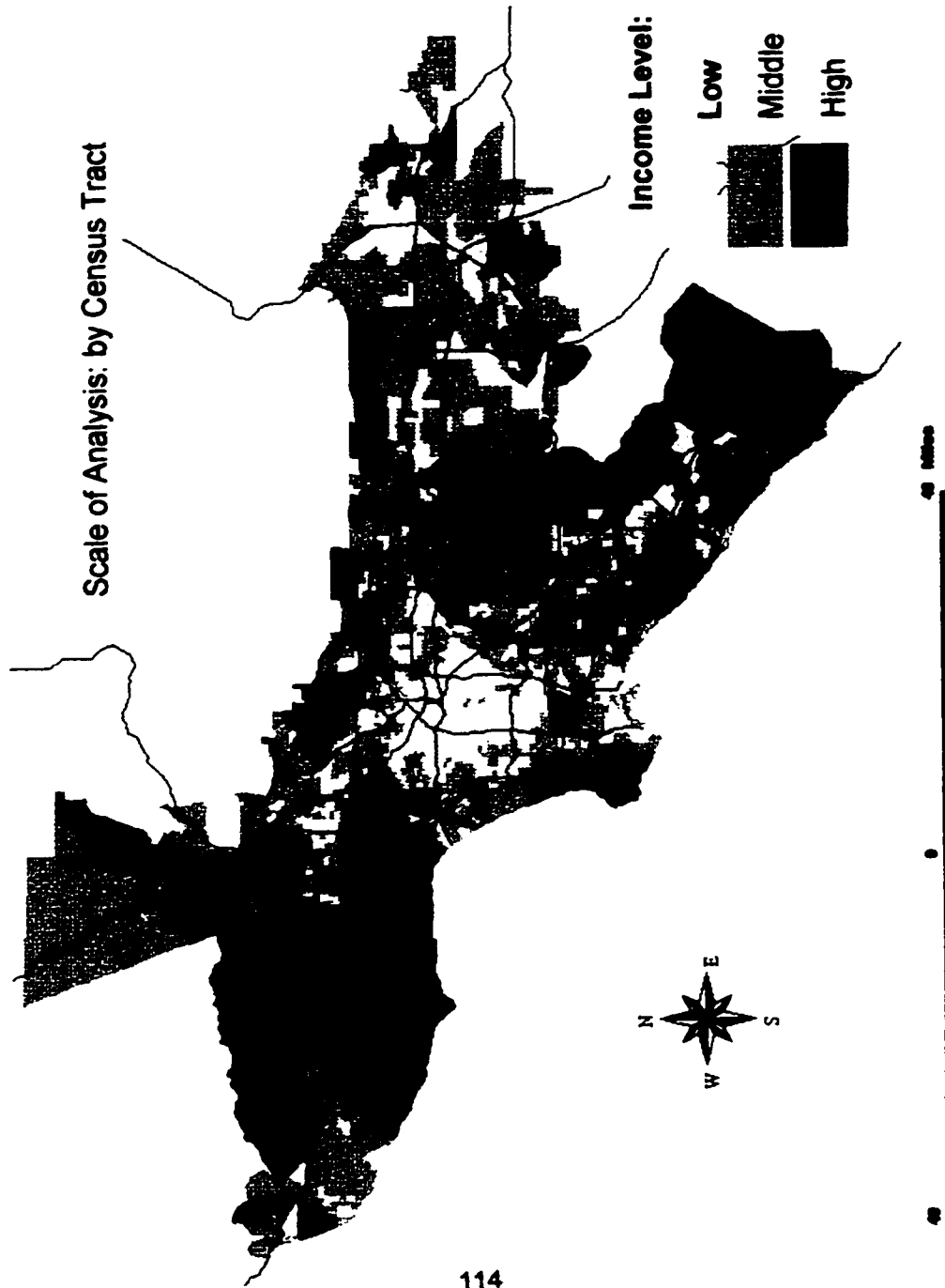
High

Figure 4.13 Tract income levels in relation to the regional median of $40937.

Scale of Analysis: 3 Miles

Legend: 1980, 1990

Job-Rich

Worker-Rich

Average Accessibility Score

LOW   MIDDLE   HIGH

Tract Median Income Level
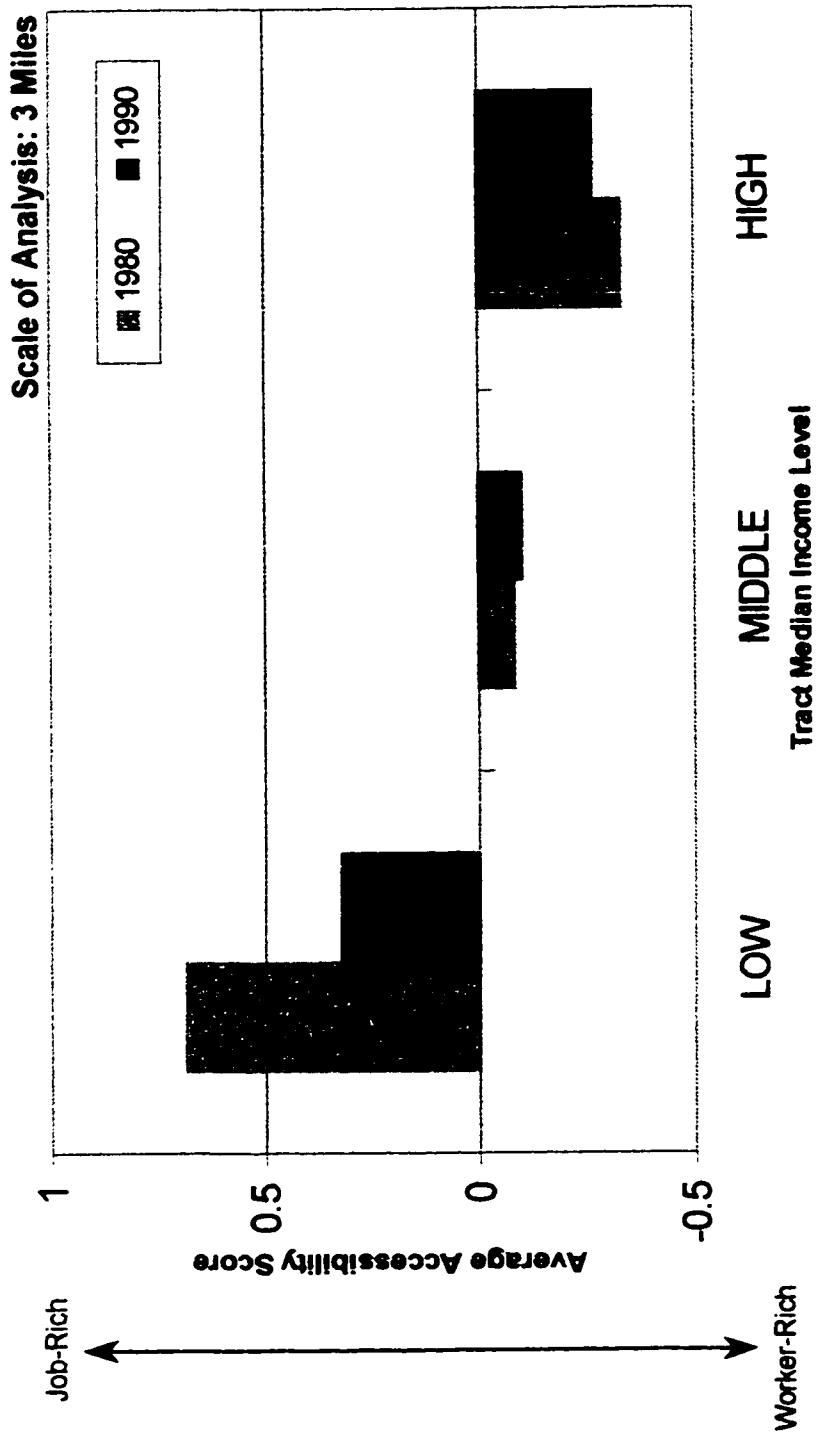
Figure 4.14 Change in average accessibility scores, 1980-1990, by income class. The low and high income classes improved level-of-service accessibility: both became more balanced in terms of their number of job opportunities and resident workers. Middle income tracts remained stable, with effective level-of-service accessibility.

115

Change in Accessibility, 1980-1990, in Relation to Median Income

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Low Income Tracts

High Income Tracts
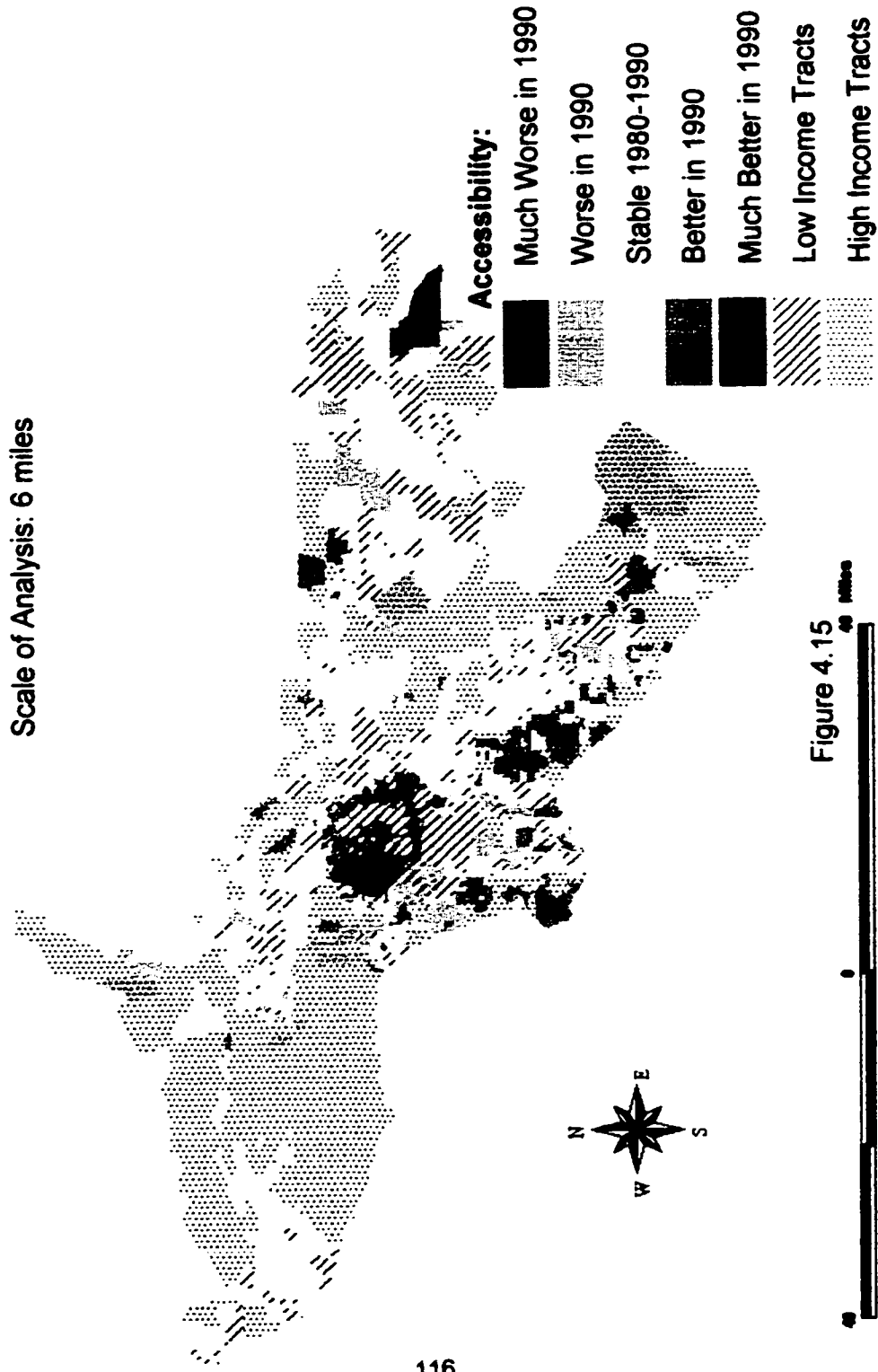
Figure 4.15

the methods used to produce the data in Figures 4.16, 4.17, and 4.18 is provided

in Appendix F, Figure AF4). Figure 4.16 shows changes in accessibility

associated with low-income tracts. Considering absolute deviation from perfect

accessibility (a level-of-service score equal to zero), low-income workers in all

occupational categories, except the agriculture, forestry, and fishing occupations,

improved level-of-service accessibility. These improvements, however, were

primarily beneficial to employers. Low-income workers in all occupational

categories were exposed to lower job intensities in 1990 than in 1980. Workers in

middle-income tracts (Figure 4.17) employed in managerial, professional,

technical, sales or clerical occupations, experienced improved level-of-service

accessibility as well. Level-of-service accessibility diminished for middle-income

blue collar and agriculture, forestry and fishing professions, however. As with

workers living in low-income tracts, workers living in middle-income tracts were

exposed to relatively fewer job opportunities in 1990 than in 1980 for all

occupational categories. Conversely, workers living in high-income tracts (Figure

4.18) improved exposure to potential employment opportunities for all but the

managerial and professional occupations. These workers, many living in tracts at

the periphery of the study area (Figure 4.13), benefited from the suburbanization

of employment opportunities occurring between 1980 and 1990.

The analyses above lend support to spatial/skills mismatch hypotheses

from the perspective that workers living in low-income tracts do, in fact, appear to

have poorer accessibility to employment opportunities in 1990 than in 1980.

Especially significant are findings that blue-collar workers living in low-income

117

tracts have diminished accessibility to potential jobs. Figures 4.19 through 4.24

map changes in structural accessibility (both for workers and employers)

associated with the managerial and professional occupations and with the low-skill

blue-collar occupations. Maps showing these same changes for each of the other

occupational categories are presented in Appendix H (Figures AH1 - AH12).

In 1980 (Figure 4.19), job-rich accessibility scores for managerial and

professional jobs are concentrated in the largest employment centers (the

Downtown Los Angeles region and the Santa Ana/Anaheim area), with job-poor

(worker-rich) concentrations associated with surrounding suburban communities.

Changes in structural accessibility for managers and professionals are presented

in Figure 4.20. These changes are similar to those seen for all occupational

categories (Figure 4.9). As firms in the Downtown region decentralize,

accessibility to workers in the managerial and professional occupations improves

for employers at the center of the study area, while at the same time, accessibility

to managerial and professional jobs also improves for workers in these

occupational categories living in the suburbs. Figure 4.21, mapping accessibility to

managerial and professional occupations in 1990, indicates a continuing worker

deficit in the Downtown and Irvine areas, with continuing worker surpluses at the

urban periphery. This same analysis is performed for low-skill blue-collar workers,

presented in Figures 4.22, 4.23, and 4.24. Notice the intensity of job-poor

accessibility scores in South Central Los Angeles, becoming more intense and

extensive in 1990.
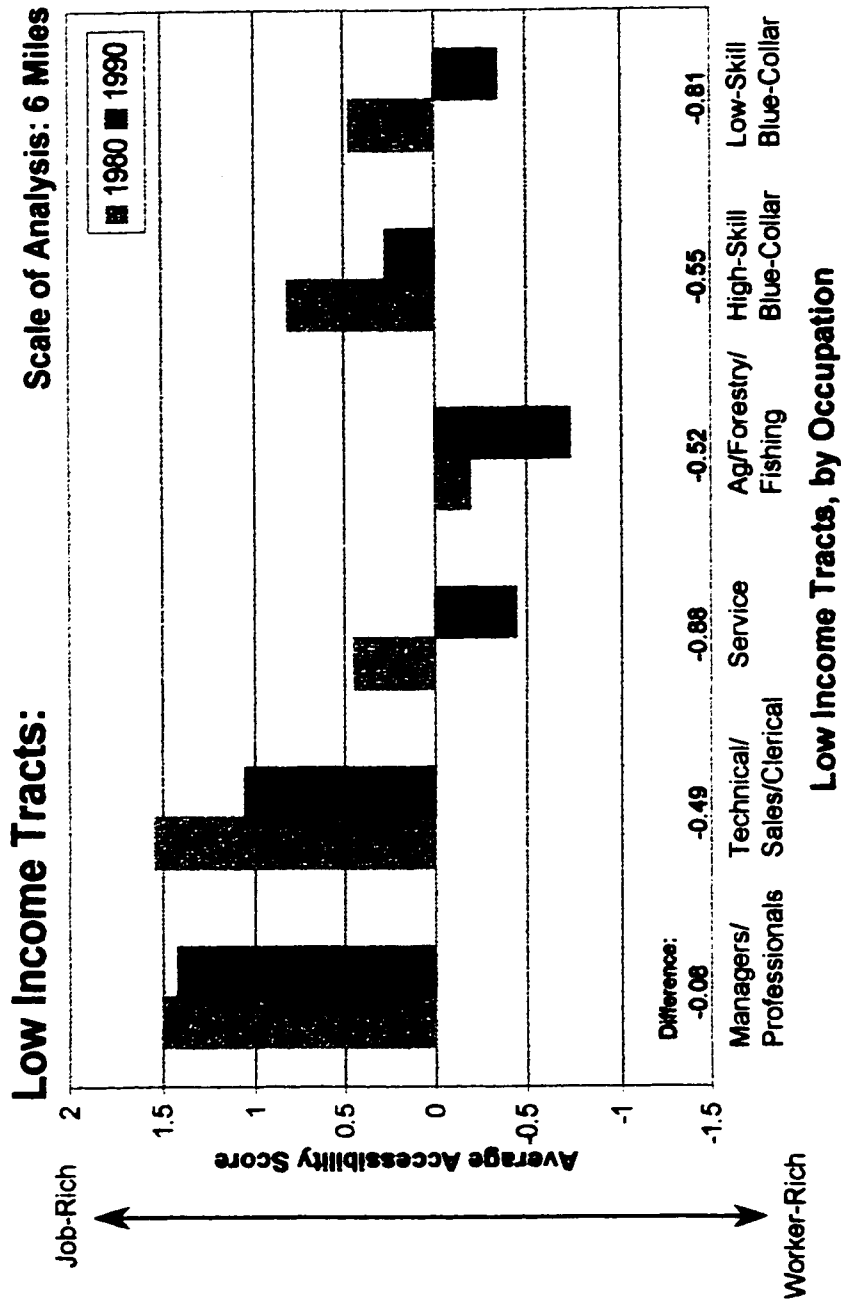
Figure 4.16 Change in average accessibility score, 1980-1990, for low income tracts by occupational category.
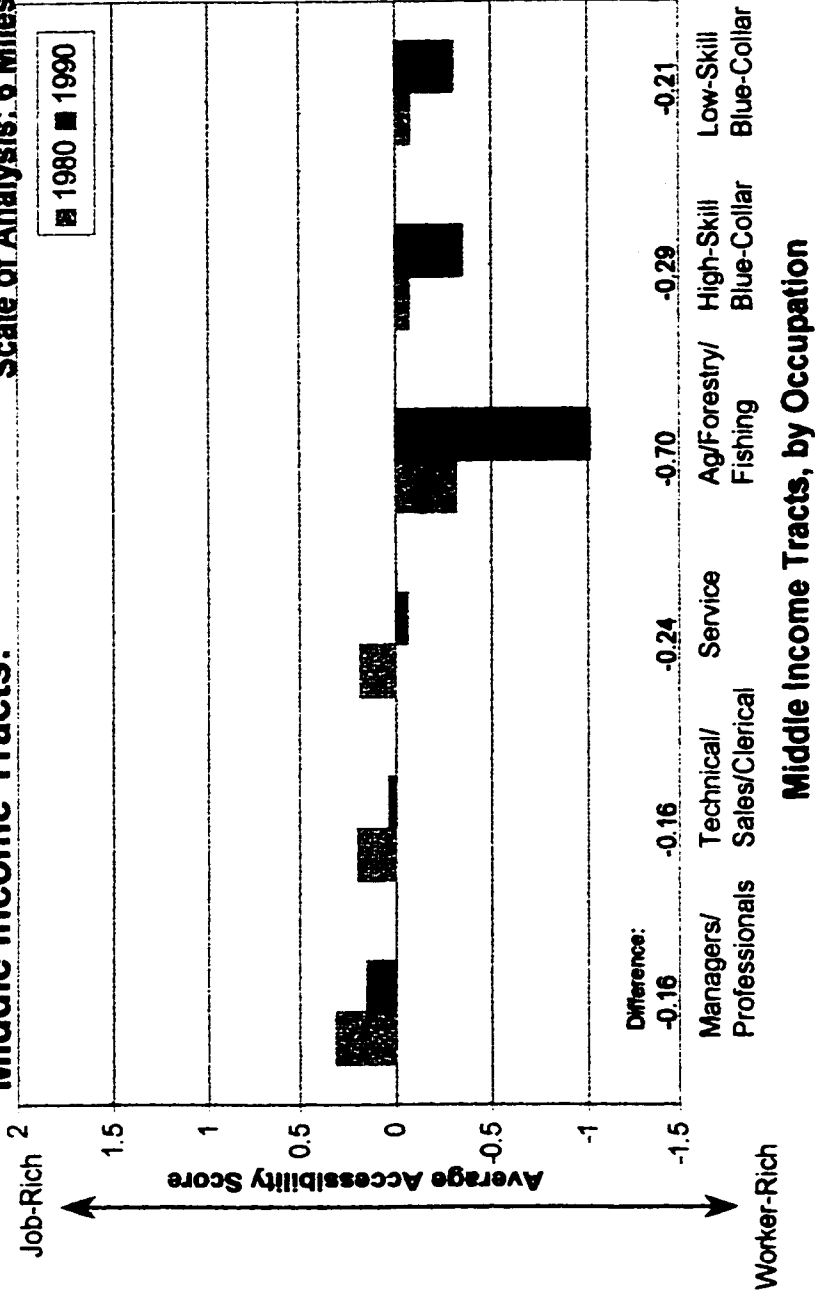
Figure 4.17 Change in average accessibility score, 1980-1990, for middle income tracts by occupational category.
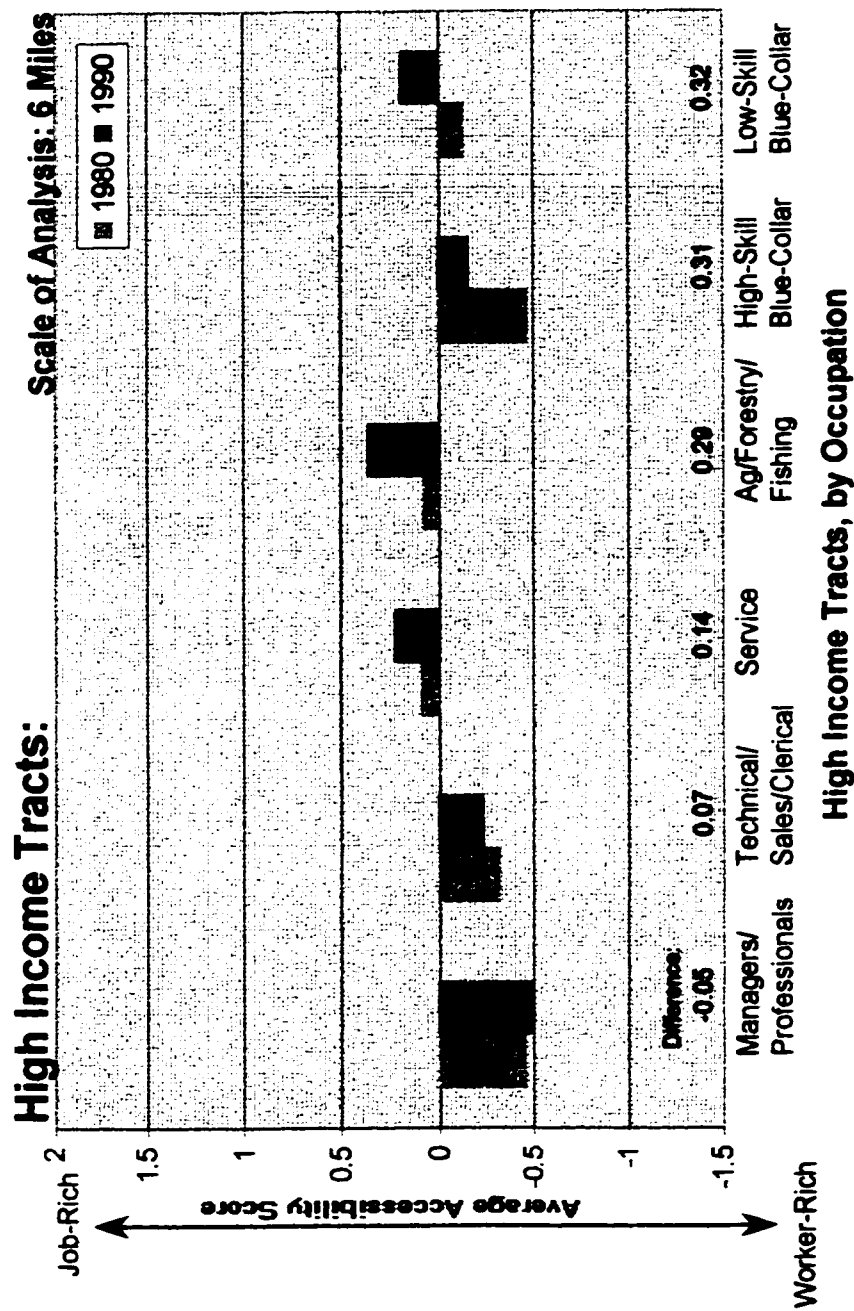
Figure 4.18 Change in average accessibility score, 1980-1990, for high income tracts by occupational category.

Structural Accessibility, 1980: Managerial and Professional Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers
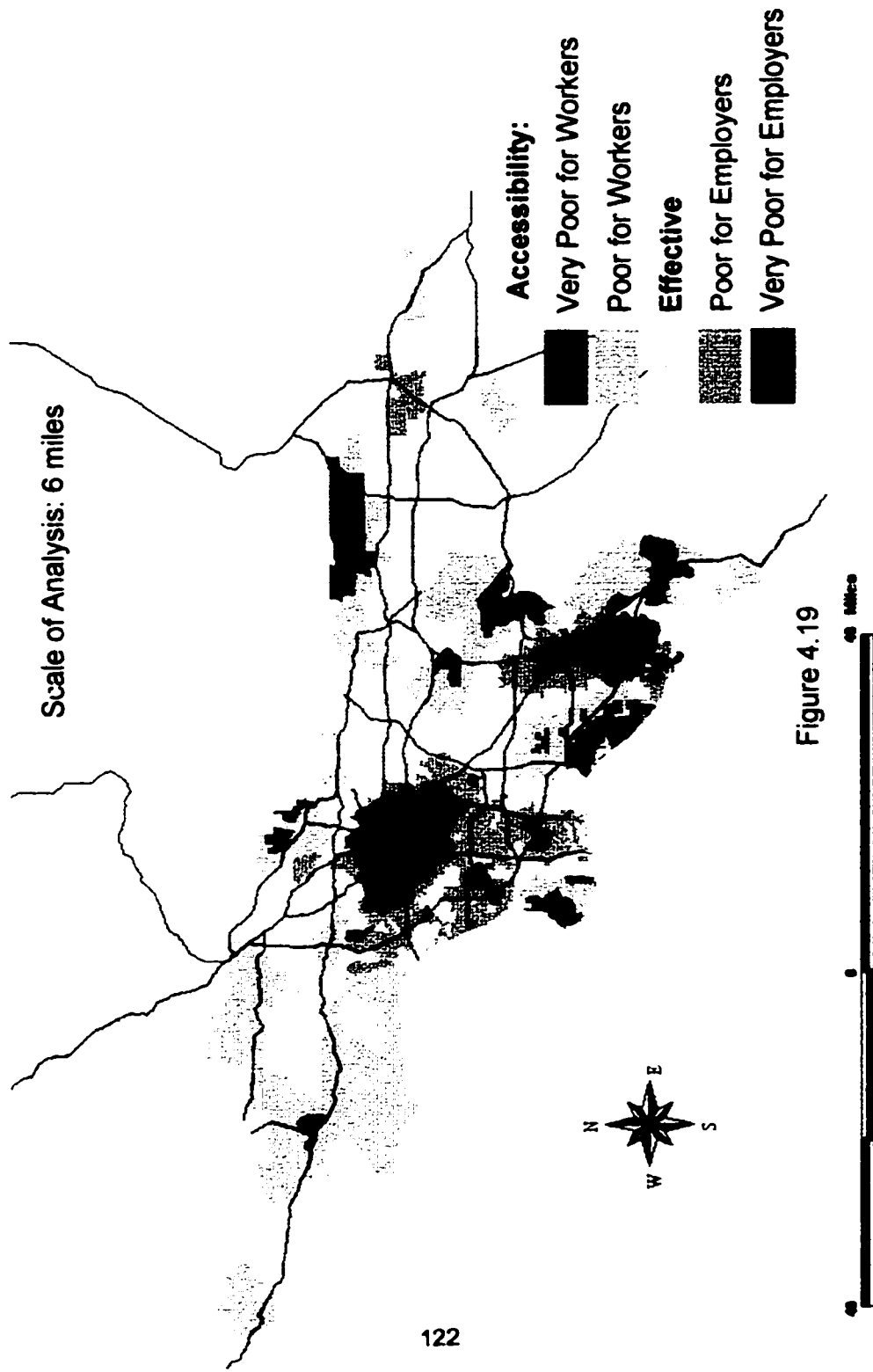
Figure 4.19

Change in Accessibility, 1980-1990: Managerial and Professional Occupations

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Figure 4.20

123
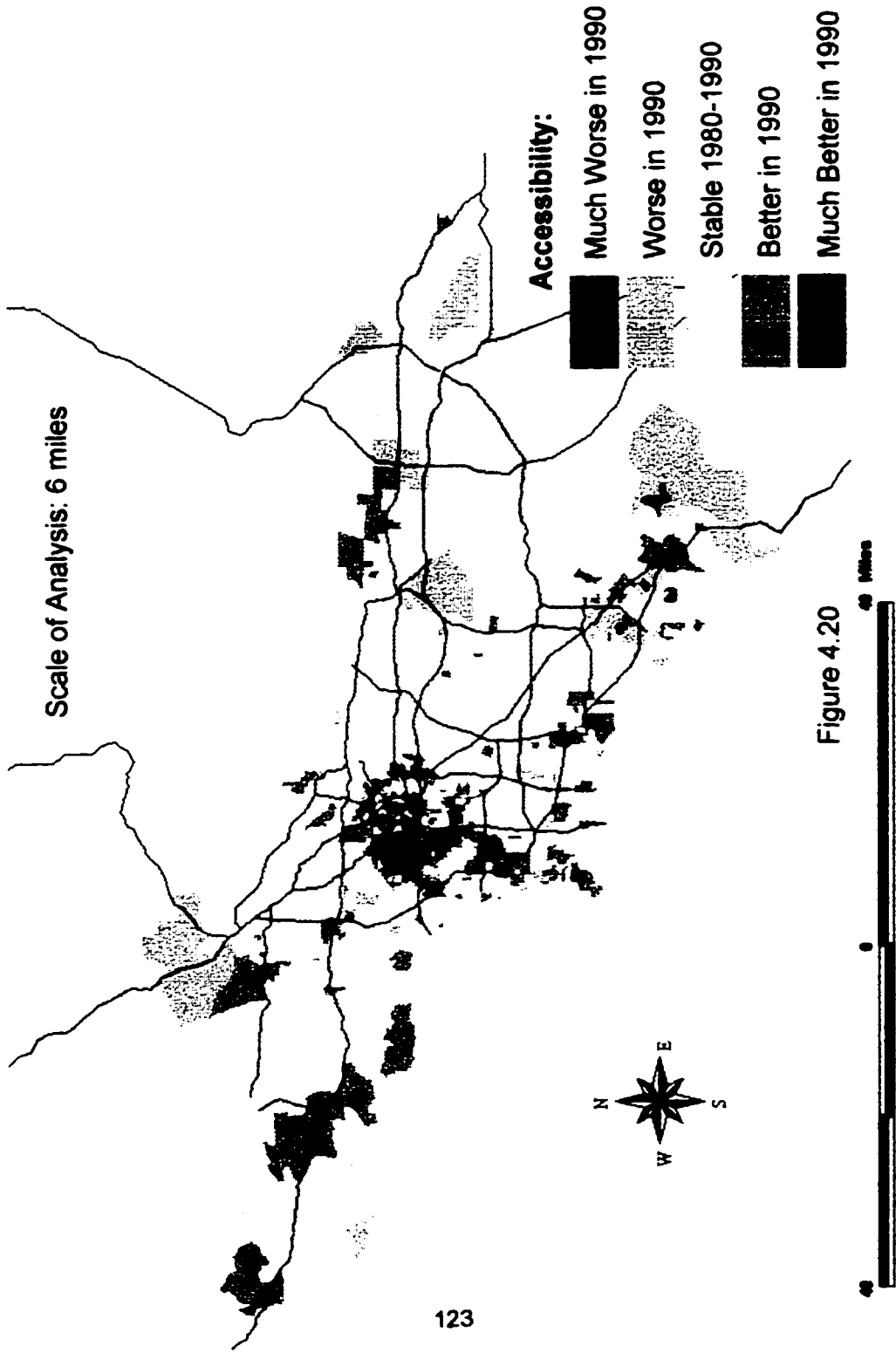
Structural Accessibility, 1990: Managerial and Professional Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers
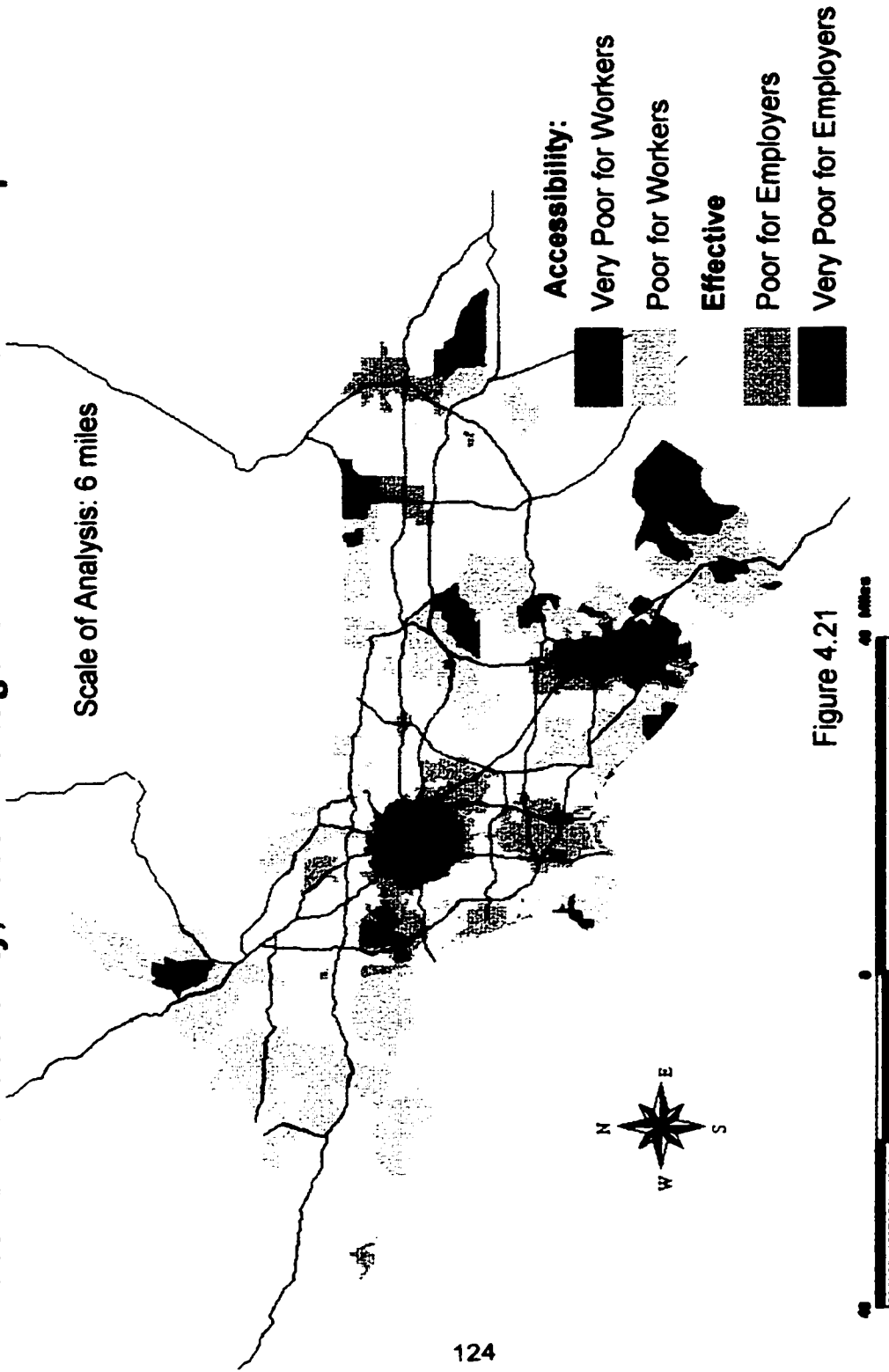
Figure 4.21

Structural Accessibility, 1980: Low-Skill Blue-Collar Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure 4.22

125
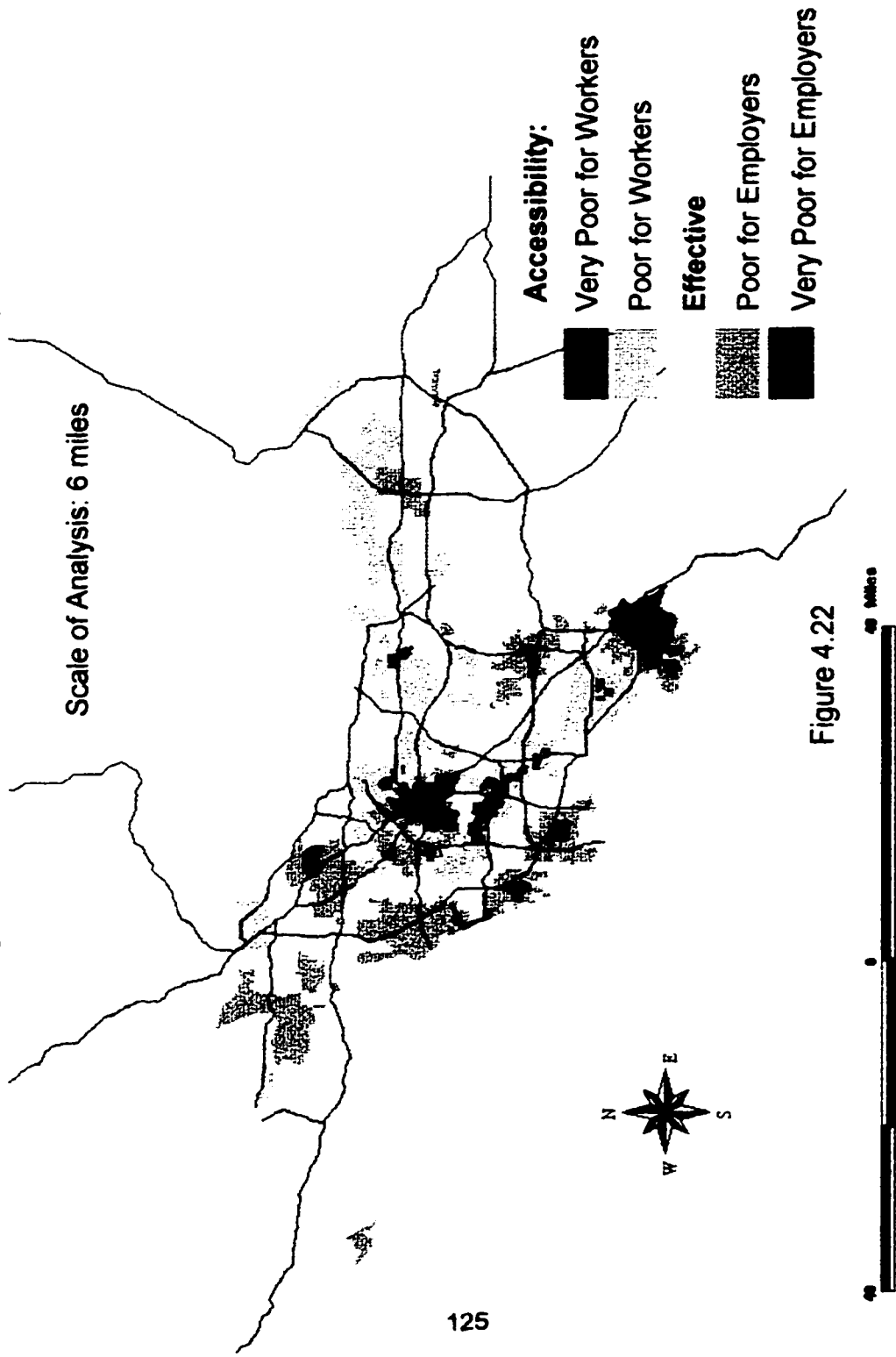
Change in Accessibility, 1980-1990: Low-Skill Blue-Collar Occupations

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Figure 4.23

126
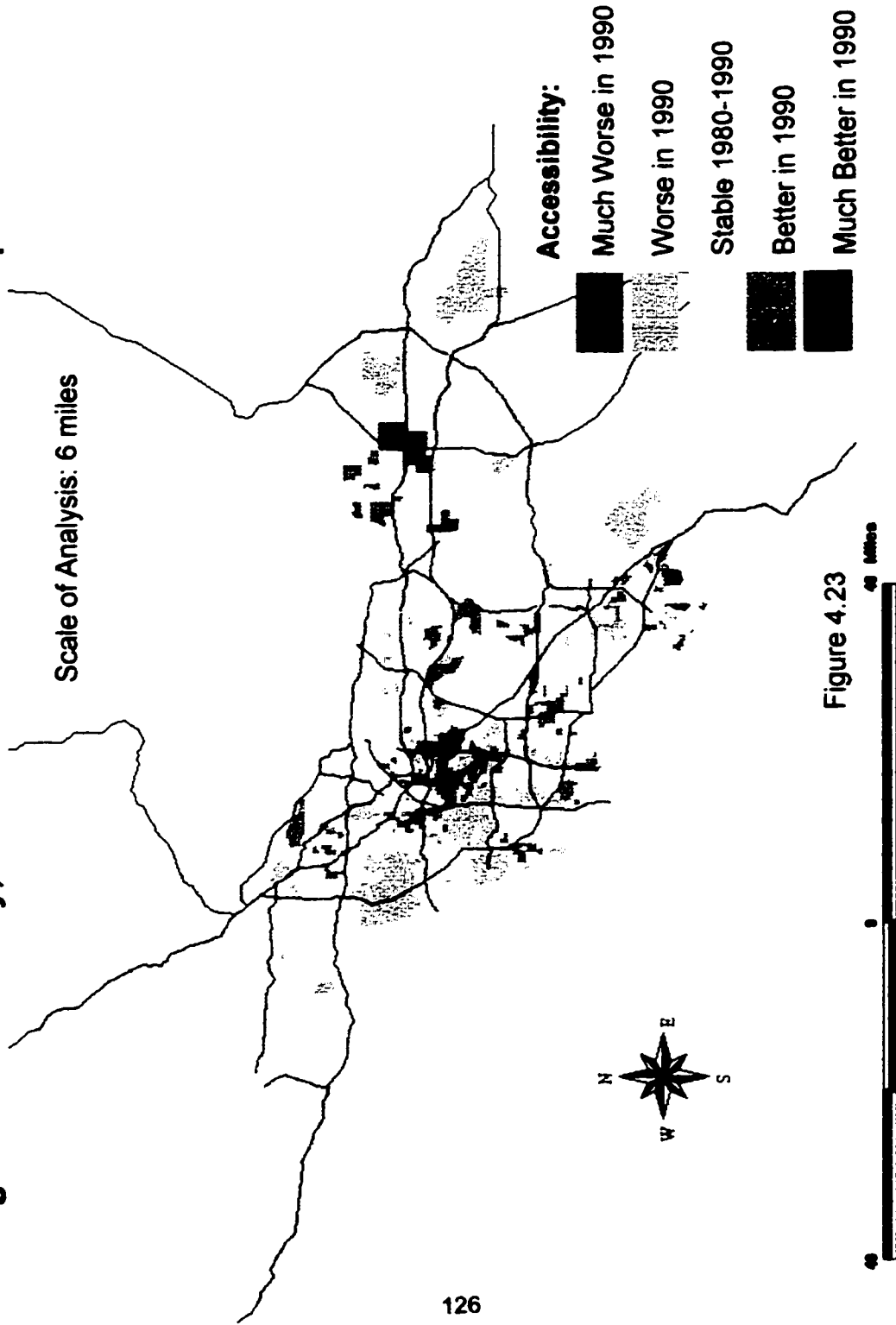
Structural Accessibility, 1990: Low-Skill Blue-Collar Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure 4.24

127
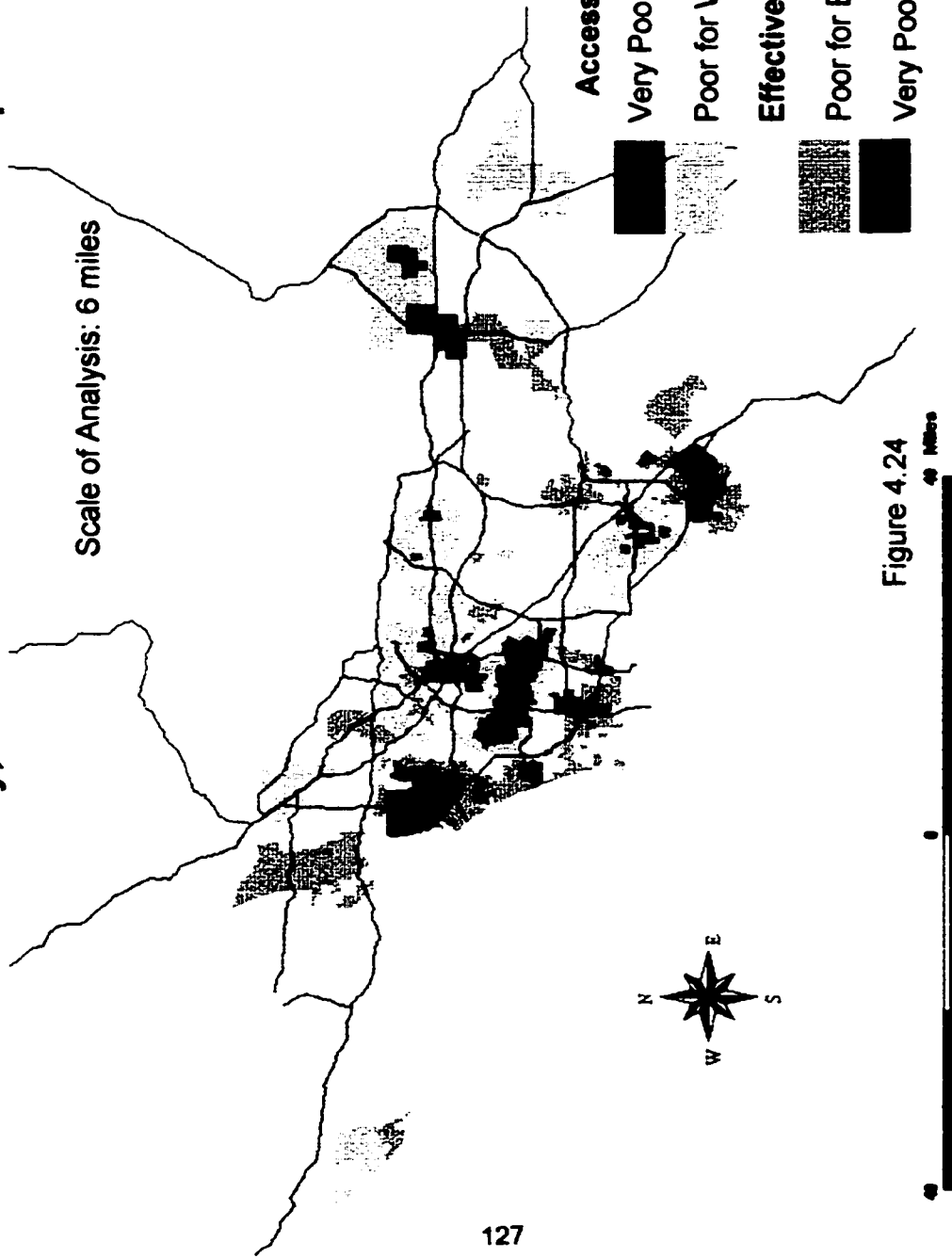
The analyses of structural accessibility presented above have only scratched at the surface of spatial/skills mismatch issues. These examples, however, demonstrate the potential of the analytical framework for investigating these issues further. For example, extending analysis to consider both employed and unemployed workers could prove useful for identifying where labor resources are being under-utilized. In addition, for most analyses presented in this research, jobs and workers have not been disaggregated by occupational categories (as done above for the skills mismatch analyses). Adding this additional detail will certainly be important for future research. Note, however, that comparing accessibility scores for 1990 where in one case jobs/workers have been disaggregated by occupation and in another case they have not (see Appendix H, Figures AH13 and AH14), visually, the differences appear to be very minor.

Transportation Infrastructure

Planning theory suggests that balancing jobs and housing can reduce commuting distances, curtail transportation-related air pollution, decrease gasoline consumption, constrain urban sprawl, and alleviate traffic congestion (Hodge, Morrill, and Stanilov, 1996; Livingston, 1992). Recently, however, the effectiveness of jobs/housing balance policies has been questioned (Gordon, Richardson, and Jun, 1991; Giuliano, 1991; 1995; Giuliano and Small, 1993). Giuliano and Small (1993), for example, argue that despite the high degree of intervention required to implement jobs/housing balance policies, evidence is weak that balancing communities will actually lead to shorter journey-to-work commuting behavior. Other researchers (Cervero, 1989; Hodge, 1992), however,

contend that many of the nation's most pressing urban problems could be relieved if jobs/housing balance could be achieved.

In this section of the dissertation, analysis moves from an exclusive focus on physical spatial distributions of jobs and resident workers to include journey-to-work travel costs. Evaluating intra-metropolitan accessibility from the perspective of travel time, rather than travel distance, allows examination of the impacts on intra-metropolitan accessibility associated with traffic congestion, as well as the implications of these impacts for transportation planning policy. Since a level-of-service definition of accessibility embodies the notion of job/worker balance, examining the relationship between changes in level-of-service accessibility and changes in journey-to-work commuting patterns provides an assessment of the effectiveness of balancing jobs and resident workers.

Congestion and mobility. In Figure 4.25, structural accessibility based on journey-to-work travel times is mapped at a 30 minute scale of analysis. The patterns that emerge are very similar to those depicted in Figure 4.6, which portrays structural accessibility based on travel distance and an 18 mile distance radius. In fact, the average travel time for all18 mile commutes in the study area is 30 minutes. While similar, the map based on travel time is more complex than the map based on travel distance, reflecting a more fragmented patterning of accessibility scores. This added complexity portrays differential consequences of traffic congestion, which can alter the geography of spatial opportunities. Traffic congestion and mobility are mapped in Figure 4.26. Heavy traffic congestion is found in the densely populated central portion of the study area with faster speeds

129

and effective mobility at the periphery. The impacts of traffic congestion on level-of-service accessibility are mapped in Figure 4.27. The map in Figure 4.27 is produced by comparing G_i^* accessibility scores based on an 18 mile distance radius to scores based on a 30 minute isochrone. The results of this analysis suggest a variety of processes at work. In worker-rich (job-poor) regions where effective mobility allows surplus workers accessibility to surplus employment opportunities nearby, traffic conditions (in this case good mobility) will have a positive impact on level-of-service accessibility. Worker-rich communities in the southern-most portion of the study area, for example, benefit from effective transportation infrastructure, which facilitates accessibility to a large number of employment opportunities near Irvine and Santa Ana. In the eastern-most portion of the study area, however, even at a 30 minute (18 mile) scale of analysis, travel exposes commuters to additional workers faster than to additional jobs, degrading the already poor accessibility scores in this region. Figure 4.28 overlays the impact of transportation infrastructure map on top of the map showing traffic conditions. Note that it would not be very useful to add new roads or additional lanes to highways in and around Riverside. Workers in these communities already have good mobility; most beneficial to these communities would be additional employment opportunities! Conversely, improving transportation infrastructure in and around the census tracts just north of Anaheim would give workers in these communities effective accessibility to job-rich tracts nearby.

130

Structural Accessibility Based on Travel Time Costs, 1990

Scale of Analysis: 30 minutes

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure 4.25

40 Miles
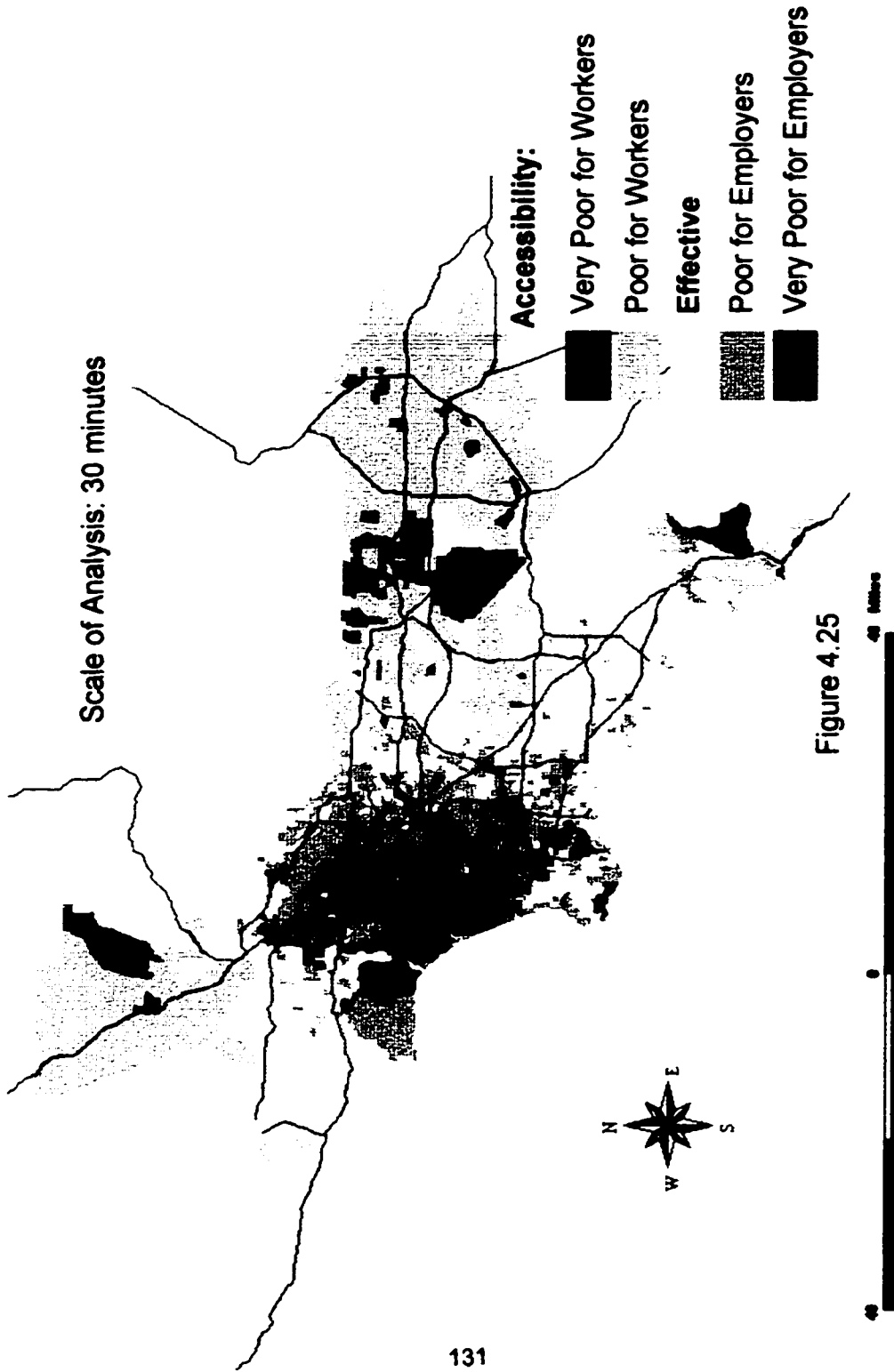
Traffic Congestion and Mobility in Greater Los Angeles, 1990

Likely Travel Speeds:

Very Slow

Slow

Moderate

Good

Fast!

Figure 4.26

132
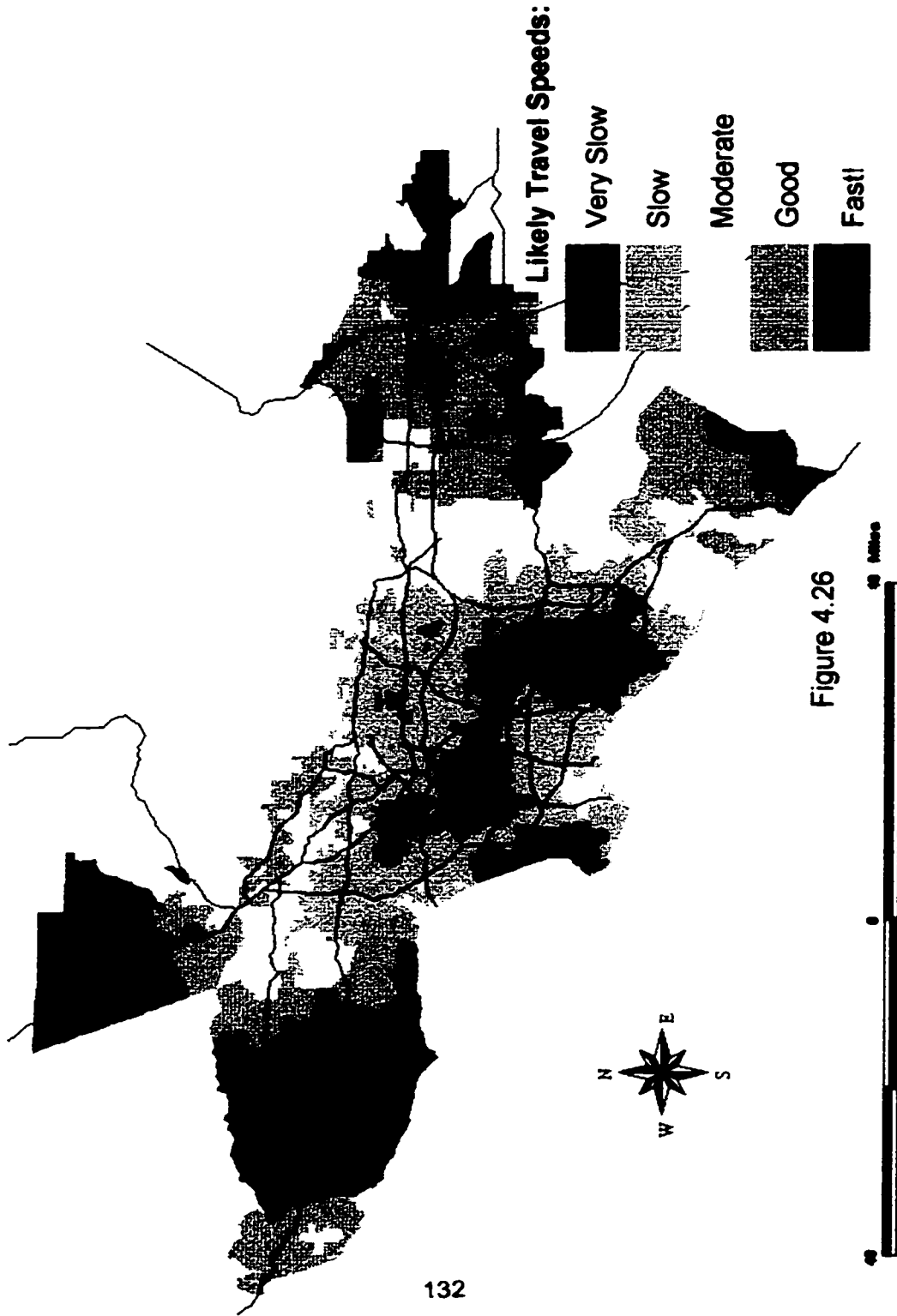
Traffic Impacts On Structural Accessibility, 1990

Scale of Analysis: 18 miles vs. 30 minutes

Traffic Conditions:

Impair Accessibility

Inhibit Accessibility

Have Little Impact

Facilitate Accessibility

Improve Accessibility

Figure 4.27
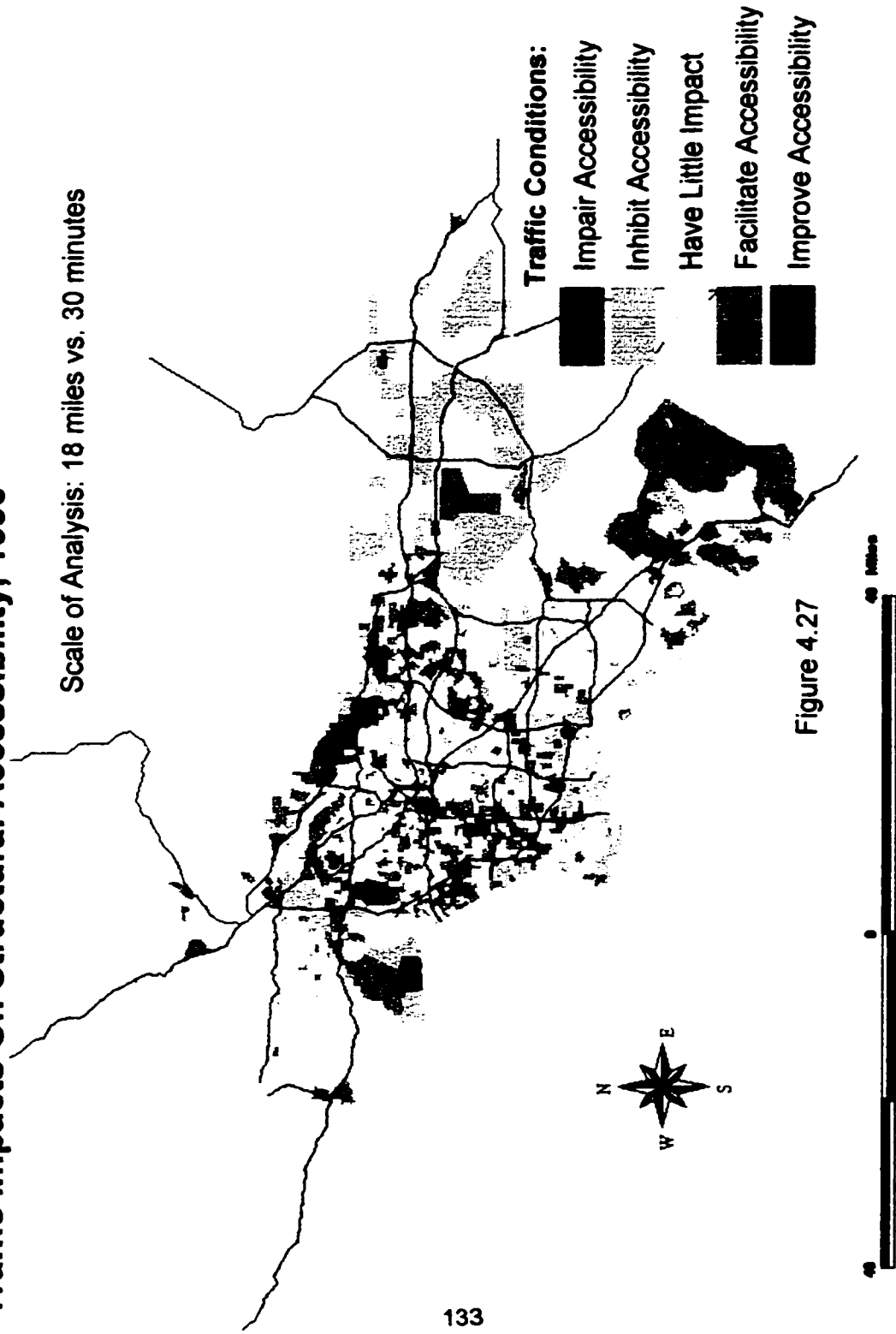
Traffic Conditions and Transportation Impacts on Accessibility, 1990

Scale of Analysis: 18 miles vs. 30 minutes

The Road Network:

- Very Slow
- Slow
- Moderate
- Good
- Fast
- Inhibits Accessibility
- Facilitates Accessibility

Figure 4.28

134
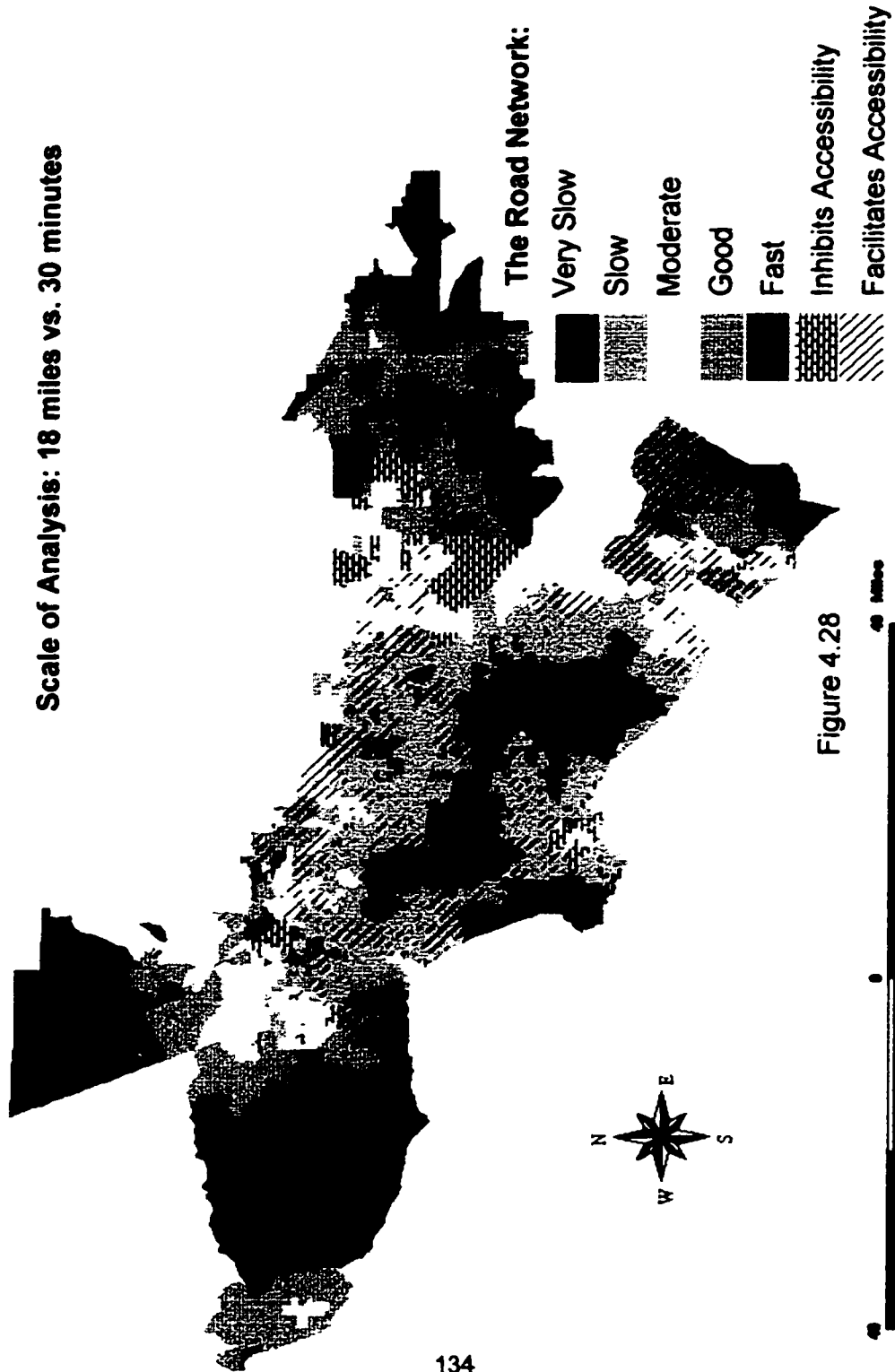
Until recently, transportation planners equated accessibility with mobility. Visual inspection of the patterns of congestion depicted in Figure 4.26 and average journey-to-work travel times in Figure 4.29 suggests a correlation. In fact, using OLS regression to test this relationship indicates a significant, positive correlation explaining 12 percent of tract average journey-to-work travel times. Regressing the congestion variable against tract average commuting *distances* explains 37 percent of the variation in tract commuting averages (Table 4.1). This regression is modeled as follows:

$$D = \beta_0 + \beta_1 T + \varepsilon$$

where:

D = average journey-to-work commuting distances, calculated to include all commutes either originating or terminating in each tract (see Appendix E).

T = a transportation component variable reflecting mobility/congestion; T is derived by comparing (for each census tract) total distance travel costs to total time travel costs, given a specific travel distance and equivalent/ associated travel time. The degree to which normalized *distance* travel costs are larger than normalized *time* travel costs, reflects a tract's traffic mobility score. The best explanatory power is obtained using a travel distance equal to 10 miles vs. a travel time equal to 20 minutes[30]. (A flowchart showing the procedures used to calculate T is provided in Appendix F, Figure AF1).

β_n = OLS regression coefficients.

ε = an error term.

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[30] The median travel time for all 10 mile journey-to-work commutes in the study area is 20 minutes. Travel costs are normalized by dividing distances/times by the study area average travel distance/time. To normalize distance travel costs for example, let m equal the distance to travel from tract i to tract j, and k equal the average journey-to-work commuting distance for the study area. Dividing m by k, then, produces a normalized cost for travel between tracts i and j.   135

Average Journey-to-Work Travel Time, 1990

Scale of Analysis: by Census Tract

Travel Times are:

Short

Moderate

Long

Very Long

Figure 4.29

136
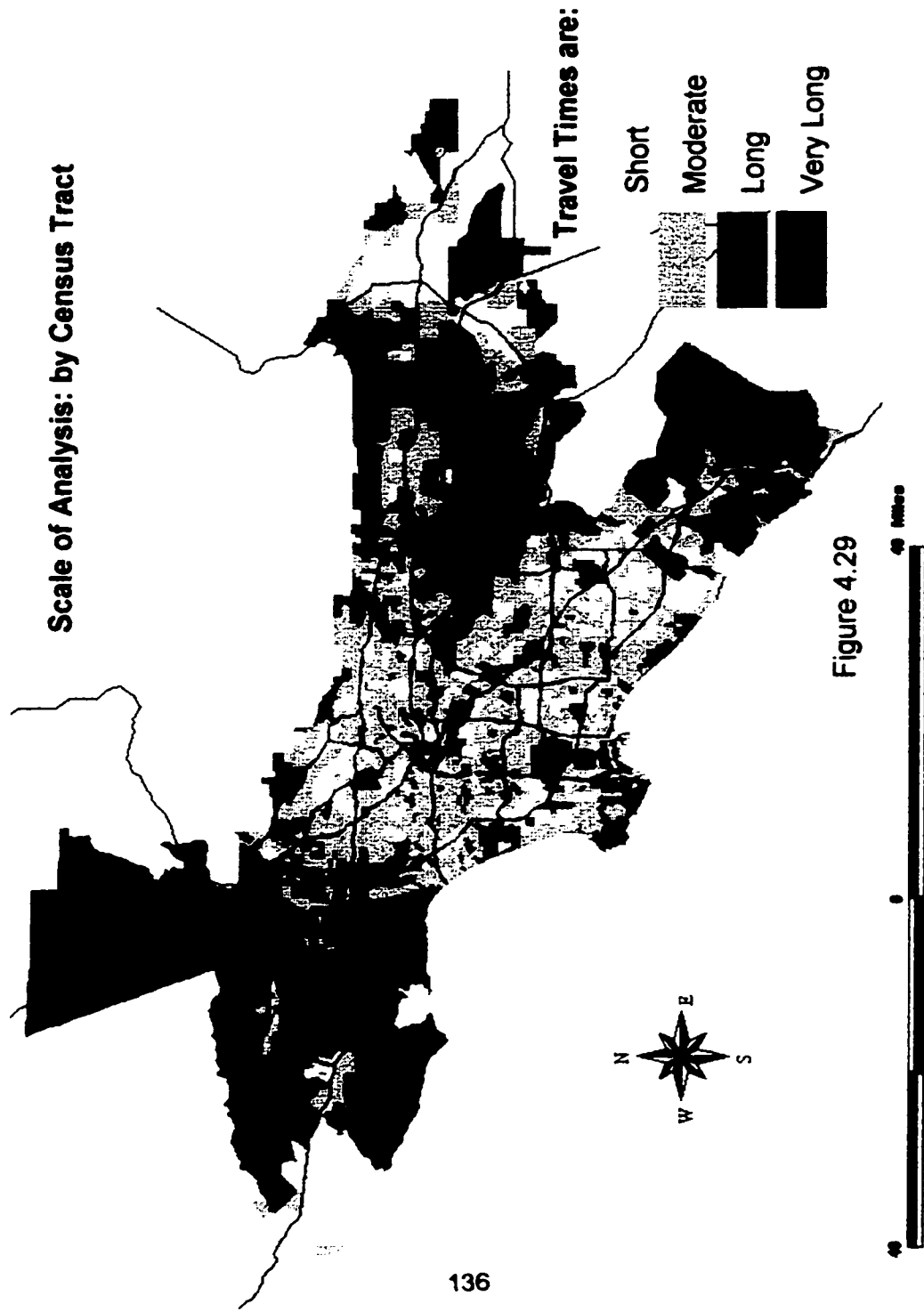
N=2381

Coefficients:

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	8.7993	0.1687	52.1543	0.0000
T^f	0.1796	0.0076	23.7428	0.0000
T^{sp}	0.1388	0.0049	28.2498	0.0000

Residual standard error: 2.582 on 2378 degrees of freedom

Multiple R-Squared: 0.3695

Table 4.1 Results from regression analysis modeling the relationship between mobility/congestion and average journey-to-work commuting distances.

137

After spatial filtering (Getis, 1995), the model may be written as:

$$D = \beta_0 + \beta_1 T^f + \beta_2 T^{sp} + \varepsilon$$

where:

T^f = the filtered component of the transportation variable T.
T^{sp}= the spatial component of the transportation variable T.
(see Appendix B, Figure AB3 and Appendix A).

The results of the regression analysis are show in Table 4.1. The coefficients on the independent variables, T^f and T^{sp}, are positive, indicating that tracts with effective mobility are associated with *longer* commuting distances. In the regression presented in Chapter 3 (Table 3.2), the level-of-service accessibility variable also has a positive sign, but since low values indicate effective accessibility, effective level-of-service accessibility is positively correlated with *short* commutes. If *urban efficiency* is a component of broader urban planning objectives, then, focusing on accessibility rather than mobility is most appropriate.

Commuting Patterns. Commuting patterns within an urban region are a fundamental component of metropolitan spatial structure, reflecting flows of energy and resources throughout the urban system (Irwin and Hughes, 1992). The average journey-to-work commute in the Greater Los Angeles urban system in 1980 was 19.5 minutes (9.5 miles). By 1990, the average commute was 22.4 minutes (12.9 miles). This increase in both commuting time and distance reflects urbanization processes occurring at the periphery of the study area. Figure 4.30 maps changes in journey-to-work travel time averages. Notice that the average travel time for most tracts increased. Job growth near Thousand Oaks in Ventura

County and near Irvine in Orange County, however, contributed to reductions in average travel times for tracts nearby.

A level-of-service definition of accessibility conceptualizes "perfect" accessibility in terms of balance among resident workers and employment opportunities. In Chapter 3 it was demonstrated that this definition of perfect accessibility provides a theoretical minimum lower bounds for commuting potential (see "Level-of-Service Definition" in Chapter 3). While effective level-of-service may offer the potential for urban efficiency, however, it does not guarantee that commuters will act on this potential. If, indeed, commuters respond to changes in structural accessibility by moving or by changing jobs to avoid congestion and lengthy commutes – as suggested by Gordon, Richardson, and Jun (1991) and Levinson and Kumar (1994) – we would expect to see a relationship between changes in journey-to-work travel time (or distance) and changes in structural accessibility levels. Performing OLS regression analysis to test this, demonstrates that the relationship is significant at the 0.001 level, has the expected negative sign (as structural accessibility improves, travel times decrease), and explains 21 percent of the variation in changes in travel time between 1980 and 1990 (Table 4.2). This regression is modeled as follows:

$$\Delta C = \beta_0 + \beta_1 \Delta A + \beta_2 C + \varepsilon$$

where:

139

Change in Average Journey-to-Work Travel Time, 1980 to 1990

Scale of Analysis: by Census Tract

Travel Time:

Decreased

Remained Stable

Increased

Increased Sharply
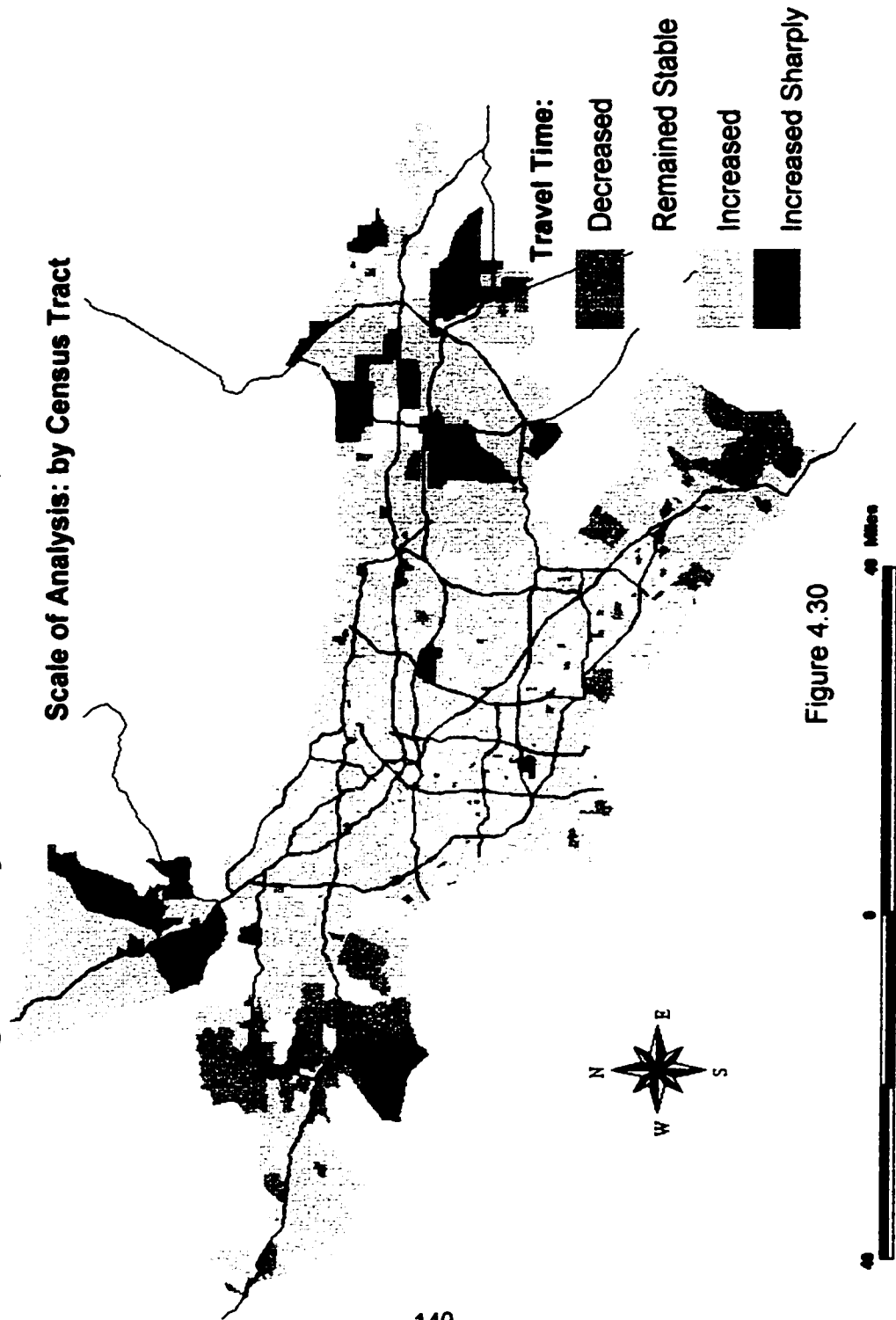
Figure 4.30

140

N=2381

Coefficients:

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	13.1699	0.5615	23.4546	0.0000
ΔA^f	-0.3861	0.0806	-4.7927	0.0000
ΔA^{sp}	-0.3047	0.0752	-4.0526	0.0000
C^f	-0.4406	0.0181	-24.3271	0.0000
C^{sp}	-0.2065	0.0209	-9.8657	0.0000

Residual standard error: 2.361 on 2376 degrees of freedom

Multiple R-Squared: 0.2127

Table 4.2 Results from regression analysis modeling changes in average journey-to-work travel time in relation to changes in level-of-service accessibility.

ΔC = the difference in tract average journey-to-work travel times between 1980 and 1990 where average travel times include all commutes either originating or terminating in each tract.

ΔA= the change in level-of-service accessibility scores for each tract expressed in terms of deviation from zero (perfect accessibility), so that positive values reflect improvements in accessibility, and negative values reflect a worsening of accessibility between 1980 and 1990. The best explanatory power is obtained using a distance radius of 6 miles to calculate accessibility scores.

C = the average journey-to-work travel times in 1980 for each tract.

β_n = OLS regression coefficients.

ε = an error term.

After spatial filtering (see Getis, 1995), the model may be written as:

$$\Delta C = \beta_0 + \beta_1 \Delta A^f + \beta_2 \Delta A^{sp} + \beta_3 C^f + \beta_4 C^{sp} + \varepsilon$$

where:

ΔA^f = the filtered component of the change in accessibility variable, A.
ΔA^{sp}= the spatial component of the change in accessibility variable, A.
C^f = the filtered component of the 1980 average commute time variable C.
C^{sp} = the spatial component of the 1980 average commute time variable C. (see Appendix B, Figure AB3 and Appendix A).

Average commuting time for 1980, C, is added to the model to provide a base for all of the various factors affecting commuting patterns in the study area. The negative coefficient for this variable indicates that tracts with the largest journey-to-work travel times in 1980 experienced the largest reductions in commuting times by 1990. Tracts with short commuting times in 1980 tended to have longer average commuting times in 1990. Since positive values for the change in structural accessibility variable, ΔA, reflect improved accessibility scores (job-rich tracts becoming less job intensive or worker-rich tracts becoming less worker intensive), the negative coefficient on this variable indicates that average

142

journey-to-work travel times became shorter when structural accessibility improved (became more balanced). This finding lends evidence that balancing jobs and resident workers is an effective strategy for encouraging shorter journey-to-work travel times. The analysis does not, however, resolve the question of whether or not jobs/housing balance *policies* are effective. Gordon, Richardson, and Jun (1991) argue that in an unfettered marketplace, businesses and households will exhibit a natural tendency to co-locate to avoid congestion and lengthy journey-to-work commuting. From their perspective, jobs/housing balance policies are both expensive and unnecessary.

Functional Accessibility

Our conceptions of space are conditioned by the realities of distance, but also by changes in culture and technology (Leven, 1991). As developments in transportation and telecommunications technologies become increasingly intertwined with day-to-day routine, our experiences of space, time, and distance – basic dimensions of human life – are altered (Graham and Marvin, 1996). Recent developments in telecommunications technologies, in particular, have prompted speculation that substitution of telecommunications for travel and for face-to-face contact will have dramatic impacts on urban spatial structure and the functioning of our urban environments (Hanson, 1995). As more and more individuals take advantage of the opportunity to telecommute to work, for example, time spent logging freeway miles will be freed for alternative uses (Janelle, 1995). Consequently, urban spaces become increasingly differentiated by social rather than purely economic factors, and spatial relations (both physical and functional)

become much more complex, extending well beyond physical contiguity (Castells, 1996).

Analyses in the previous two sections focused on physical spatial relations, evaluating accessibility from the perspective of time and distance. In the final examples of applying the analytical framework to employment data in the Greater Los Angeles region, emphasis shifts to a focus on functional components of accessibility represented by functional travel costs. Functional travel costs are one instance of what Gatrell (1983) refers to as "interaction proximities". The concept of functional time costs (or functional distances) is based on the idea that two places with high rates of spatial interaction are functionally "closer" than two places with very little spatial interaction. Participation in place-based activities promotes familiarity, which may be expressed through extended social networks, development of strategic contacts, and/or expanded knowledge about a place or a region (see Hanson, 1999). In a recursive manner, participation in place-based activities promotes familiarity, while familiarity increases the likelihood of participation in place-based activities. Using a similar logic, two places with very limited spatial interaction may be represented as being functionally distant (Scott, 1999). The model implemented to derive the functional travel costs used in the analyses presented below is outlined in Chapter 3 (see "Representing Accessibility as a Multi-Dimensional Construct", and Appendix D).

Figures 4.31 and 4.32 map accessibility based on functional travel time costs for 1990. Notice the dramatic differences between these maps and those presented earlier. While job surpluses in and around both the Downtown and

144

Accessibility Based on Functional Travel Time Costs, 1990

Scale of Analysis: 10 functional minutes

Functional Accessibility:

Dominated by Interaction with Worker-Rich Tracts

Effective

Dominated by Interaction with Job-Rich Tracts

Figure 4.31

145
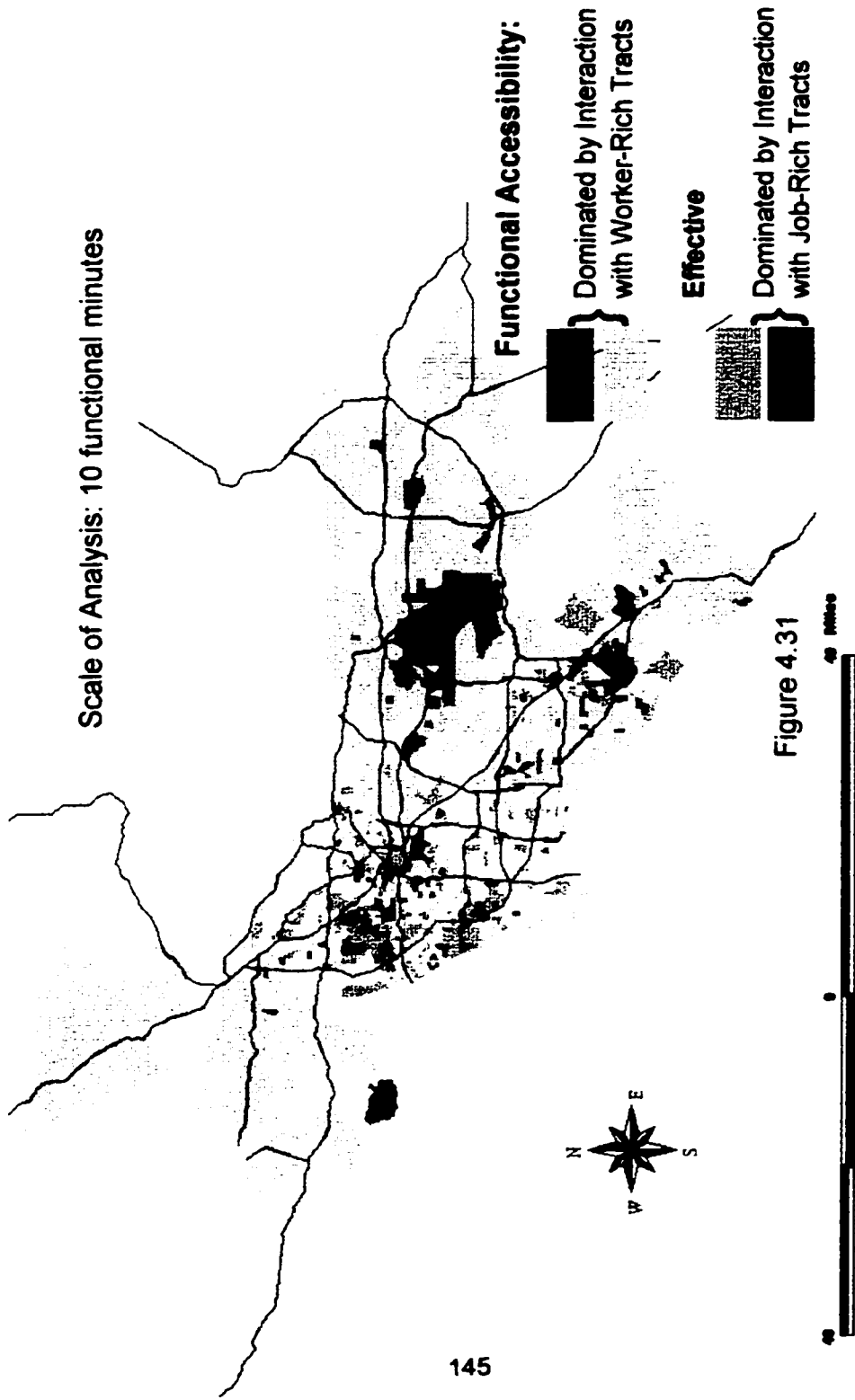
Accessibility Based on Functional Travel Time Costs, 1990

Scale of Analysis: 30 functional minutes

Functional Accessibility:

Dominated by Interaction
with Worker-Rich Tracts

Effective

Dominated by Interaction
with Job-Rich Tracts

Figure 4.32

146
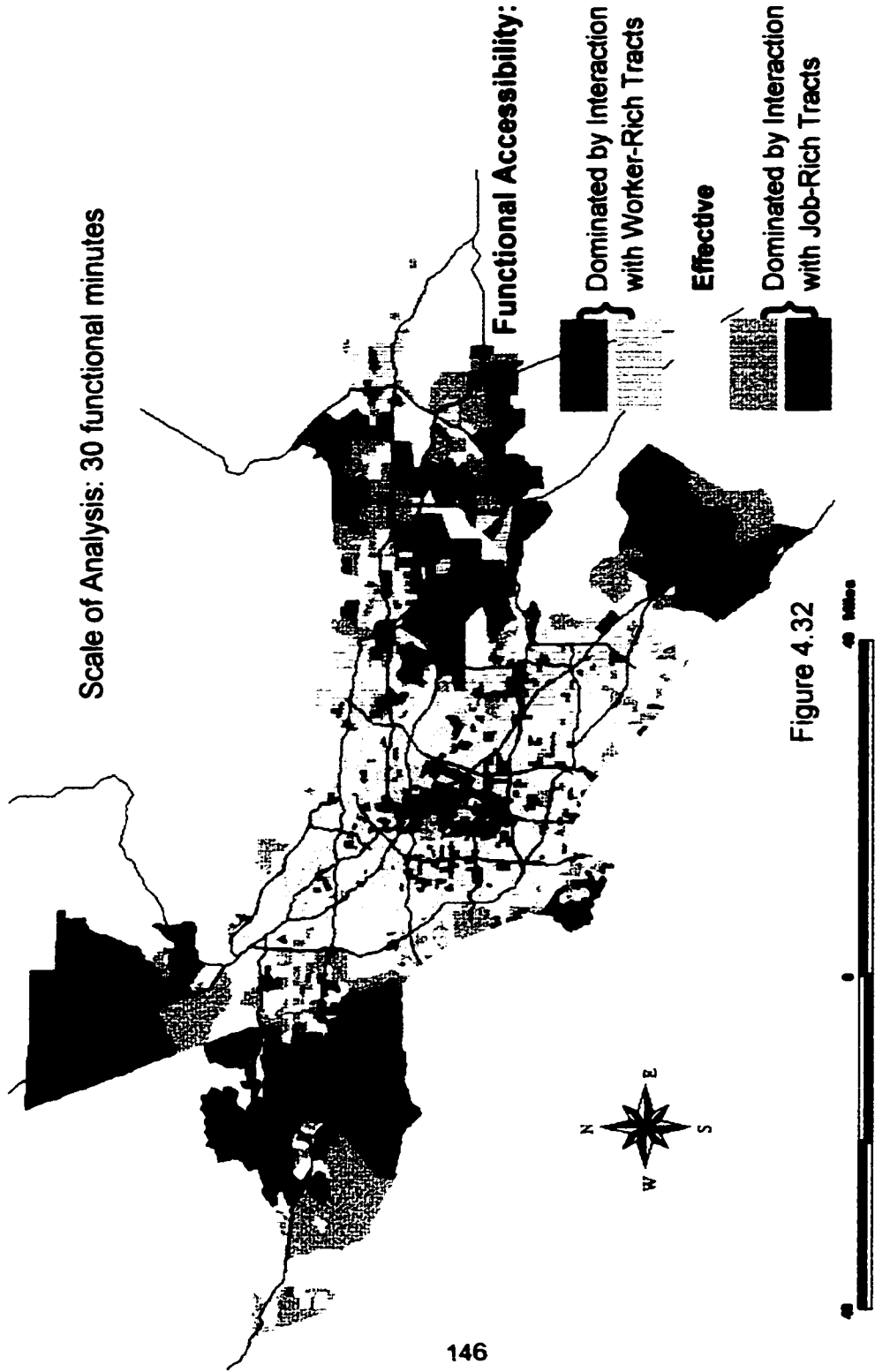
Irvine regions remain evident in Figure 4.31 (10 minute scale of analysis), the

intensity and concentration of these surpluses have diminished significantly. In

Figure 4.32 (30 minute scale of analysis), accessibility patterns are profoundly

different from those based on structural accessibility. Many of the tracts near

Downtown Los Angeles, for example, while physically closer to job-rich

(worker-poor) tracts nearby, are *functionally* closer to worker-rich tracts in

surrounding suburban communities. Similarly, the job-poor tracts in the

southern-most portion of the study area are functionally linked to job-rich tracts to

their north, indicating that workers in south Orange County are exposed to a large

number of jobs as a result of their commuting behavior. Figure 4.32 is not,

however, a complete reversal of the patterns seen in Figure 4.25 (based on actual

30 minute travel time costs). Worker surpluses in several tracts near San

Bernardino and north of Anaheim remain worker-rich, while a number of tracts just

north of Santa Monica and in coastal regions north of Long Beach remain job-rich

in both physical and functional space. The tracts in Figure 4.32 associated with

the most dramatic changes in accessibility scores (comparing actual to function

travel times), reflect communities with few ties to local employment opportunities.

Conversely, tracts with similar accessibility scores in both physical and functional

space reflect communities strongly rooted to local opportunities.

Figure 4.33 plots the relationship between functional travel times and

actual travel times for both 1980 and 1990. To produce Figure 4.33, observed

journey-to-work travel flows were utilized to calculate tract average journey-to-work

travel times based on cost matrices reflecting both actual travel times and

147
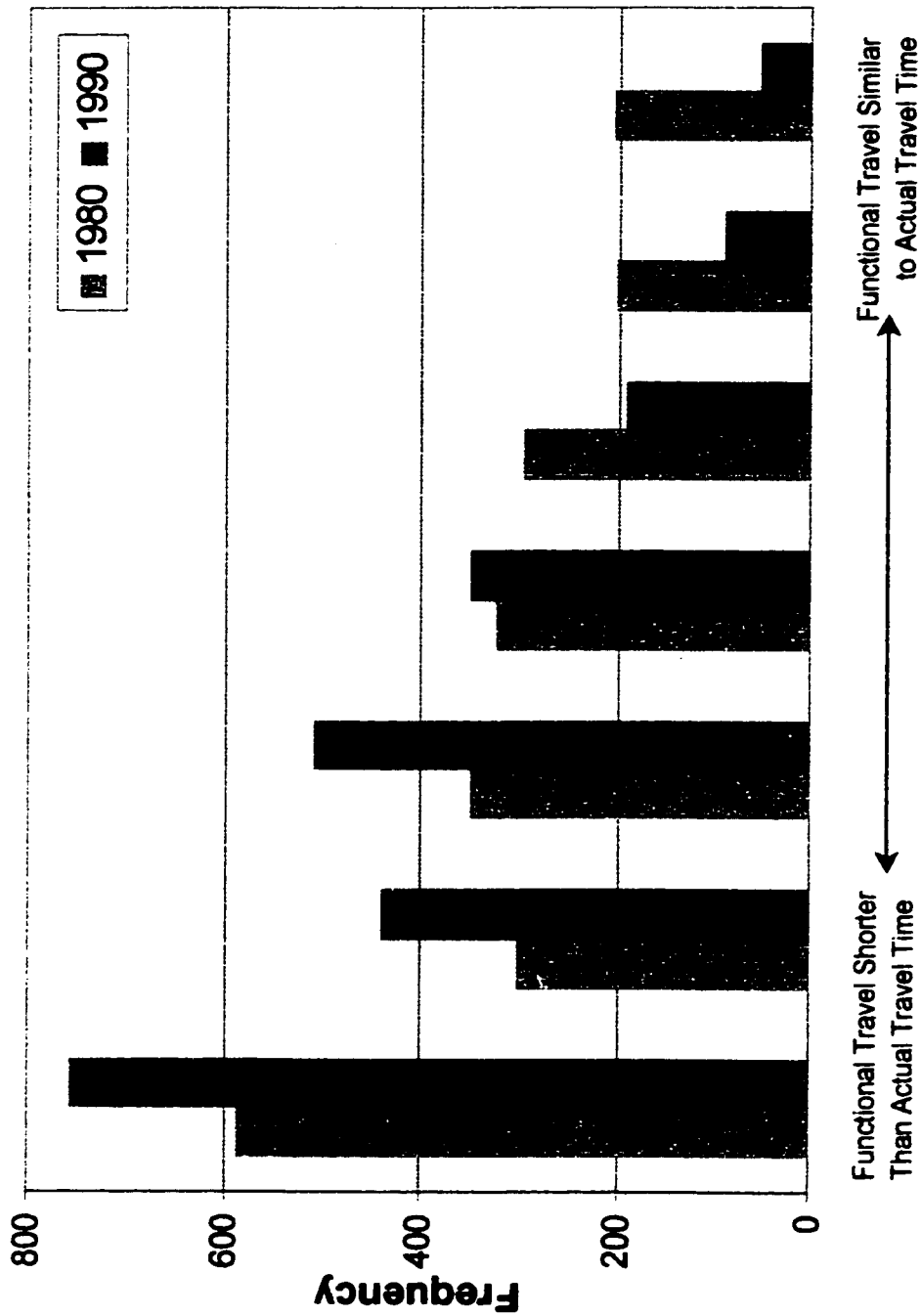
Figure 4. 33 Frequency of actual vs. functional average journey-to-work travel times.

functional travel times[31]. As we might expect, the frequency of tracts with large discrepancies between functional and actual travel times has increased; functional travel times became shorter between 1980 and 1990, reflecting diminishing rooted-ness to physical spaces.

For clarity in the discussion that follows, I will refer to census tracts with large differences between actual travel times and functional travel times as "unimpeded", and those with similar travel times in both physical and functional space as "rooted". The spatial distributions of these relationships in 1990 are shown by Figure 4.34 (see Appendix F, Figure AF5, for a flowchart detailing the procedures used to produce this map). Notice the intermingling of both rooted and unimpeded communities. Nonetheless, concentrations of rooted tracts are found in Ventura County near Oxnard, in San Bernardino and Riverside Counties at the eastern edge of the study area, and in Orange County near Santa Ana. Concentrations of unimpeded tracts are found in the northern-most portion of the study area and associated with communities in coastal neighborhoods just west of Malibu.

Of broad interest is the question of what factors might contribute to making some communities "unimpeded" while others remain "rooted". This question is explored by examining socioeconomic characteristics of workers in both the unimpeded and rooted tracts depicted in Figure 4.34, and comparing them to the

---

[31] Differences in average travel times reflect the commuting behavior of resident workers in each tract (it does not combine both incoming and outgoing flows).

Comparison of Actual Travel Time and Functional Travel Time Costs, 1990

Scale of Analysis: by Census Tract

Functional Travel Times are:

- Very Similar
- Fairly Comparable
- Shorter
- Much Shorter
- Shorter Still!!

Figure 4.34

150
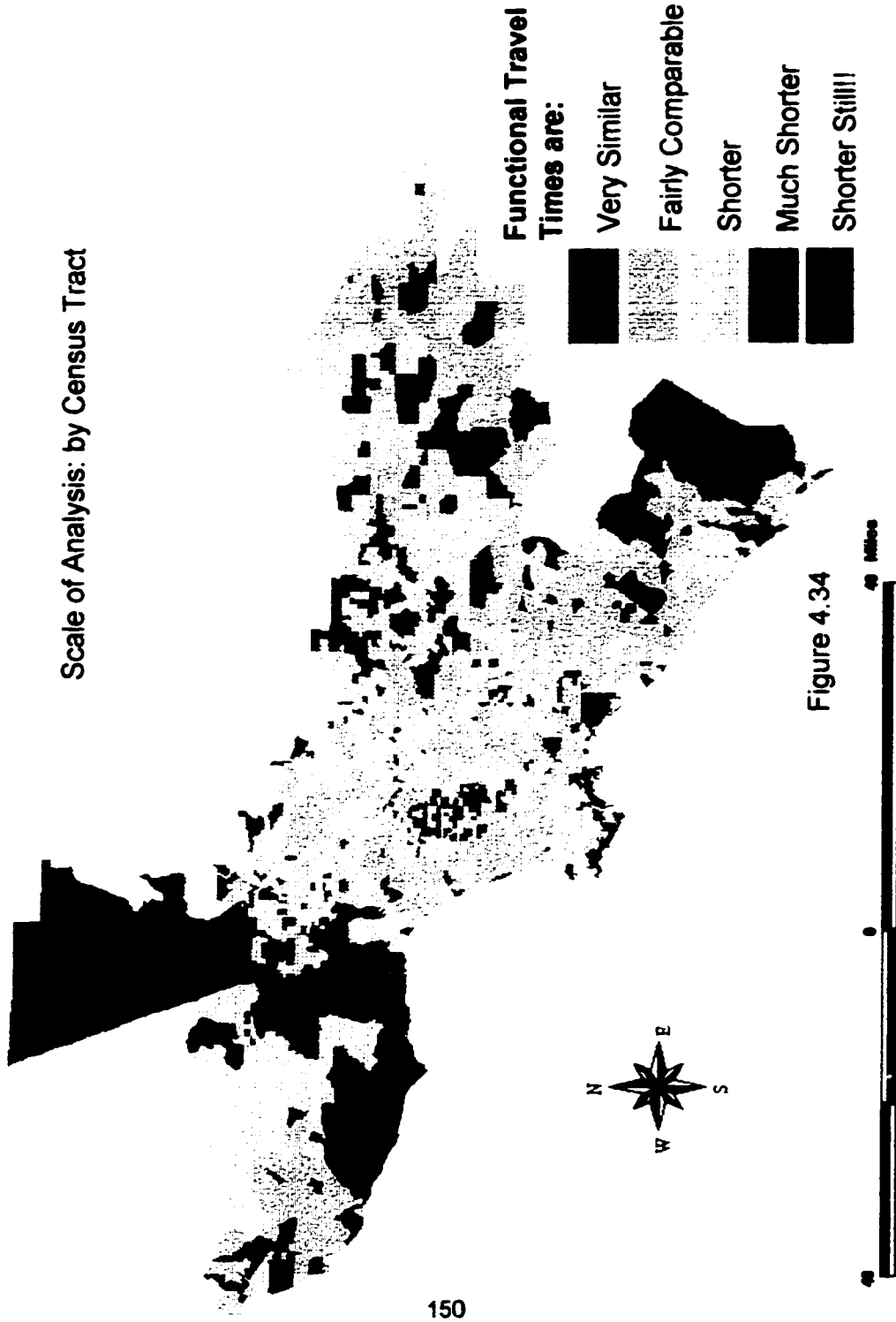
remaining study area worker population. There were a total of 5,987,881 workers

both employed and living in the Greater Los Angeles study area in 1990. Of 2381

census tracts, 431 may be classified as "unimpeded", representing 14 percent of

the total worker population. In Figure 4.34, 679 tracts reflect "rooted" commuting

behavior comprising 33 percent of the total worker population. While a variety of

socioeconomic characteristics could certainly be considered in examining these

two samples, analysis is limited to household composition, income, structural

accessibility, and occupational patterns, since each of these topics has been

discussed previously in the chapter. Results from all of the analyses below are

summarized in Table 4.3[32].

We might speculate, for example, that unimpeded tracts will be composed

of a larger number of traditional families (married couples with children) than other

census tracts in the study area. Traditional families must balance a wide variety of

objectives including neighborhood characteristics and quality of schools in making

residential locational decisions. Perhaps with this large set of objectives, locational

decisions are less tied to commuting concerns. In addition, since traditional

families are likely to be less mobile than non-traditional families (non-family or

single parent family structures), it may be more practical for workers in these

households to commute longer distances than to move when they are faced with a

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[32] To determine if observed differences are statistically significant, the standard error and confidence interval for each sample estimate are calculated using methods suggested in Myers (1992). Differences larger than the confidence interval are said to be statistically significant. See Appendix B, Figure AB5.

151

	Tracts			Tracts		
	Unimpeded	Others	CI	Rooted	Others	CI
Traditional Families	0.271	0.254	.005*	0.247	0.262	.004*
Managers/Professionals	0.303	0.278	.004*	0.270	0.287	.003*
Technical/Sales/Clerical	0.334	0.326	.004	0.322	0.329	.003*
Service	0.113	0.120	.005	0.123	0.118	.003
Agriculture/Forestry/Fishing	0.012	0.016	.005	0.020	0.013	.004
High-Skill Blue-collar	0.109	0.111	.005	0.112	0.110	.003
Low-Skill Blue-collar	0.130	0.149	.005*	0.153	0.143	.003*
Income	$46,669	$40,016	102*	$38,347	$42,204	59*
Accessibility (d=3miles)	-0.206	0.012	.006*	0.232	-0.140	.005*
Accessibility (d=6miles)	-0.181	0.342	.007*	0.679	0.069	.006*
Accessibility (d=12miles)	-0.065	0.624	.008*	0.753	0.419	.006*

* Indicates sample differences are larger than the confidence interval (CI), significant at the 0.95 level.

Table 4.3 A comparison of "unimpeded" to "rooted" tracts for a variety of socioeconomic variables: household composition, occupation, income, and structural accessibility.

152

job change. Similarly, it could be argued that rooted tracts would be associated with higher proportions of single parent families than other census tracts in the study area, since single parents needing to balance both care-taking and wage-earning activities, will have incentive to find housing near their workplace. In fact, comparing unimpeded tracts in 1990 to all other tracts in the study area indicates unimpeded communities have slightly higher percentages of traditional family structures (27 percent of all households) than the remaining census tracts (25 percent of all households). As expected, rooted communities are associated with slightly lower proportions of traditional family structures (25 percent) than other tracts in the study area (26 percent). These differences, while not large, are statistically significant at the 0.05 level. Household composition, therefore, may provide some clues for understanding differences between these two samples.

Early developers of classic urban economic theory were probably disconcerted to find the richest individuals in an urban region living at the urban periphery on the cheapest land, while poorer households occupied expensive land in urban employment centers. A number of theories were proposed to explain this apparent paradox (Alonso, 1973). Alonso, for example, explains this finding by suggesting accessibility is an "inferior good". Although effective accessibility is certainly desirable, as individuals become wealthier and transportation costs represent a smaller portion of their total expenses, they tend to substitute accessibility for other amenities (such as larger plots of land). We might expect, therefore, to find higher median incomes associated with unimpeded tracts, and lower median incomes associated with rooted tracts. Comparing incomes for

1990, the average tract median income for the unimpeded communities is $46,669, much higher than the average tract median income for all other study area tracts ($40,016). The average tract median income for rooted communities is $38,347, much lower than all other tracts ($42,204). These differences are statistically significant at the 0.05 level, lending evidence to the idea that higher income levels provide individuals with greater locational flexibility.

It may be that unimpeded tracts have fewer ties to physical space because their local communities offer few employment opportunities, requiring extensive commuting. Similarly, if rooted tracts are associated with job-rich communities, there will be little incentive to travel far from home. As expected, using a 3, 6, and 12 mile distance radius to evaluate structural accessibility, unimpeded tracts are consistently associated with worker-rich average accessibility scores. These scores are significantly more worker-rich (statistically significant at the 0.05 level) than averages for all other tracts in the study area. Similarly, rooted tracts are consistently associated with job-rich average accessibility scores. These scores are significantly more job-rich than averages for all other tracts in the study area. These findings provide evidence that structural accessibility plays a role in shaping the commuting patterns of both the unimpeded and rooted samples.

Preliminary evaluation of the impacts of telecommuting and the development of intelligent transportation systems on urban spatial structure (Office of Technology Assessment, 1995; Hodge, Morrill, and Stanilov, 1996), suggests continued dispersion of both resident workers and employment opportunities as technological developments increase mobility and locational flexibility. Strongly

related to recent advances in transportation and telecommunications technologies is a restructuring of economic activities, practices, and organizational structures: extensive restructuring of the manufacturing sector, massive growth of the service sector, and a general vertical disintegration of production processes (see Figure 2.8 and "Los Angeles and Changing Employment Patterns" in Chapter 2). This shift away from manufacturing toward a service-oriented economy means that more of our employment opportunities involve working with data and information rather than with machinery and materials, providing increasing opportunities for telecommuting. Occupational patterns, therefore, may impact the degree to which resident workers are tied to local communities. It is unfortunate that the CTPP and UTPP data used for analyses in this chapter do not distinguish between producer and consumer services, as I suspect these occupational categories would offer interesting insights regarding variations between the unimpeded and rooted samples. Nonetheless, we might speculate unimpeded tracts to have a higher association with managerial, professional, technical, and clerical occupations, as these professions deal primarily with information or tasks that might be accomplished using desktop computer technologies. Conversely, rooted tracts may be associated with higher proportions of agricultural, forestry, fishing, and blue-collar professions, occupations primarily focused on natural resources, machines, and the production of goods and materials. A comparison of occupational distributions confirms that the unimpeded tracts are associated with larger proportions of managers and professionals, and smaller proportions of low-skill blue-collar workers than all other tracts in the study area. Differences for

155

the other occupational categories, however, are not statistically significant. Rooted tracts are associated with fewer managerial, professional, technical, sales, and clerical workers, and with a larger proportion of low-skill blue-collar workers than all other tracts in the study area. Differences for the other occupational categories are not statistically significant at the 0.05 level. While the differences in occupational patterns are not entirely conclusive, they probably reflect accurately the low rates of telecommuting occurring in 1990 (Handy and Mokhtarian, 1995). It will be interesting to repeat this analysis using more up-to-date data and with additional details regarding occupational categories, industry, race/ethnicity, and gender.

As a final look at accessibility in the Greater Los Angeles region, Figure 4.35 identifies tracts with consistent accessibility scores in both physical and functional space at a 30 minute scale of analysis. Tracts consistently associated with worker-rich (job-poor) accessibility scores represent a high priority for implementation of urban planning strategies promoting job development. Tracts consistently associated with job-rich (worker-poor) accessibility scores represent priority areas for urban planning promoting housing development. Finally, careful study of the tracts consistently associated with effective accessibility may provide guidelines for promoting more efficient, equitable, and sustainable communities.

156

Accessibility Score Stability Based on Actual Time and Functional Time

Scale of Analysis: 30 actual and functional minutes

Accessibility Scores
Consistently:

Poor for Workers

Effective

Poor for Employers

Inconsistent

Figure 4.35

157
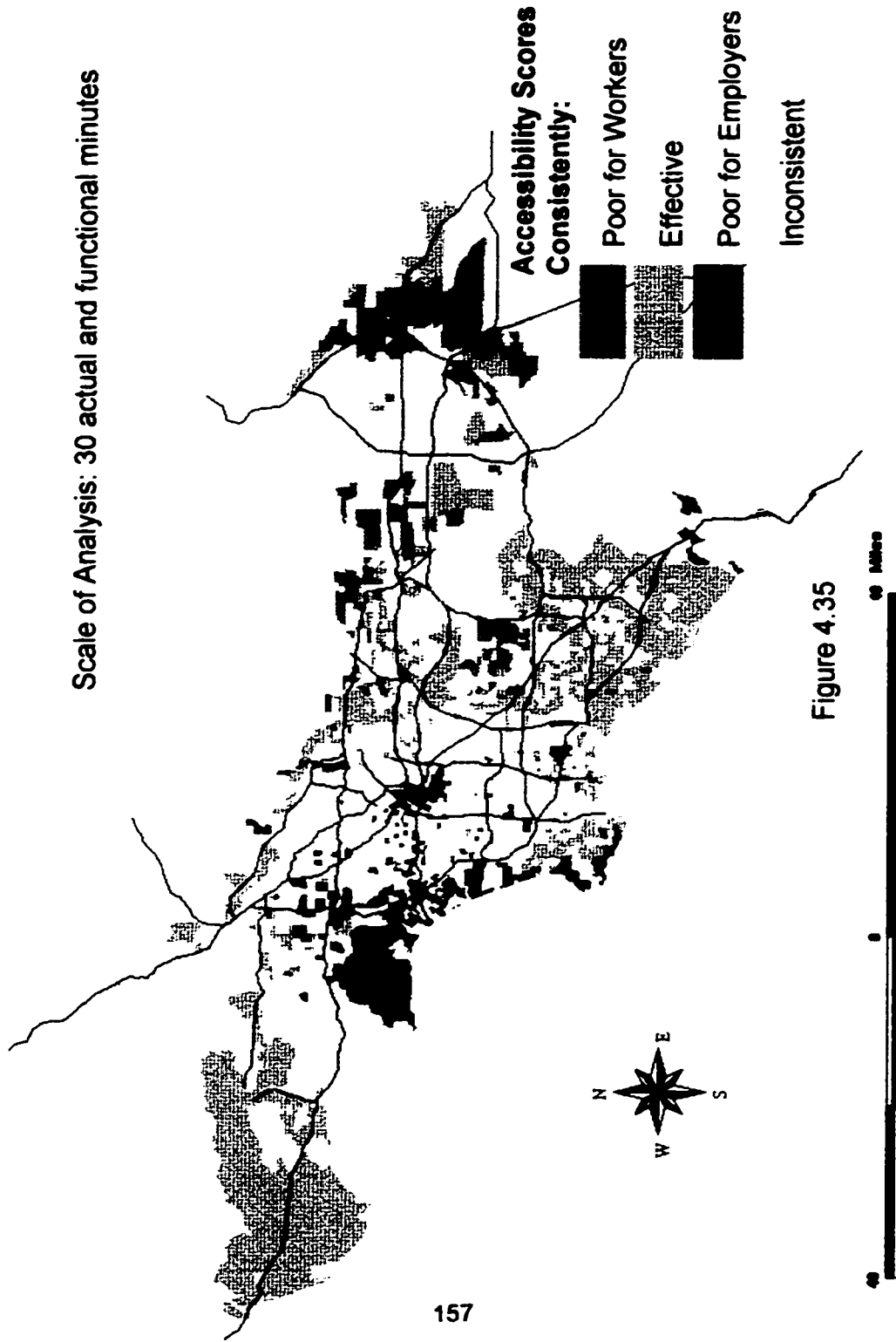
CHAPTER 5

CONCLUSIONS

While the informal development of our ideas and our projects rarely unfolds in an orderly, sequential manner, formal presentation of ideas no matter how simple or complex must start at the beginning with a foundation, a method, and a plan. The primary objective in this dissertation research has been to propose an analytical framework for evaluating intra-metropolitan accessibility, and to begin the process of assessing its value, potential, and effectiveness. Accordingly, in meeting this objective the principal accomplishment of the dissertation has been to lay essential groundwork for a much larger project. Each of the themes presented in Chapter 2, and each of the sample analyses presented in Chapter 4, offers the potential for fuller development, and the possibility for numerous variations in approach. So it is both ironic and galvanic that the final chapter of this dissertation presents more beginnings than endings.

In concluding this research, four tasks remain: (1) to summarize preceding chapters, emphasizing how each component of the dissertation is tied to the dissertation's primary objective; (2) to outline the contributions of this research with regard to urban and regional studies, urban and transportation planning, spatial analysis and GIS, and, most specifically, research concerned with defining, representing, and measuring intra-metropolitan accessibility; (3) to articulate the limitations of the dissertation research, and (4) to outline an agenda for future research directions.

Looking Back

The primary objective of this research has been to provide an effective analytical framework and flexible working environment for evaluating, exploring, and monitoring intra-metropolitan accessibility within the changing urban metropolis. Providing a context, scope, and a focus for the dissertation research, therefore, Chapter 2 reviews the broad spatial processes re-shaping our cities and urban environments: extensive suburbanization, broad economic restructuring, and rapid developments in transportation and telecommunications technologies. By emphasizing these developments, the chapter underscores the need for new approaches, new methods, and new tools to allow pragmatic evaluation, exploration, and monitoring of intra-metropolitan accessibility.

In Chapter 3, a new approach to examining intra-metropolitan accessibility is proposed. This analytical framework is founded on (1) the Couclelis proximal space construct; (2) the Getis/Ord G_i^* spatial statistic; (3) a level-of-service, social equity, definition of accessibility to employment opportunities and labor market resources; (4) multiple scale analysis in order to represent accessibility as a function of space, time and available technology; and (5) a multi-dimensional conceptualization of accessibility incorporating both structural and functional elements. Along the way, the chapter grapples with definitional, methodological, and technical issues associated with effectively *representing* intra-metropolitan accessibility – a concept so familiar, so taken-for-granted, yet at the same time so very imprecise. As a consequence, the guidelines developed in Chapter 3 have application and implications for further research on accessibility (discussed below).

159

Chapter 4 presents an implementation strategy to integrate the proposed analytical framework within the *ArcView* 3.1 GIS software environment, providing a flexible and easy-to-use utility for exploring accessibility at multiple spatial scales and for a variety of spatial contexts. The implementation issues addressed in developing this software environment, however, have broader implications for geographic research using GIS. These implications are outlined below. Some of the most important contributions of the dissertation research, however, relate to urban planning and regional studies. Chapter 4 demonstrates through sample analyses that the analytical framework, implemented within the GIS environment, offers broad utility for addressing a wide range of empirical research questions, for contributing to urban theory, and for assisting urban and transportation planners.

Looking Forward

Each chapter in the dissertation summarized above, while emphasizing development and demonstration of the proposed analytical framework, presents broader implications for informing and contributing to regional studies, urban and transportation planning, GIS and spatial data analyses, and future directions in intra-metropolitan accessibility research.

Accessibility Research

An important component of the dissertation assesses the effectiveness of existing measures of intra-metropolitan accessibility for examining broad changes in urban spatial structure. A question that arose early in the research asked how existing measures define and represent intra-metropolitan accessibility, and

160

whether or not these representations are appropriate and practical. This question is an important one because so many of the models in regional studies, economic geography, and urban planning include an accessibility component. The effectiveness of these models will in large part depend on the approach taken to conceptualize, define, and represent intra-metropolitan accessibility.

Accessibility, however, is not necessarily a physical entity; it is a concept – a perception. It is crucial, therefore, that we justify and clearly articulate how the concept of accessibility will be defined and operationalized in our models and measurements. The analytical framework outlined in this research gives the concept of accessibility substance by representing it as a characteristic and attribute of proximal space: a material expression of the complex urban activity system we call in this case, Los Angeles. We can conceptualize this urban activity system as a mosaic of scarce and unevenly distributed resources from which surrounding populations may benefit if they are willing and able to overcome the physical, social, financial, educational, and psychological barriers imposed by distance and by society (Knox, 1980). Within this urban activity system, accessibility takes the form of a multi-dimensional attribute of proximal space, reflecting the variety of intrinsic spatial relations that both define and structure its impacts. Accessibility is multi-dimensional because the concept comprises both structural and functional elements, encompassing both potential accessibility and realized access. The structural elements of accessibility comprise the spatial distribution of people and opportunities, as well as the transportation and communications infrastructure connecting them; different locations in space will

161

offer a different range, or baseline, of potential opportunities. Functional elements of accessibility, on the other hand, comprise the variety of attributes and characteristics associated with different groups of individuals (their resources, aptitudes, constraints, preferences, ingenuity, etc.), which lead to different patterns of realized accessibility.

In this way, the research presented in this dissertation contributes to the methodological literature investigating definitional, representational, and operational issues associated with evaluating and representing intra-metropolitan accessibility. It defines and operationalizes intra-metropolitan accessibility as a multidimensional attribute of proximal space and then demonstrates that this representation provides better explanatory power than existing accessibility measures. These findings present evidence that the multi-dimensional, level-of-service representation of accessibility to employment opportunities proposed in this research may have broad application for urban modeling.

Research to provide additional evidence, however, is needed. The analytical framework proposed in this research presents a very specific perspective of intra-metropolitan accessibility. While an important contribution of Chapter 3 is illustration that this representation of intra-metropolitan accessibility is more inclusive than existing measures, the proposed framework still limits evaluation of intra-metropolitan accessibility to a *relative* measurement, contingent on study area boundary definitions, the spatial resolution of the data used for analysis, and the particular study area being evaluated. In addition, while spatial filtering techniques (Getis, 1995) to address spatial autocorrelation in regression

162

residuals have been demonstrated in this research, remediation for possible

spatial heterogeneity effects has not[33]. Careful consideration of all of these issues

must precede future analysis, particularly if the objective is to compare

intra-metropolitan accessibility among multiple geographic regions.

In addition, comparison of the proposed representation of

intra-metropolitan accessibility to existing accessibility indicators in Chapter 3

focuses exclusively on accessibility to employment opportunities and labor market

resources in relation to journey-to-work commuting behavior. This focus is

selected because researchers have typically found a weak relationship between

commuting costs and commuting behavior, and because the commuting theme

provides links to a variety of topics central to urban planning: jobs/housing

balance, spatial/skills mismatch, traffic congestion, and urban spatial efficiency.

Research evaluating the proposed framework in relation to other urban processes,

however, represents an important direction for future research. Examining

relationships between accessibility and urban densities, economic growth, land

values, patterns of land use, and a variety of socioeconomic characteristics, for

example, will provide avenues not only for further testing the effectiveness of the

proposed representation of intra-metropolitan accessibility, but also for testing the

viability of classic urban economic theory (strongly based on an assumed

relationship between accessibility and urban spatial processes).

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[33] Informal visual inspection of regression residuals did not indicate strong heterogeneity
effects for the regression models presented in this research.

This research focuses on aggregate-level analysis using census tract employment data in order to examine broad processes of urban restructuring. Some of the most interesting developments in the area of accessibility research, however, focus on disaggregate-level analysis incorporating the space-time concepts first proposed by Hägerstrand (e.g., Kwan, 1998; Miller, 1991; see also Hägerstrand, 1970; Hanson and Schwab, 1995). The proximal space construct implemented using the Getis/Ord G_i^* statistic may provide an effective approach for modeling space-time prism accessibility relations and, thus, presents the potential for contributing directly to these developments as well.

Spatial Data Analysis and GIS

GIS have been both promoted and distinguished from cartographic and drafting computer systems on the basis of their spatial analysis capabilities. DeMers (1997, 11), in fact, identifies spatial analysis as the heart of GIS. Moreover, there have been a variety of other attempts to characterize the relationship between GIS and spatial data analysis. Goodchild (1997) notes, however, that these characterizations largely consider GIS to be a vehicle for the delivery of spatial analytic functionality – functionality primarily developed, tested, applied, and extended outside the GIS environment. As a consequence, much of the dialog between the GIS and the spatial analysis communities has focused on supplementing GIS delivery of spatial analytic tools. That is, there is a sense that GIS is still maturing and that once a sufficient number of analytical capabilities (or the essential analytical capabilities) have been shoveled (in effect) into the GIS framework, GIS will achieve its full potential. In fact, the relationship between GIS

164

and spatial data analysis is much more integrated and intertwined than this view

portrays, and while spatial analysis is shaping GIS, the GIS working environment is

also shaping spatial analysis (Goodchild, 1997).

The chapters in this dissertation contribute to the dialog between the GIS

and spatial analysis communities in at least two areas. Much of the literature

concerned with integrating spatial analysis (or statistical analysis) within GIS has

characterized these approaches in terms of tight, close, or loose coupling (or

similar classifications). The implementation presented in Chapter 4, however,

provides evidence that these classifications may no longer be useful. Current

commercial GIS software includes hooks, procedures, and rich scripting

languages to allow all three approaches (tight, close, loose) to be effectively

combined – and combined in such a way that the user may not even be aware

that external software is being utilized. Tools in Avenue, for example, not only

allow for the development of elaborate user interface environments, but also

promote development of flexible, and extendable, modular frameworks to

dynamically support growing libraries of utilities, application software, and spatial

analytic functions[34]. This flexibility holds potential to further close the gap between

developments in GIS and developments in spatial data analysis. An interesting

avenue for future research would address formalization of a modular framework or

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[34] Figure AG1 in Appendix G, for example, illustrates that the accessibility menu option is
associated with 5 functions: G_i 1992, G_i 1995, Total Cost, Deviation, and Difference.
Adding additional functionality involves adding another "branch" to the Avenue framework.
Removing functionality involves cutting a branch from the framework. Many of the Avenue
scripts developed for one function (Total Cost, for example) are re-used to support all of
the other functions.

interface for dynamically extending GIS functionality. This formalization will be particularly useful if it includes recommendations for fostering collaboration among researchers, research departments, and various institutions.

Another important contribution of the dissertation relates to its implementation of the proximal space construct (Couclelis, 1997; Takeyama and Couclelis, 1997) to perform empirical analyses of intra-metropolitan accessibility. Chapters 3 and 4 emphasize the value of both the proximal space construct and multiple scale analysis in representing the notion of accessibility. In fact, these concepts have much broader application. All geographic data are situated in space and time, and are likely to vary with changes in scale and with changes in spatial/temporal context. Accordingly, developments to incorporate this notion of proximal space more generically within GIS could have profound impacts on spatial data analysis (tools, methods, and practice). Integrating capabilities to construct topology reflecting attribute, interaction, or other proximity relations represents a first step. The bigger challenges, however, involve developing techniques and procedures to allow visualization of these relations as intrinsic components of spatial objects.

For the dissertation research, changing patterns of accessibility based on various spatial relations (at multiple spatial scales) has been primarily represented as snapshots for 1980 and 1990 (with no attempt to interpolate the dynamic processes and relations driving these changes). Additional research is needed to explore other possibilities, both for creative modeling of various proximity relations and for effective cartographic representation of the proximal space construct.

166

Urban and Transportation Planning

Our notions about the "quality of life" in a city or a region are closely tied to the concept of accessibility – a concept linking the spatial opportunities in a region (employment, schools, public services, for example) to the spatial distribution of a region's inhabitants. It is not surprising, therefore, to find the term "accessibility" appearing frequently in local, regional, and national documents; accessibility is commonly cited as a fundamental objective for urban and transportation planning. Nonetheless, the concept of accessibility is seldom given an operational definition in these documents, and accessibility measures are rarely utilized to monitor urban system performance, to construct regional profiles, to compile social inventories, or to evaluate proposed planning strategies (Knox, 1980).

This research contributes to the urban and transportation planning literature by demonstrating that effective measurement of intra-metropolitan accessibility allows assessment of a variety of very real concerns in urban and transportation planning: traffic congestion, journey-to-work commuting patterns, and a range of social equity issues that have been linked, very generally, to urban restructuring processes.

Developments in transportation, information, and telecommunications technologies have had a dramatic impact on the spatial distribution of firms and resident populations, and thus, have also impacted journey-to-work commuting behavior. These impacts have consequences for transportation-related air pollution, gasoline consumption, urban development, and traffic congestion. Where these externalities diminish quality of life, further impacts relating to

167

economic growth (and even civil unrest) may come into play. In this way, the research presented in this dissertation highlights linkages between empirical measurements of intra-metropolitan accessibility and broad processes shaping the urban landscape. The sample analyses presented to demonstrate these linkages include examination of jobs/housing balance, spatial/skills mismatch, and changes in commuting behavior in the Greater Los Angeles study region.

Sample analyses dealing with spatial mismatch issues, for example, highlight the value in utilizing a normative model of intra-metropolitan accessibility, precisely because these models force us to articulate very clearly our definition of "perfect" accessibility. It was noted that the spatial/skills mismatch literature has produced mixed results. Notice that Figure 4.14[35] confirms findings that low-income workers have *poorer* accessibility to employment opportunities in 1990 than they did in 1980. From this conclusion, it is possible to infer that urban restructuring has had a negative impact on low-income workers. Overall, however, both low- and high-income census tracts improved *level-of-service* accessibility between 1980 and 1990, while level-of-service accessibility remained stable for middle-income census tracts. Notice also that low-income workers reside primarily in job-rich tracts. From these findings, it is possible to infer that urban restructuring has *not* diminished accessibility to employment opportunities for low-income workers. One of the most contentious issues associated with the spatial/skills mismatch debate involves questions relating to methodology.

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[35] The specific details of these findings should be tempered given the data quality issues discussed in Chapter 4.

Specifying more precisely our operational definitions of intra-metropolitan accessibility allows qualification of empirical findings while also permitting richer analyses.

In presenting a variety of sample analyses, Chapter 4 evaluates structural, transportation infrastructure, and functional components of intra-metropolitan accessibility separately, making comparisons where appropriate. Many of the examples focus primarily on structural accessibility and physical distances, however, because the data for these analyses are the most reliable. Important future research will utilize higher quality data, ideally disaggregated by industry, occupation, race/ethnicity, gender, residential tenure, income, education, and/or age, where available. Future research might also consider both employed and unemployed workers. The analyses presented in Chapter 4 focus exclusively on workers both residing and employed in the study area. Comparing results to data incorporating unemployed workers should allow identification of geographic locations where human resources may be under-utilized.

Urban and Regional Studies

The broad spatial processes shaping the urban metropolis incorporate and integrate elements of both continuity and change (Hodge, Morrill, and Stanilov, 1996). Rapid advancements in telecommunications and transportation technologies make possible new organizational structures, new geographic arrangements of economic activities, new products, and new modes of production (Golledge and Stimson, 1997). Yet these developments take place within the context of enduring investments in the inherited built environment (roads,

buildings, and infrastructure), conditioned by established social, political, and cultural practices and principles (Graham and Marvin, 1996). The challenge in assessing how broad processes of urban restructuring – suburbanization, globalization, economic restructuring, and rapid technological developments – are impacting intra-metropolitan accessibility, becomes how to integrate the old with the new – the fixed with the fluid. One trend in the literature has been to focus exclusively on virtual spaces and the electronic pulses flowing through cyberspace (see, for example, Janelle and Hodge, 1999). While research focusing on virtual spaces is important (also tremendously challenging), at present, it reflects a very small component of urban life. Much of our day-to-day activities are still very much grounded in space and time. This fact becomes impossible to forget whenever we find ourselves stuck in traffic, at the end of a long line, or coordinating multi-stop errands from one end of town to the other.

An important aim in developing the proposed analytical framework, therefore, was to identify essential components that would embody fundamental and enduring elements of spatial data – components flexible enough to accommodate emerging spatial relations (telecommuting, for example), yet grounded enough to accurately reflect limits imposed by space and time. (1) The proximal space construct is an integral component of the analytical framework because it encourages exploration of the variety of relations, both physical and functional, that may be defined for any given set of spatial objects. (2) The G_i^* statistic is essential to the analytic framework because it measures spatial dependence, an intrinsic and fundamental characteristic of all spatial data. Spatial

170

patterns – clustering, dispersion, density – are a primary concern in regional analyses, often providing important clues regarding underlying spatial processes. (3) The key element associated with the level-of-service definition of accessibility is a move from predictive to normative. The normative model framework demands precision in defining criteria guiding evaluation. (4) While not developed fully in the dissertation research, the forth component of the analytical framework – multiple scale analysis – provides an avenue for progressing to a more dynamic analytical framework, an important area for future research very much dependent on developments in visualization of highly dimensional data. (5) The final component of the analytical framework recognizes that urban spatial processes are fundamentally complex and multidimensional, encouraging exploration of spatial data from a variety of spatial, temporal, physical, and functional perspectives.

Future research must determine how robust the proposed analytical framework will be for extended analyses in urban and regional studies. The research presented in this dissertation initiates this process. By contributing to a more precise definition and representation of intra-metropolitan accessibility – across space, over time, at multiple spatial scales of analysis, and from a variety of different contextual perspectives – this dissertation constitutes a necessary and important first step toward development of "The Accessible City".

171

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172

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Appendix A

Spatial Filtering Software

Spatial Filtering Software Documentation

The FILTER software was developed to perform the Getis spatial filtering technique for regression analysis. The filtering technique transforms a vector of data points, Z, from a spatially dependent set of values to a spatially independent set of "filtered" and "spatial" component variables. The filtered component variables, Z^f, and the spatial component variables, Z^{sp}, are both used in place of the spatially autocorrelated Z values in performing regression analyses.

Running the FILTER software requires the following files:

FILTER.EXE   the spatial filtering software executable.
FILTER.PRM   an ASCII text resource file setting a variety of software parameters.
< X Y Z file>   an input file containing a vector of Z values to be filtered, given in X Y Z format where X and Y are the geographic coordinates for the Z values. The input file should be space(s), comma, or <TAB> delimited, and X, Y and Z values should be numeric.

FILTER.EXE is executed from a DOS window. Below is a sample run of the FILTER program using an input file named TESTXYZ.PRN. (The text in *Italics* are software prompts, the **boldface text** are user input):

C:> **FILTER**

Enter XYZ input filename:	**TESTXYZ.PRN**
Enter initial d value:	**1.0**
Enter increment size:	**0.1**
Enter maximum interations:	**10**

The software performs the following steps:

1) It calculates the Moran's I spatial autocorrelation statistic for Z, documenting the level of spatial dependency present prior to filtering.
2) Beginning with the "*initial d value*", it then performs spatial filtering on the Z values. The filtering process creates two new vectors: Z^f and Z^{sp}.
3) Moran's I spatial autocorrelation statistic is then calculated for the new Z^f values.
4) If spatial autocorrelation has been effectively removed, the program ends. Otherwise the distance radius d is incremented by the "*increment size*", spatial filtering is performed again on the original Z values using this incremented d value, and a new set Z^f and Z^{sp} vectors are created.
5) Steps 3 and 4 are repeated until either a d value effectively removing spatial autocorrelation is found, or the "*maximum iterations*" have been performed.

The software produces three output files:

BESTF.OUT this file contains the best Z^f filtered values in X Y Z format.

BESTSP.OUT this file contains the best Z^{sp} spatial component values.

FILTER.OUT this file summarizes the Moran's I and significance level scores (Z scores) before spatial filtering, at each iteration, and for the d value most effective in removing spatial autocorrelation. The FILTER.OUT file for the sample run above with TESTXYZ.PRN is listed below:

```
Step:                        .0000
  Moran's I       =          .6908
  ZScore          =         7.5843

Step:                       1.0000
  Moran's I       =         -.1730
  ZScore          =        -1.4185

Step:                       1.1000
  Moran's I       =         -.1280
  ZScore          =         -.9520

Step:                       1.2000
  Moran's I       =         -.1366
  ZScore          =        -1.0379

Step:                       1.3000
  Moran's I       =         -.1138
  ZScore          =         -.8029

Step:                       1.4000
  Moran's I       =         -.1281
  ZScore          =         -.9586

Step:                       1.5000
  Moran's I       -         -.1186
  ZScore          =         -.8572

Step:                       1.6000
  Moran's I       =         -.1317
  ZScore          -         -.9943

Step:                       1.7000
  Moran's I       =         -.1326
  ZScore          =        -1.0051

Step:                       1.8000
  Moran's I       =         -.0887
  ZScore          =         -.5523
------------------------------------------------

Moran Scores before spatial filtering:
  Initial I value:           .69
  Initial Z value:          7.58

After filtering:
  Best I value:             -.09
  Best Z value:             -.55
      At Step:             1.80
```

The FILTER.OUT file above indicates that the Z values in the TESTXYZ.PRN input file have significant positive spatial autocorrelation: the Moran's significance level for the Z values before spatial filtering is 7.58 standard deviations. Since the X and Y values in TESTXYZ.PRN are given in MILES, the *"initial d value"* of 1.0 indicates spatial filtering should begin at 1.0 miles. The *"increment size"* is 0.1 miles at each iteration. The FILTER.OUT report file indicates a d value of 1.80 miles is most effective in removing spatial autocorrelation: the Moran's significance level for the derived filtered component variable Z' (written to BESTF.OUT) is – 0.55 standard deviations.

Changing Software Parameters

In the example above, distance calculations were based on Euclidean distance, distances for self-potential (the distance to travel from a point i to itself) was fixed at 0.4 miles, and the impedance function used to calculate the Moran's I statistic was 2.0. These parameters are set in the FILTER.PRM resource file, listed below:

```
This file contains parameters for the FILTER.FOR program.  Note: the maximum #
of xyz data points is hard-coded in FILTER.FOR.  See FILTER.DOC to modify.
0.75     : line 3 specifies an acceptable Moran's Z tolerance.
E        : line 4,column 1:"M"-Manhattan Dist.;"U"-prompt for matrix; ELSE Euclidean.
2.0      : line 5 sets the impedance parameter for the Moran's I calculations.
F        : line 6, column 1: "A"=prompt for AREAS file ELSE fixed self-potential value.
0.4      : line 7 contains a fixed cost for self-potential (used when line 6 is not A).
```

The first two lines in the FILTER.PRM file are comments, and are not used by the FILTER.EXE software. The first "token" on line 3 of the file sets an acceptable tolerance for the Moran's I Z scores (set to 0.75 in the sample FILTER.PRM file above). Once the filtering process produces a Z score with an absolute value less than this tolerance, the program ends. The user, for example, may specify that 100 iterations should be performed. If at iteration 3, the absolute value of the Moran's I significance level (Z Score) is less than the tolerance specified on line 3 of the FILTER.PRM file, the program will only perform a total of 3 iterations.

The first token on line 4 specifies a method to use in calculating distances. If the first column on line 4 contains an "M", the filter software will use Manhattan distance. If the first column on line 4 is "U", the software will prompt the user for the name of a cost matrix. If the first column in line 4 is neither "U" nor "M", FILTER.EXE will perform distance calculations using Euclidean distance. The option, "U", to specify a user-defined cost matrix is helpful for applications using travel costs other than straight-line distance (travel time or road network distances, for example). The filtering software expects the cost matrix to be in table format with matrix dimensions specified on line 1. The cost matrix should have a row and column entry for each Z value. So, for example, the cost matrix associated with an XYZ input file containing 5 data points might look like this:

5				
0.0	2.1	1.2	2.2	5.2
2.1	0.0	0.9	0.2	6.3
1.2	0.9	0.0	1.0	5.4
2.2	0.2	1.0	0.0	6.4

The first token on line 5 of the FILTER.PRM file sets an impedance function for use in the Moran's I calculations. While it is common to use 1.0 or 2.0 for the impedance parameter, the user will want to utilize a more accurate value if known. In the process of calibrating a gravity model, for example, a "friction of distance" beta value will be identified; this beta value may be used in place of the default value set in FILTER.PRM by simply modifying line 5 of FILTER.PRM using a text editor.

The first column on line 6 of the FILTER.PRM file sets the method used in calculating self-potential. Self-potential is the distance or cost associated with intra-zonal travel—the distance to travel from point i to itself. Often self-potential is set at 0.0. When data points reflect centroids for polygon features (census tracts, for example), self-potential may be estimated to reflect average intra-zonal travel costs, based on polygon size. When the first token on line 6 of the FILTER.PRM file is the character "A", the FILTER.EXE software will prompt the user for the name of an X Y A areas file. X and Y are the same geographic coordinates used in the XYZ input file. The third column, A, should contain the area of the polygon associated with each Z value centroid. A value for self-potential will then be calculated individually for each data point as follows:

$$d_{ii} = 0.5*((A_i / pi)**0.5)$$

An example AREAS file for an XYZ input file containing 5 data points is given below:

238.09	2357.29	5.4141
237.10	2355.85	0.5216
238.02	2355.47	1.0085
236.53	2355.34	2.3105
235.40	2354.96	7.5892

The filtering software will look for a fixed value for self-potential on line 7 of the FILTER.PRM file if the first character on line 6 is not an "A". The first token on line 7 sets this fixed value for self-potential. Setting this value to 0.0 is fine and will not cause a zero divide in the software.

System Requirements

The FILTER.EXE software is written in FORTRAN77 which does not allow for dynamic array allocation. Array dimensions have therefore been hard-coded to handle up to 2400 data points. Changing this maximum is very easy. Only one line in the source code (FILTER.FOR) needs to be modified. Before changes to the source code will take effect, however, the source must be recompiled. Instructions for recompiling the source code are given below.

With 2400 data points, the FILTER software uses only 25K of memory. To estimate the amount of memory used for other maximums, simply multiply the maximum by 10 and add 1: 2400*10+1 = 25 K

If the memory requirements exceed the amount of memory available, the software will still run, but will swap data to disk, greatly degrading performance. Note, however, that most PCs contain *at least* 4MG of memory. The FILTER software is, therefore, appropriate for very large data sets (even when a user-specified cost matrix is used). The FILTER source code has been optimized to run very quickly. The Moran and Gi statistics, however, require a large number of calculations and as the number of data points increases, the time to complete multiple iterations will rise. (On my 166mhz machine, with 2400 data points, 10 iterations take about 3 minutes).

To increase the maximum number of data points the software can handle, simply modify the parameter MAXPTS in the source code, FILTER.FOR, and recompile. The FILTER.EXE executable was compiled using the Microsoft (R) FORTRAN PowerStation Optimizing Compiler Version 1.0, utilizing the following build file (FMAKE.BAT):

```
@echo off
  if not /%1/==// goto start
  echo ***usage: fmake name
  goto wrap
:start
rem debug compile/build
:   if /%2/==/c/ fl32 %1.for /G4 /c > xx
:   if not /%2/==/c/ fl32 %1.for /G4 /4Yb /Ge /Fe%1.exe
rem optimized compile/build
    if /%2/==/c/ fl32 %1.for /Ox /G4 /Gs /c > xx
    if not /%2/==/c/ fl32 %1.for /Ox /G4 /Gs /Fe%1.exe
del *.obj > nul
:wrap
```

Typing "fmake" at the DOS prompt in the directory containing the FMAKE.BAT build file will display usage information:

C:> **FMAKE**
```
***usage: fmake name
```

191

Building a new FILTER.EXE executable can be accomplished with the following command:

C:> **FMAKE FILTER**

FILTER.FOR does not contain any non-standard FORTRAN code, so should compile clean using other FORTRAN compilers as well (but the user would need to develop an appropriate build file).

More Information:

For more information about the spatial filtering technique, refer to:

Getis, Arthur. 1995. "Spatial Filtering in a Regression Framework: Examples Using Data on Urban Crime, Regional Inequality, and Government Expenditures." Pp. 172-85 in *New Directions in Spatial Econometrics*, eds. L. Anselin and R. Florax. Berlin: Springer-Verlag.

Spatial Filtering Source Code

```
      PROGRAM FILTER
C This program performs the Getis spatial filtering for a range of
C distance isochrones, identifying the isochrone and producing the
C spatial and non-spatial variables for regression analysis where
C spatial autocorrelation has been effectively removed.  Program
C parameters are set by a resource file, FILTER.PRM.  The input file
C is a space delimited table with 3 columns representing X, Y, and Z
C values.  The cost matrix, if used, has an integer N representing
C the matrix dimensions followed by an N by N table of cost values.
C
C Variable definitions
C
      PARAMETER           (MAXPTS=2400)
      CHARACTER*128       XYZNM, COSTNM, AREANM
      CHARACTER*1         ACODE
      INTEGER             ITERS, MTHCST, MTHSLF
      REAL                DBEGIN, STEP, BETA, TOLER, SELF
      REAL                X(MAXPTS),Y(MAXPTS),Z(MAXPTS),AREAS(MAXPTS),
     +                    FZ(MAXPTS),SPZ(MAXPTS),BSTZ, BSTI, OZ, OI,
     +                    BFZ(MAXPTS),BSPZ(MAXPTS),COSTS(MAXPTS),
     +                    SS2X(MAXPTS),MIDX,MZ
      DOUBLE PRECISION    SUMZ
      DATA                INPT,IOUT,IOUT2 /8,9,10/
C
C Read the parameter file, FILTER.PRM, and get additional parameters
C from the user.
      CALL OPENFL (INPT,'FILTER.PRM','OLD')
      READ (INPT,'(1X)',END=811,ERR=811)         ! Skip comments in line
1
      READ (INPT,'(1X)',END=811,ERR=811)         ! Skip comments in line
2
      READ (INPT,*,END=815,ERR=815)     TOLER    ! Get tolerance
      READ (INPT,'(1A)',END=817,ERR=817) ACODE   ! Get cost method
```

192

```fortran
      MTHCST = 1
      IF (ACODE .EQ. 'M' .OR. ACODE .EQ. 'm') MTHCST = 2
      IF (ACODE .EQ. 'U' .OR. ACODE .EQ. 'u') MTHCST = 3
      READ (INPT,*,END=819,ERR=819)          BETA    ! Get impedance
      READ (INPT,'(1A)',END=821,ERR=821)     ACODE   ! Get self-poten. meth.
      MTHSFL = 1
      IF (ACODE .EQ. 'A' .OR. ACODE .EQ. 'a') MTHSLF = 2
      SELF = 0.1
      IF (MTHSFL .EQ. 1)
     +    READ(INPT,*,END=823,ERR=823)       SELF    ! Get fixed self-poten.
      CLOSE (INPT)
C  Get input filenames from the user.
      WRITE(*,'(A,1X,\)')    ' Enter XYZ input filename:     '
      READ (*,'(A)',ERR=825)  XYZNM
      COSTNM = ' '
      IF (MTHCST .EQ. 3) THEN
        WRITE(*,'(A,1X,\)') ' Enter COST MATRIX filename:   '
        READ (*,'(A)',ERR=825)COSTNM
      END IF
      AREANM = ' '
      IF (MTHSLF .GT. 1) THEN
        WRITE(*,'(A,1X,\)') ' Enter AREAS filename:         '
        READ (*,'(A)',ERR=825)AREANM
      END IF
C  Open files and read in data values.
      CALL OPENFL(INPT,XYZNM,'OLD')
      SUMZ = 0.0
      IDIM = 1
  100 READ(INPT,*,END=110,ERR=110) X(IDIM),Y(IDIM),Z(IDIM)
      IF (Z(IDIM).LT. 0.0) THEN
        WRITE(*,*) 'Filtering requires positive Z values.'
        WRITE(*,*) 'Exiting...'
        CLOSE (INPT)
        STOP '*** ERROR.'
      END IF
      BFZ(IDIM)  = Z(IDIM)
      BSPZ(IDIM) = 0.0
      SUMZ = SUMZ + Z(IDIM)
      IDIM = IDIM + 1
      IF (IDIM .GT. MAXPTS) THEN
        WRITE(*,*) 'Too many data points: see FILTER.DOC'
        WRITE(*,*) 'Exiting...'
        CLOSE (INPT)
        STOP '*** ERROR.'
      END IF
      GO TO 100
  110 CLOSE (INPT)
      IDIM = IDIM - 1
      CNT = IDIM
      IF (IDIM.LT.2) STOP 'ERROR: INVALID XYZ INPUT FILE'
      ZMEAN = SUMZ/CNT
C  Make sure we don't have any problems reading the cost matrix.
      IF (MTHCST .EQ. 3) THEN
        CALL OPENFL(INPT,COSTNM,'OLD')
        READ(INPT,*,END=118,ERR=118) MDIM
        IF (MDIM .NE. IDIM) THEN
          WRITE(*,*) 'Unexpected cost matrix dimensions reading line 1'
          WRITE(*,*) 'Expected integer: ',IDIM,'  Got: ',MDIM
          WRITE(*,*) 'Exiting...'
          CLOSE (INPT)
          STOP '***ERROR.'
        END IF
      END IF
```

193

```
            READ(INPT,*,END=118,ERR=118)(COSTS(J),J=1,MDIM)
            GO TO 119
     118    WRITE(*,*) 'Error reading line 2 of cost matrix.  Exiting...'
            CLOSE(INPT)
            STOP '***ERROR.'
     119    CLOSE(INPT)
         END IF
C
         IF (MTHSLF .GT. 1) THEN
            CALL OPENFL(INPT,AREANM,'OLD')
            DO 120 I = 1, IDIM
               READ(INPT,*,END=122,ERR=122)XX,YY,AREAS(I)
               IF ((XX.NE.X(I)).OR.(YY.NE.Y(I))) THEN
                  WRITE(*,*) 'Unexpected X,Y coordinate reading AREAS file.'
                  WRITE(*,*) 'Input files should be sorted.  Exiting...'
                  CLOSE(INPT)
                  STOP '***ERROR.'
               END IF
     120    CONTINUE
     122    CLOSE (INPT)
         END IF
C
C  Get additional parameters from user.
C
C  Beginning distance radius:
         WRITE(*,'(A,1X,\)') ' Enter initial d value:        '
         READ (*,*,ERR=827)    DBEGIN
C  Increment:
         WRITE(*,'(A,1X,\)') ' Enter increment size:         '
         READ (*,*,ERR=827)    DINCRE
C  Number of iterations:
         WRITE(*,'(A,1X,\)') ' Enter maximum iterations:     '
         READ (*,*,ERR=827)    TMP
         ITERS = TMP
C
C  Determine pre-filtering Moran's I values.
C
         CALL OPENFL (IOUT2,'FILTER.OUT','NEW')
         N = IDIM
         STEP = 0.0
         WRITE(*,*) ' '
         WRITE(*,*) 'Before spatial filtering... '
         CALL MORAN(MAXPTS,N,X,Y,Z,AREAS,COSTS,ZMEAN,OI,OZ,SS2X,
     +             BETA,MTHCST,COSTNM,MTHSLF,SELF,STEP)
         BSTI = OI
         BSTZ = OZ
         BSTP = 0.0
         FMEANZ = ZMEAN
         STEP = DBEGIN - DINCRE
         WRITE(*,*) ' '
         WRITE(*,*) 'With filtering...'
C
C  Begin iterations of Gi* filtering and Moran's I calculations.
C
         DO 500 II = 1, ITERS
            WRITE(*,*) ' '
            STEP = STEP + DINCRE
            CALL GISTAR(MAXPTS,N,X,Y,Z,COSTS,FMEANZ,FZ,SPZ,STEP,
     +             MTHCST,COSTNM)
            CALL MORAN(MAXPTS,N,X,Y,FZ,AREAS,COSTS,FMEANZ,MIDX,MZ,SS2X,
     +             BETA,MTHCST,COSTNM,MTHSLF,SELF,STEP)
```

194

```
              IF (ABS(MZ) .LT. ABS(BSTZ)) THEN
                 BSTI = MIDX
                 BSTZ = MZ
                 BSTP = STEP
                 DO 310 I = 1, N
                    BFZ(I)  = FZ(I)
                    BSPZ(I) = SPZ(I)
  310         CONTINUE
              END IF
C
C  May we stop yet?
C
              IF (ABS(MZ).LT. TOLER) GO TO 900
  500 CONTINUE
      GO TO 900
C
C  Error messages and error handling.
C
  811 WRITE(*,*) 'Unable to read FILTER.PRM file.'
      GO TO 899
  815 WRITE(*,*) 'Error reading FILTER.PRM LINE 3, the tolerance.'
      GO TO 888
  817 WRITE(*,*) 'Unexpected READ error on LINE 4 of FILTER.PRM.'
      GO TO 899
  819 WRITE(*,*) 'Error reading FILTER.PRM LINE 5, BETA parameter.'
      GO TO 888
  821 WRITE(*,*) 'Unexpected READ error on LINE 6 of FILTER.PRM.'
      GO TO 899
  823 WRITE(*,*) 'Error reading FILTER.PRM LINE 7, SELF-POTENTIAL.'
      GO TO 888
  825 WRITE(*,*) 'Unexpected ERROR reading user INPUT.'
      WRITE(*,*) 'Expecting a FILENAME. Exiting...'
      GO TO 999
  827 WRITE(*,*) 'Unexpected ERROR reading user INPUT.'
      WRITE(*,*) 'Expecting a NUMBER. Exiting...'
      GO TO 999
  888 WRITE(*,*) 'Expecting the first token to be a NUMERIC value.'
  899 WRITE(*,*) 'Exiting...'
      CLOSE (INPT)
      GO TO 999
C
  900 WRITE(*,*)
      WRITE(*,*) '------------------------------------------------------'
      WRITE(*,*) ' Moran Scores before spatial filtering: '
      WRITE(*,'(A,F12.2)') '    Initial I value:',OI
      WRITE(*,'(A,F12.2)') '    Initial Z value:',OZ
      WRITE(*,*) ' '
      WRITE(*,*) ' After filtering:'
      WRITE(*,'(A,F12.2)') '    Best I value:    ',BSTI
      WRITE(*,'(A,F12.2)') '    Best Z value:    ',BSTZ
      WRITE(*,'(A,F12.2)') '        At Step:    ',BSTP
      WRITE(IOUT2,*)' '
      WRITE(IOUT2,*) '------------------------------------------------------'
      WRITE(IOUT2,*) ' Moran Scores before spatial filtering: '
      WRITE(IOUT2,'(A,F12.2)') '    Initial I value:',OI
      WRITE(IOUT2,'(A,F12.2)') '    Initial Z value:',OZ
      WRITE(IOUT2,*) ' '
      WRITE(IOUT2,*) ' After filtering:'
      WRITE(IOUT2,'(A,F12.2)') '    Best I value:    ',BSTI
      WRITE(IOUT2,'(A,F12.2)') '    Best Z value:    ',BSTZ
      WRITE(IOUT2,'(A,F12.2)') '        At Step:    ',BSTP
```

195

```fortran
      CALL OPENFL (IOUT,'BESTF.OUT','NEW')
      DO 910 I = 1, N
        WRITE(IOUT,'(1X,2F12.2,F12.4)') X(I),Y(I),BFZ(I)
  910 CONTINUE
      CLOSE (IOUT)
      CALL OPENFL(IOUT,'BESTSP.OUT','NEW')
      DO 920 I = 1, N
        WRITE(IOUT,'(1X,2F12.2,F12.4)') X(I),Y(I),BSPZ(I)
  920 CONTINUE
      CLOSE(IOUT)
C
C  Wrap it up.
C
      CLOSE (IOUT2)
      WRITE(*,*)' '
      WRITE(*,*)' Output: BESTF.OUT, BESTSP.OUT, FILTER.OUT'
C
  999 STOP ' '
      END
C ================================================================
      SUBROUTINE MORAN (MAXPTS,N,X,Y,Z,AREAS,COSTS,ZMEAN,MIDX,MZ,SS2X,
     +                  BETA,MTHCST,COSTNM,MTHSLF,SELF,STEP)
C
C  Perform's Moran's I calculations given X, Y, Z input.
C
      REAL      ZMEAN,      ! mean of Z (or FZ) values
     1          CIJ,        ! covariance between a pair of Z values
     2          WIJ,        ! weighted distance between a pair of points
     3          SUMWC,      ! summation of all wij*cij
     4          SUMW,       ! summation of all wij
     5          M2,         ! sample variance -- the Z values
     6          B2,         ! sample kurtosis -- the Z values
     7          RVAR1       ! moran's variance under randomization
C
      REAL      SS0,SS1,SS2, ! variables used to calculate Moran's
     1          M4,TMP,      !     variance
     2          TMP1,TMP2
C
      REAL      MZ,         ! Zscores for Moran's I
     1          EINDEX,     ! Expected Moran's I
     2          MIDX        ! Moran's I index
C
      REAL      Z(MAXPTS),  ! point attribute values
     1          SS2X(MAXPTS) ! working array for calculating variance
C
      INTEGER I,J,N         ! point i, point j, total # of points
      CHARACTER*128 COSTNM
      DIMENSION X(MAXPTS),Y(MAXPTS),AREAS(MAXPTS),COSTS(MAXPTS)
      DATA INPT,IOUT2 /8,10/, PI /3.141592654/
C
C  Initialize working variables for Moran I calculation.
      SUMWC = 0.0
      SUMW  = 0.0
      M2    = 0.0
      M4    = 0.0
      SS1   = 0.0
      RN    = N
      DO 200 I = 1, N
        SS2X(I) = 0.0
  200 CONTINUE
C
```

```
      IF (MTHCST .EQ. 3) THEN
        CALL OPENFL(INPT,COSTNM,'OLD')
        READ(INPT,*) MDIM
      END IF
C
C  Loop through all array values.
C
      DO 400 I = 1, N
        TMP = Z(I) - ZMEAN
        M2  = M2 + TMP**2
        M4  = M4 + TMP**4
C
C         get cost vector for row i, if needed.
C
        IF (MTHCST.EQ.3) READ(INPT,*)(COSTS(J),J=1,MDIM)
C
        DO 300 J = I, N
          CIJ = TMP * (Z(J) - ZMEAN)
C
C         The method used to calculate WIJ depends on MTHCST and MTHSLF.
C
          IF (MTHCST .EQ. 3) THEN
            WIJ = COSTS(J)
          ELSE IF (I.EQ.J) THEN
            IF (MTHSLF.EQ.1) THEN
              WIJ = SELF
            ELSE
              WIJ = 0.5*((AREAS(I)/PI)**0.5)
            END IF
          ELSE
            WIJ = SQRT((X(I)-X(J))**2.0 + (Y(I)-Y(J))**2.0)
            IF (MTHCST .EQ. 2) WIJ = ABS(X(I)-X(J)) + ABS(Y(I)-Y(J))
          END IF
          IF (WIJ .GT. 0.0) WIJ = 1.0/WIJ**BETA
C
          SUMWC   = SUMWC + (WIJ*CIJ)
          SUMW    = SUMW + WIJ
          SS1     = SS1 + (2*WIJ)**2
          SS2X(I) = SS2X(I) + WIJ
          SS2X(J) = SS2X(J) + WIJ
C
  300   CONTINUE
  400 CONTINUE
      CLOSE (INPT)
C
C  Calculate working variables for I and variance.
      SUMWC = 2*SUMWC
      SUMW  = 2*SUMW
      SS0   = SUMW
      M2    = M2/RN
      M4    = M4/RN
C
      SS2 = 0.0
      DO 500 I = 1, N
        SS2 = SS2 + ((2*SS2X(I))**2)
  500 continue
C
      B2 = M4/M2**2
      EINDEX = -1.0 / (RN-1.0)
C
```

```
C Calculate Moran's I
C
      MIDX = SUMWC / (M2*SUMW)
C
C Calculate Moran's Variance and Significance
C
      TMP1 = RN*((RN**2.0-(3.0*RN)+3.0)*SS1-(RN*SS2)+3.0*(SS0**2.0))
      TMP1 = TMP1 / ((RN-1.0)*(RN-2.0)*(RN-3.0)*(SS0**2.0))
      TMP2 = B2*((RN**2.0-RN)*SS1-(2.0*RN*SS2)+6.0*(SS0**2.0))
      TMP2 = TMP2 / ((RN-1.0)*(RN-2.0)*(RN-3.0)*(SS0**2.0))
C
      RVAR1 = TMP1 - TMP2 - EINDEX**2.0
      MZ    = (MIDX - EINDEX) / SQRT(RVAR1)
C
C Report results.
C
      WRITE(*,'(1X,A,F12.4)') ' Step:              ',STEP
      WRITE(*,'(1X,A,F12.4)') '  Moran''s I      = ',MIDX
      WRITE(*,'(1X,A,F12.4)') '  ZScore         = ',MZ
      WRITE(*,*) ' '
      WRITE(IOUT2,'(1X,A,F12.4)') ' Step:              ',STEP
      WRITE(IOUT2,'(1X,A,F12.4)') '  Moran''s I      = ',MIDX
      WRITE(IOUT2,'(1X,A,F12.4)') '  ZScore         = ',MZ
      WRITE(IOUT2,*) ' '
C
C Stop when filtering has been successful.
      RETURN
      END
C -------------------------------------------------------------------
      SUBROUTINE GISTAR(MAXPTS,N,X,Y,Z,COSTS,ZMEAN,FZ,SPZ,
     +                  STEP,MTHCST,COSTNM)
C
C Routine to perform the Gi* filtering procedure.
C
      DOUBLE PRECISION ZSUM,ZS,FZSUM
      REAL ZMEAN
      LOGICAL IFLG
      CHARACTER*128 COSTNM
      DIMENSION Z(MAXPTS),SPZ(MAXPTS),FZ(MAXPTS)
      DIMENSION X(MAXPTS),Y(MAXPTS),COSTS(MAXPTS)
      DATA INPT /8/
C
      OBS  = N
      IFLG = .FALSE.
      NNO  = 0
      FZSUM= 0.0
      IF (MTHCST .EQ. 3) THEN
        CALL OPENFL(INPT,COSTNM,'OLD')
        READ(INPT,*) MDIM
      END IF
C
C Gi* (1992) statistic:
C
C 100 DO 150 I = 1, N
      ZSUM = 0.0
      ZS   = 0.0
      IWT  = 0
      IF (MTHCST.EQ.3) READ(INPT,*)(COSTS(J),J=1,MDIM)
C
      DO 130 J = 1, N
        IF(J.EQ.I) GO TO 130
        ZSUM = ZSUM + Z(J)
```

```fortran
            IF (MTHCST .EQ. 3) THEN
               WIJ = COSTS(J)
            ELSE
               WIJ = SQRT((X(I)-X(J))**2.0 + (Y(I)-Y(J))**2.0)
               IF (MTHCST .EQ. 2) WIJ = ABS(X(I)-X(J))+ABS(Y(I)-Y(J))
            END IF
            IF (WIJ.LE.STEP) THEN
               ZS = ZS + Z(J)
               IWT = IWT + 1
            ENDIF
  130    CONTINUE
         WT = IWT
C
C        Calculate Gi value and expected value.
         GI  = ZS/ZSUM
         EGI = WT/(OBS-1.0)
C
C        Perform filtering.
         IF (GI .GT. 0.0) THEN
            FZ(I) = Z(I)*(EGI/GI)
            SPZ(I)= Z(I) - FZ(I)
         ELSE
            IFLG = .TRUE.
            NNO = NNO + 1
            FZ(I) = Z(I)
            SPZ(I) = 0.0
         END IF
         FZSUM = FZSUM + FZ(I)
  150 CONTINUE
      CLOSE (INPT)
C
      IF (IFLG) WRITE(*,'(1X,I6,A,F8.4)') NNO,
     +   ' points with no neighbors at step:',STEP
      ZMEAN = FZSUM/OBS
C
      RETURN
      END
C - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
      SUBROUTINE OPENFL(LUN, FILNAM, LLOPT)
      LOGICAL TSTFIL
      CHARACTER LLOPT*3, FILNAM*(*)
      IF (LLOPT.EQ.'OLD') THEN
         INQUIRE(FILE=FILNAM, EXIST=TSTFIL)
         IF (.NOT.TSTFIL) THEN
            WRITE(*,*) '***unable to locate ',FILNAM
            STOP ' '
         ENDIF
         OPEN(LUN, FILE=FILNAM, FORM='FORMATTED',
     1        ACCESS='SEQUENTIAL', STATUS='OLD')
      ELSE
         INQUIRE(FILE=FILNAM, EXIST=TSTFIL)
         IF (TSTFIL) THEN
            OPEN(LUN, FILE=FILNAM, STATUS='OLD')
            CLOSE(LUN, STATUS='DELETE')
         ENDIF
         OPEN(LUN, FILE=FILNAM, FORM='FORMATTED',
     1               ACCESS='SEQUENTIAL', STATUS='NEW')
      ENDIF
      RETURN
      END
```

Appendix B

Procedure Examples

Calculating 1992 G_i^* Scores:

Consider the 5 mile by 5 mile square study area below, containing 25 census tracts, each one square mile in area. With a binary spatial weights matrix ($w_{ij}(d)$ = 1 if j is within d of i; 0 otherwise), and d = 1 mile, the G_i^* score for tract 7 (row 2, column 2) is calculated as follows:

$$G_i^* (d) = [\sum_j w_{ij} (d) e_j] / \sum_j e_j$$

4	■	4	1	1
■	■	■	4	2
4	■	7	3	1
1	2	4	7	0
2	1	1	0	1

$$G_7^*(1.0) = \frac{10 + 8 + 8 + 8 + 6}{90} = \frac{4}{9} = 0.44444$$
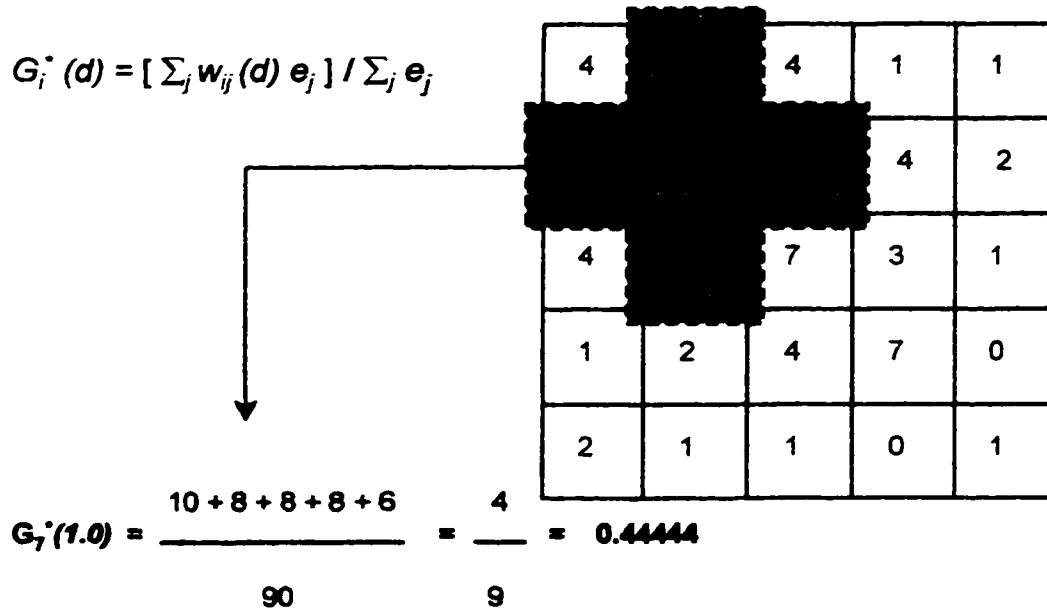
Tract ID	X	Y	Job Count (e)	G_i^* Score
1	1	1	$e_1 = 4$	0.2000
2	1	2	$e_2 = 8$	0.2889
3	1	3	$e_3 = 4$	0.2333
4	1	4	$e_4 = 1$	0.1111
5	1	5	$e_4 = 1$	0.0444
6	2	1	$e_6 = 6$	0.2667
7	2	2	$e_7 = 10$	**0.4444**
.	. .		.	.
.	. .		.	.
.	. .		.	.
24	5	4	$e_{24} = 0$	0.1000
25	5	5	$e_{25} = 1$	0.0111

The 1992 G_i^* scores (proportions) range from 0 to 1. If high values of e cluster within distance d of a point i, the G_i^* score associated with point i will be large. To determine whether or not a particular G_i^* proportion is significantly large, its significance level (Z score) is calculated as shown in Figure AB2.

Figure AB1

Calculating 1992 G_i^* Significance Levels:

To determine whether or not a particular G_i^* score proportion is significant, its significance level (Z score) is calculated. Given the 5 mile by 5 mile square study area shown on the previous page (Figure AB1), a binary spatial weights matrix, and $d = 1$ mile, the G_i^* significance level (Z score) for tract 7 (row 2, column 2) may be calculated as follows:

$$Z_i = \{G_i^* (d) - Exp[G_i^* (d)] \} / \sqrt{Var\ G_i^* (d)}$$

Where the variance of $G_i^* (d)$ is:

$$\frac{W_i^* (n - W_i^*) Y_2^*}{n^2 (n-1) (Y_1^*)^2} \qquad \frac{5 (25-5) 8.4}{25^2 (24) 3.6^2} = \frac{840}{194400} = 0.0043$$

and:

$$W_i^* = \sum_{j=1}^{n} w_{ij} (d) \qquad \begin{array}{l} W_7^* = 5 \\ (\text{for } d = 1.0 \text{ miles}) \end{array}$$

In the case of binary contiguity:

$w_{ij}(d) = 1$ if j is within d of i
            0 otherwise

$$Y_1^* = \frac{\sum_{j=1}^{n} e_j}{n} \qquad \begin{array}{l} Y_{7_1}^* = 90 / 25 \\ = 3.6 \end{array}$$

$$Y_2^* = \frac{\sum_{j=1}^{n} e_j^2}{n} - (Y_1^*)^2 \qquad \begin{array}{l} Y_{7_2}^* = (534/25) - 12.96 \\ = 8.4 \end{array}$$

The expected G_i^* value is:

$$Exp[G_i^* (d)] = W_i^* / n \qquad \begin{array}{l} Exp[G_7(1.0)] = 5 / 25 \\ = 0.2 \end{array}$$

ID	G_i^* Score	Z Score
1	0.20	1.5
2	0.29	2.1
3	0.23	1.2
4	0.11	-0.8
5	0.04	-1.4
6	0.27	1.8
7	0.44	3.7
.	.	.
.	.	.
.	.	.
24	0.10	1.0
25	0.01	-2.0

$$Z_7 = (0.4444 - 0.2) / 0.0657 = 3.719$$

The null hypothesis states that the sum of all values within distance d of location i is not more (or less) than would be expected by chance, given all other values in the study area (both within and beyond d). If spatial association exists at site i, however, so that there is a clustering of high values, the G_i^* significance levels will be positive. Clustering of low values yields negative significance scores. The significance levels (Z scores) may be interpreted as standard normal variates where the expectation under the null hypothesis is 0 and the variance is 1 (Getis and Ord, 1992).

Figure AB2   202

Spatial Filtering Example:

If E is a spatially dependent vector of values e_i for each census tract i in Figure AB1, the following formula may be employed to filter E into its filtered and spatial components. The first step in performing the spatial filtering procedure is to identify an appropriate critical distance, d. Appendix A presents one approach for finding this critical distance. For illustration purposes in the example below, however, let $d = 1.0$ miles:

$$e^f_i = e_i \{ w_i / (n - 1) \} / G_i(d)$$

$$e^{sp}_i = e_i - e^f_i$$

where:

e^f_i = the filtered component of e_i

e^{sp}_i = the spatial component of e_i

w_i = $\sum_j w_{ij} (d)$; In the case of binary contiguity w_{ij} is
equal to 1 if j is within d of i; 0 otherwise
j may not equal i

n = the total number of observations

$G_i(d)$ = the 1992 G_i statistic:
$$G_i(d) = [\sum_j w_{ij}(d) e_j] / \sum_j e_j$$
j may not equal i

Given the 5 mile by 5 mile square study area shown in Figure AB1, the employment variable associated with census tract 7 (row 2, column 2) with a value of 10, may be filtered by dividing the expected $G_7(1.0)$ value by the observed $G_7(1.0)$ value as follows:

Expected $G_7(1.0)$ value = $w_7 / (n - 1)$
Observed $G_7(1.0)$ value = $[\sum_j w_{7j}(d) e_j] / \sum_j e_j$; j may not equal i

Expected	=	5 / (25 - 1)	= 0.2083
Observed	=	30 / 90	= 0.3333

e^f_7	=	10 (0.2083) / 0.3333	= 6.25
e^{sp}_7	=	10 - 6.25	= 3.75

Calculating 1995 G_i^* Scores:

Consider the 5 mile by 5 mile square study area below, containing 25 census tracts, each one square mile in area. With a binary spatial weights matrix — $w_{ij}(d)$ = 1 if j is within d of i; 0 otherwise — and d = 1 mile, the 1995 G_i^* score for tract 7 (row 2, column 2) is calculated as follows:

$$G_i^* = \frac{\Sigma_j \; w_{ij}(d) \; e_j \; - \; W_i \overline{E}}{s \{ [(n s_{1i}) - W_i^2] / (n - 1) \}^{\frac{1}{2}}}$$

e_j = the number of jobs at zone j

$w_{ij}(d)$ = spatial weights matrix; in the case of binary contiguity, equal to 1 if j is within d of i, otherwise equal to 0

W_i = the sum of column entries for row i of the spatial weights matrix

$\overline{E}$ = the mean for all e_j observations

s = the square root of the variance for all e_j observations

n = the total number of observations

s_{1i} = the sum of squared column entries for row i of the spatial weights matrix

4		4	1	1
			4	2
4		7	3	1
1	2	4	7	0
2	1	1	0	1

$\Sigma_j \; w_{7j}(d) \; e_j$ = 40

W_7 = 5

$\overline{E}$ = 3.6

$s^2 = [(\Sigma_j \; e_j^2)/n] - \overline{E}^2$ = 8.4

n = 25

s_{17} = 5

$$G_i^* = \frac{40 - 5 \; (3.6)}{2.898 \{ [(25)(5) - 25]/(25-1) \}^{1/2}}$$

= 3.719

Tract ID	X	Y	Job Count (e)	G_i^* Score
1	1	1	e_1 = 4	1.50
2	1	2	e_2 = 8	2.14
3	1	3	e_3 = 4	1.22
4	1	4	e_4 = 1	- 0.81
5	1	5	e_4 = 1	- 1.41
6	2	1	e_6 = 6	1.77
7	2	2	e_7 = 10	3.72
.	.	.		. .
.	.	.		. .
.	.	.		. .
24	5	4	e_{24} = 0	- 1.00
25	5	5	e_{25} = 1	- 2.04

Calculating Confidence Intervals for Estimates in Table 4.3:

To calculate standard error for the estimated percentages:

$$SE(p) = \sqrt{(p(1-p))/(n/5)}$$

where:

SE = the standard error

$n/5$ = the number of workers in the sample divided by 5 (to account for the 1 in 6 census sample)

p = the estimated percentage

To calculate standard error for the estimated mean income:

$$SE(I) = s / \sqrt{n/5}$$

where:

SE = the standard error

$n/5$ = the number of workers in the sample divided by 5 (to account for the 1 in 6 census sample)

s = the standard deviation for the sample incomes

The 0.05 confidence interval **(CI)** for the difference between two samples ("unimpeded" vs. all others, or "rooted" vs. all others) is found by squaring the standard error for each separate estimate, then summing the two, taking the square root of this sum, and multiplying by 1.96.

Figure AB5

205

Appendix C

Travel Time Estimation Algorithm

Travel Time Estimation Algorithm

Figure AC1

{Proximity is initially defined to be within 3 miles, but is relaxed (after several iterations) to be within 5 miles.}

{The Time Matrix has a row and column for each census tract centroid. Initially the Time Matrix contains the tract-to-tract median travel times provided with the CTPP/ UTPP survey data.}

{Missing time cost values, or values falling outside the inner-quintile range for commutes with similar road network distances, are not feasible.}

{Road network distances were derived by performing shortest path analysis in ArcView using DYNAMAP2000 road network coverages for the study area.}

{Similar commutes consist of like road network distances (e.g. for a 3 mile commute, distances greater than 2 miles and less than 4 miles are considered similar), and proximal origins and destinations. Proximity is defined by PROX.}

{Time estimates are calculated for every tract-to-tract combination. Few actual commutes, however, involve more than 60 miles. Since few if any similar commutes can be found to help estimate travel times for tracts more than 80 miles away from each other, these travel times are calculated as a function of road network distances, assuming 65mph travel speeds.}

{The new time matrix becomes the input matrix for subsequent iterations.}

{After several iterations, most tract-to-tract travel time estimates have been calculated. Any remaining missing travel times are assigned the median travel time for all commutes with similar road network distances.}

Start

Initialize Proximity (PROX)

A

Input the Time Matrix

For each row (R) in the Time Matrix

For each column (C) in the Time Matrix

Is the (R to C) commute time feasible?

YES

Loop for next column (C)

Loop for next row (R)

Output the updated Time Matrix

A ← YES — Another iteration? — NO → Stop

Look up the (R to C) commute road network distance (DIST)

Is DIST < PROX — YES → C

NO

Find all similar commutes

Did we find at least 3? — YES → Assign the median travel time for all similar commutes to this (R to C) commute → C

NO

Is this a long commute? — NO → C

YES

Calculate time value based on road network distance

→ C

207

Appendix D

Deriving Functional Travel Times or Functional Distance Cost Matrices

**Procedures to Calculate
Functional Time/Distance
Cost Matrices**

Start

Input: Jobs by Tract

Workers by Tract

Cost Matrix

Actual Tract-toTract
flow matrix

loop

* Select a Beta
impedance factor
* Initialize A vector
scaling factors

{ The initial value for Beta is
1.00. The best Beta value
is found systematically by
performing multiple
interations, incrementing
the tested Beta value first
by 0.10, then by 0.01. }

No

loop

No

Calculate B vector
scaling factors
Calculate A vector
scaling factors

Have A's and B's
Stablilized?

Yes

No

Does this Beta
provide the *best*
estimates?

Compare actual
journey-to-work
flow patterns with
estimated flow
patterns

Use gravity model to
estimate tract-to-tract
flows

{ End of
Calibration
Procedure }→ Yes

Invert gravity
model, then
replace estimated
flows with actual
tract-to-tract flows

For each Cost

Set functional cost
equal to actual cost

Calculate functional
cost using inverted
gravity formula

No

Are actual flows
equal to estimated
flows?

Yes

next cost

Output: Functional
Cost Matrix

Stop

Figure AD1

209

Appendix E

Select FORTRAN Utilities:
ACCESS92
GETCOMM

ACCESS92 Software

The ACESS92 software was developed to perform a variety of accessibility measurements to allow comparison among a variety of approaches. The FORTRAN executable is launched from the ACCESS92.BAT batch file:

```
@echo off
rem --- access.bat feb99 -- lms
   if not /*4/==// goto OK
   echo *** usage: access92 xy-file z-file output (cost matrix or areas)
   goto WRAP
:OK
   echo *1 *2 *3 *4 *5>zgistr.ctl
   acess92x
:wrap
```

The source code for this software is listed below:

```
PROGRAM ACCESS92
C
C  This program performs accessibility measurements by calculating
C  Gi* as presented in Getis and Ord (1992), a gravity model, an
C  isochronic model, or a network model.
C
C  NOTE: *** This program assumes input units are UTM meters, and
C               reporting units are miles, if Euclidean distance or
C               Manhattan distance travel costs are selected.
C
       PARAMETER (MAXPTS=2400, MAXITR=50)
       DOUBLE PRECISION ZSUM,ZS,ASUM,AWT
       DIMENSION ID(MAXPTS),X(MAXPTS),Y(MAXPTS),Z(MAXPTS),
      1 GI(MAXPTS,MAXITR),CMATRX(MAXPTS,MAXPTS),
      2 AREA(MAXPTS),ACESS(MAXPTS)
       COMMON /DST/ X, Y, CMATRX, AREA
       DATA INPT1,INPT2,IOUT,INPT3,INPT4/ 7,8,9,10,11/
C
C  Initialize input/output.
       CALL ZGINIT('ZGISTR.CTL', INPT1, INPT2, IOUT, INPT3, INPT4)
C
C  Get user selections.
       WRITE(*,*) 'Enter a travel cost method:'
       WRITE(*,*) '  1) Euclidian Distance'
       WRITE(*,*) '  2) Manhattan Distance'
       WRITE(*,*) '  3) User Supplied Cost Matrix'
       READ (*,*) JCOST
       IF (JCOST.LT.1 .OR. JCOST.GT.3) STOP '***Error in selection'
       WRITE(*,*) ' '
       WRITE(*,*) 'Select a measure:'
       WRITE(*,*) '  1) Gi* (1992)'
       WRITE(*,*) '  2) Gravity Model'
       WRITE(*,*) '  3) Isochronic Measure'
       WRITE(*,*) '  4) Network Model:  Total Cost'
       WRITE(*,*) '  5) Network Model:  Total Cost with Impedance'
       WRITE(*,*) '  6) Gi* with Imedance'
       READ (*,*) JMETH
       IF (JMETH.LT.1 .OR. JMETH.GT.6) STOP '***Error in selection'
       IF (JMETH.EQ.1 .OR. JMETH.EQ.3) THEN
          WRITE(*,*) 'Enter search radius/increment:'
          READ (*,*) RADI
          STEP = 0.0
       END IF
```

211

```fortran
      IF (JMETH.EQ.1) THEN
        WRITE(*,*) 'Enter number of iterations'
        READ (*,*) ITRS
        IF (ITRS.GT.MAXITR) STOP '***too many iterations'
        ICNT = 0
      END IF
      IF (JMETH.EQ.2 .OR. JMETH.EQ.5 .OR. JMETH.EQ.6) THEN
        WRITE(*,*) 'Enter impedance:'
        READ(*,*) BETA
      END IF
      IF (JMETH.EQ.6) THEN
        WRITE(*,*) 'Enter zone of indifference:'
        READ(*,*) ZOI
      END IF
C
C Read in X, Y, and Z values.
C
      DO 10 I = 1, MAXPTS
        READ(INPT1,*,END=20) ID(I),X(I),Y(I)
        READ(INPT2,*,END=20) IDCHK,Z(I)
        IF (IDCHK.NE.ID(I)) STOP '***ID''s not sorted'
        IF (Z(I).LT.0.0) STOP '***Positive Z values only'
   10 CONTINUE
      STOP '***too many points'
   20 CLOSE(INPT1)
      CLOSE(INPT2)
      NOBS = I - 1
      OBS  = NOBS
C
C For Euclidean/Manhattan Distance, get AREAS vector to calculate
C self-potential values.
C
      IF (JCOST.LT.3) THEN
        DO 30 I = 1, MAXPTS
          READ(INPT3,*,END=40) IDCHK,AREA(I)
          IF (IDCHK.NE.ID(I)) STOP '***ID''s not sorted'
   30   CONTINUE
        STOP '***too many points'
   40   CLOSE(INPT3)
C
C If costs come from a specified matrix, read this matrix.
C
      ELSE
        READ(INPT3,*,END=28) IVAL
        IF (IVAL .NE. NOBS) STOP 'Mismatch: NOBS, IVAL'
        DO 25 II = 1, IVAL
          READ(INPT3,*,END=28,ERR=28)(CMATRX(II,JJ),JJ=1,IVAL)
   25   CONTINUE
   28   CLOSE(INPT3)
      END IF
C
C Do it.
C
   90 IF (JMETH .EQ. 2) GO TO 200
      IF (JMETH .EQ. 3) GO TO 300
      IF (JMETH .EQ. 4) GO TO 400
      IF (JMETH .EQ. 5) GO TO 500
      IF (JMETH .EQ. 6) GO TO 600
C
```

212

```
C***PROCESS
C
C  Gi* (1992) statistic:
C
  100 STEP = STEP + RADI
      ICNT = ICNT + 1
C
      DO 150 I = 1, NOBS
        ZSUM = 0.0
        ZS = 0.0
C
        DO 130 J = 1, NOBS
          ZSUM = ZSUM + Z(J)
          IF (COST(JCOST,I,J).LE.STEP) THEN
            ZS = ZS + Z(J)
          ENDIF
  130   CONTINUE
C
C       Calculate Gi* value.
C
        GI(I,ICNT) = ZS/ZSUM
  150 CONTINUE
C
C  Another iteration?
      IF (ICNT.GE.ITRS) GO TO 910
      GO TO 100
C
C  Gravity model.
C
  200 DO 230 I = 1, NOBS
        ASUM = 0.0
        DO 220 J = 1, NOBS
          DIST = COST(JCOST,I,J)
          IF (DIST.LT.1.0) DIST = 1.0
          ASUM = ASUM + (Z(J)/DIST**BETA)
  220   CONTINUE
        ACESS(I) = ASUM
  230 CONTINUE
      GO TO 920
C
C  Isochronic Accessibility Measure
C
  300 DO 330 I = 1, NOBS
        ASUM = 0.0
        DO 320 J = 1, NOBS
          DIST = COST(JCOST,I,J)
          IF (DIST.LE.RADI) ASUM = ASUM + Z(J)
  320   CONTINUE
        ACESS(I) = ASUM
  330 CONTINUE
      GO TO 920
C
C  Total Cost Measure
C
  400 DO 430 I = 1, NOBS
        ASUM = 0.0
        DO 420 J = 1, NOBS
          ASUM = ASUM + COST(JCOST,I,J)
  420   CONTINUE
        ACESS(I) = ASUM/OBS
  430 CONTINUE
      GO TO 920
```

213

```
C  Gi* performing total cost with impedance.
C
  500 DO 550 I = 1, NOBS
         ZSUM = 0.0
         ZS = 0.0
C
         DO 530 J = 1, NOBS
           ZSUM = ZSUM + 1.0
           AWT = COST(JCOST,I,J)
           IF (AWT .LT. 1.0) AWT = 1.0
           ZS = ZS + (100*(1/AWT**BETA))
  530    CONTINUE
C
C        Calculate Gi* value.
         ACESS(I) = ZS/ZSUM
C
  550 CONTINUE
      GO TO 920
C
C  Gi* statistic with impedance.
C
  600 DO 650 I = 1, NOBS
         ZSUM = 0.0
         ZS = 0.0
C
         DO 630 J = 1, NOBS
           ZSUM = ZSUM + Z(J)
           AWT = COST(JCOST,I,J)
           IF (AWT .LE. ZOI) THEN
             AWT = 1.0
           ELSE
             AWT = AWT - ZOI + 1.0
           END IF
           AWT = 1/AWT**BETA
           ZS = ZS + (Z(J)*AWT)
  630    CONTINUE
C
C  Calculate Gi* Z value.
         ACESS(I) = ZS/ZSUM
C
  650 CONTINUE
      GO TO 920
C
C***WRAP:  Output results.
C
C  Write Gi* output.
  910 DO 912 I = 1, NOBS
         WRITE(IOUT,'(1X,I9.9,100F12.4)')
     1      ID(I),(GI(I,J),J=1,ICNT)
  912 CONTINUE
      GO TO 990
C
C  Write gravity, isochronic, network, and Gi* variation model output.
  920 DO 922 I = 1, NOBS
         WRITE(IOUT,'(1X,I9.9,F14.4)') ID(I),ACESS(I)
  922 CONTINUE
C
  990 CLOSE(IOUT)
      STOP ' '
      END
```

```
C - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
      FUNCTION COST(JCOST, I, J)
      PARAMETER (MAXPTS=2400)
      DIMENSION X(MAXPTS),Y(MAXPTS),CMATRX(MAXPTS,MAXPTS),
     1         AREA(MAXPTS)
      COMMON /DST/ X, Y, CMATRX, AREA
      DATA MMILE /1609.0/,PI /3.141592654/
C
C***COMPUTE TRAVEL COST
C
C  For Euclidean/Manhattan distance, if I is equal to J,
C  calculate self-potential distance based on tract area.
C  This calculation for self potential is suggested
C  by Warntz in Goodchild, Milliff, and Davis (1981, 341).
C
C - EUCLIDEAN DISTANCE
      IF (JCOST.EQ.1) THEN
        IF (I.EQ.J) THEN
          COST = (0.5*((AREA(I)/PI)**0.5))/MMILE
        ELSE
          XDIST = X(I) - X(J)
          YDIST = Y(I) - Y(J)
          COST = SQRT(ABS(XDIST*XDIST+YDIST*YDIST))/MMILE
        END IF

C - MANHATTAN DISTANCE
      ELSE IF (JCOST.EQ.2) THEN
        IF (I.EQ.J) THEN
          COST = (0.5*((AREA(I)/PI)**0.5))/MMILE
        ELSE
          XDIST = X(I) - X(J)
          YDIST = Y(I) - Y(J)
          COST = ABS(XDIST+YDIST)/MMILE
        END IF
C - COST MATRIX
      ELSE IF (JCOST.EQ.3) THEN
        COST = CMATRX(I,J)
        IF (COST.LT.0.0001) THEN
          COST = 0.1
          IF (I.NE.J) WRITE(*,*) 'ZERO COST:',I,J
        END IF
      ENDIF
C
  999 RETURN
      END
C - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
      SUBROUTINE ZGINIT(CTLFIL, INPT1, INPT2, IOUT, INPT3,INPT4)
C
C  GET FILE NAMES FROM CTL FILE, AND OPEN
C
      PARAMETER (MAXFIL=5)
      CHARACTER CTLFIL*(*),FILNMS(MAXFIL)*20
C
      CALL GETCTL(CTLFIL, INPT1, FILNMS, MAXFIL)
      CALL OPENFL(INPT1, FILNMS(1),'OLD')
      CALL OPENFL(INPT2, FILNMS(2),'OLD')
      CALL OPENFL(IOUT,  FILNMS(3),'NEW')
      CALL OPENFL(INPT3, FILNMS(4),'OLD')
      IF (FILNMS(5).NE.' ') CALL OPENFL(INPT4,FILNMS(5),'OLD')
C
      RETURN
      END
```

215

```fortran
C - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
      SUBROUTINE GETCTL(CTLFIL, INPT, FILNMS, MAXFIL)
C
C  GET FILE NAMES FROM CTL FILE
C
      LOGICAL TSTFIL
      CHARACTER LLINE*80,CTLFIL*(*),FILNMS(MAXFIL)*(*)
C
      INQUIRE(FILE=CTLFIL, EXIST=TSTFIL)
      IF (.NOT.TSTFIL) THEN
        WRITE(*,*) '*** unable to locate ',CTLFIL
        STOP ' '
      ENDIF
      OPEN(INPT, FILE=CTLFIL, FORM='FORMATTED',
     1          ACCESS='SEQUENTIAL', STATUS='OLD')
      READ(INPT,'(A)') LLINE
      CLOSE(INPT, STATUS='DELETE')
C
      I1 = 0
      DO 100 J = 1, MAXFIL
        FILNMS(J) = ' '
        I2 = INDEX(LLINE(I1+1:),' ')
        IF (I2.LE.1) GO TO 100
        I2 = I2 + I1
        FILNMS(J) = LLINE(I1+1:I2-1)
        I1 = I2
  100 CONTINUE
C
      RETURN
      END
C - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
      SUBROUTINE OPENFL(LUN, FILNAM, LLOPT)
C
C  OPEN FILE, LLOPT='OLD'/'NEW'
C
      LOGICAL TSTFIL
      CHARACTER LLOPT*3, FILNAM*(*)
C
      IF (LLOPT.EQ.'OLD') THEN
        INQUIRE(FILE=FILNAM, EXIST=TSTFIL)
        IF (.NOT.TSTFIL) THEN
          WRITE(*,*) '***unable to locate ',FILNAM
          STOP ' '
        ENDIF
        OPEN(LUN, FILE=FILNAM, FORM='FORMATTED',
     1          ACCESS='SEQUENTIAL', STATUS='OLD')
      ELSE
        INQUIRE(FILE=FILNAM, EXIST=TSTFIL)
        IF (TSTFIL) THEN
          OPEN(LUN, FILE=FILNAM, STATUS='OLD')
          CLOSE(LUN, STATUS='DELETE')
        ENDIF
        OPEN(LUN, FILE=FILNAM, FORM='FORMATTED',
     1          ACCESS='SEQUENTIAL', STATUS='NEW')
      ENDIF
C
      RETURN
      END
```

GETCOMM Software

The GETCOMM software was developed to calculate an average travel cost for each tract in the study area based on all incoming and outgoing journey-to-work travel flows. The FORTRAN executable is launched from the GETCOMM.BAT batch file:

```
@echo off
rem --- getcomm.bat -- lms 2/99
  if not /%4/==// goto OK
  echo *** usage: GETCOMM (tract IDs) (flow matrix) (cost matrix) (output)
  goto WRAP
:OK
  copy %1 trinp > nul
  copy %2 fminp > nul
  copy %3 cminp > nul
  tm start
  getcomx
  tm stop
  copy comout %4
  del trinp > nul
  del fminp > nul
  del cminp > nul
  del comout > nul
:wrap
```

The FORTRAN source code is listed below:

```
PROGRAM GETCOM
C
C  This program gets average commute times/distances based on a
C  flow matrix (FMAT??.OUT) and a cost matrix (such as ROADD.OUT
C  or NTMATRX.OUT) -- these filenames are read from the command
C  line in the batch file (GETCOMM.BAT).  The average commute value
C  is based on all incoming AND outgoing commutes for each
C  census tract.  Output: a vector list with census tract ID
C  and average commute, one per record.
C
      LOGICAL EXST
      CHARACTER*9  CTRACT, CTRACTSS(2400)
      INTEGER      IR, IC, IDIM, FLOWS(2400,2400)
      REAL         COSTS(2400,2400),COMMUT(2400)
      DOUBLE PRECISION CSUM,AVEC,TOTC,TVAL
      DATA INPT, IOUT /7, 8/
C
C  Open the tract file containing a sorted list of all census
C  tracts in the study area.  Read in the tract data.
C
      OPEN (INPT,FILE='TRINP',FORM='FORMATTED',
     +      ACCESS='SEQUENTIAL',STATUS='OLD')
      IDIM = 0
  100 READ (INPT,'(A)',END=110,ERR=110) CTRACT
      IF (CTRACT.EQ.'  ') GO TO 100
      IDIM = IDIM + 1
      CTRACTSS(IDIM) = CTRACT
      GO TO 100
C
  110 CLOSE (INPT)
C
```

217

```fortran
C  Get flows.
C
      OPEN (INPT, FILE='FMINP',FORM='FORMATTED',
     +        ACCESS='SEQUENTIAL',STATUS='OLD')
C
      READ(INPT,*) IVAL
      IF (IVAL .NE. IDIM) THEN
        WRITE(*,*) 'IDIM/IVAL MISMATCH'
        STOP
      END IF
      DO 120 IR = 1, IDIM
        READ(INPT,*,END=122,ERR=122) (FLOWS(IR,IC),IC=1,IDIM)
  120 CONTINUE
  122 CLOSE (INPT)
C
C  Get costs.
C
      OPEN (INPT,FILE='CMINP',FORM='FORMATTED',
     +        ACCESS='SEQUENTIAL',STATUS='OLD')
      READ(INPT,*) IVAL
      IF (IVAL .NE. IDIM) THEN
        WRITE(*,*) 'Unexpected IDIM mismatch... stopping.'
        STOP
      END IF
      DO 127 IR = 1, IDIM
        READ(INPT,*,END=128,ERR=128)(COSTS(IR,IC),IC=1,IDIM)
  127 CONTINUE
  128 CLOSE(INPT)
C
C  Collect ingoing and outgoing commutes for each tract.
C
      CSUM = 0.0
      KNT = 0
      DO 220 IR = 1, IDIM
        NFLWS = 0
        TVAL = 0.0
        DO 210 IC = 1, IDIM
          IF (FLOWS(IR,IC).GT.0) THEN
            WT = FLOWS(IR,IC)
            TVAL = TVAL + (COSTS(IR,IC)*WT)
            NFLWS = NFLWS + FLOWS(IR,IC)
            CSUM = CSUM + (WT*COSTS(IR,IC))
            KNT = KNT + FLOWS(IR,IC)
          END IF
          IF (FLOWS(IC,IR).GT.0) THEN
            WT = FLOWS(IC,IR)
            TVAL = TVAL + (COSTS(IC,IR)*WT)
            NFLWS = NFLWS + FLOWS(IC,IR)
          END IF
  210   CONTINUE
C
        IF (NFLWS.LT.1) THEN
          COMMUT(IR) = 0.0
          WRITE(*,*) CTRACTSS(IR), ' no jobs or workers?'
        ELSE
          COMMUT(IR) = TVAL/NFLWS
        END IF
  220 CONTINUE
C
```

```
C  Write out the average commute vector.
C
      INQUIRE(FILE='COMOUT',EXIST=EXST)
      IF (EXST) THEN
        OPEN (IOUT,FILE='COMOUT',STATUS='OLD')
        CLOSE(IOUT,STATUS='DELETE')
      ENDIF
      OPEN (IOUT,FILE='COMOUT',FORM='FORMATTED',
     +      ACCESS='SEQUENTIAL',STATUS='NEW')
C
      DO 530 IR = 1, IDIM
        WRITE(IOUT,'(A,F9.1)') CTRACTSS(IR),COMMUT(IR)
  530 CONTINUE
      CLOSE (IOUT)
C
C  Calculate the global average commute costs.
C
      TOTC = KNT
      AVEC = CSUM/TOTC
      WRITE(*,*) 'Overall average commuting cost: ',AVEC
C
  999 RETURN
      END
```

Appendix F

Procedural Flowcharts

Input:

A travel distance D and corresponding travel time T

Start

Study area ave. travel distance, $aved_{ij}$, and ave. travel time, $avet_{ij}$

for each census tract i

Road network distance cost matrix

Initialize:
S = 0
n = 0

Journey-to-work estimated travel time cost matrix

in relation to every other census tract j

sum the normalized difference:
$$S = S + (d_{ij} / aved_{ij}) - (t_{ij} / avet_{ij})$$
$$n = n + 1$$

Is $d_{ij} <= D$ or $t_{ij} <= T$?

Yes

where:
d_{ij} = distance between i and j
t_{ij} = travel time between i and j
$aved_{ij}$ = average commute distance
$avet_{ij}$ = average commute time

No

next j

Divide the sum by the number of tracts summed to obtain tract average (tract congestion): S / n

Calculating a Congestion Variable, T, for each Census Tract

Figure AF1

next i

Output: Tract Congestion Scores

Stop

221

Calculating a Functional Component Variable, *F*

Figure AF2

Start

Input:

Tract Median Income 1980 | Tract Worker Counts 1980 | Gi* Level-of-Service Accessibility Scores, d=3 miles, 1980

Tract Median Income 1990 | Tract Worker Counts 1990 | Gi* Level-of-Service Accessibility Scores, d=3 miles, 1990

For 1980 and 1990

Initialize SUM and CNT variables to zero

Procedures Used to Calculate Tract Average Level-of-Service Accessibility Scores by Income Class

For each tract

INC < 75% Study Area Median Income? — No → INC > 125% Study Area Median Income? — No → Add $(ASCR*WCT)$ to SUMMID Add WCNT to WMID

Yes

Add $(ASCR*WCT)$ to SUMLOW Add WCNT to WLOW

Yes

Add $(ASCR*WCNT)$ to SUMHI Add WCNT to WHI

next tract

Low Inc Ave $ASCR=SUMLOW/WLOW$ Mid Inc Ave $ASCR=SUMMID/WMID$ Hi Inc Ave $ASCR=SUMHI/WHI$

next decade

Report: Average Accessibility Score by Income Class

Variable Names Used in Flowchart:

INC	= tract median income value
WCNT	= tract worker count
ASCR	= tract level-of-service Gi* accessibility score
SUMLOW	= sum for low income class
SUMMID	= sum for middle income class
SUMHI	= sum for high income class
WLOW	= workers in low income class
WMID	= workers in middle income class
WHI	= workers in high income class

Stop

Figure AF3

223

Procedures Used to Calculate Tract Average Level-of-Service Accessibility Scores by Occupation and Income Class

Start

Input:

Gi* Accessibility Scores by Occupation. d=6 miles, 1980

Tract Worker Counts by Occupation, 1980

Tract Median Incomes, 1980

Gi* Accessibility Scores by Occupation, d=6 miles, 1990

Tract Worker Counts by Occupation 1990

Tract Median Incomes, 1980

For 1980 and 1990

For each occupation, 1 to 6

Initialize SUM and CNT variables to zero

For each tract

INC < 75% of study area median income? — No → *INC > 125% of study area median income?* — No → Add (*ASCRO*WCNTO*) to *SUMMID* Add *WCNTO* to *WMID*

Yes

Yes

Add (*ASCRO*WCNTO*) to *SUMLOW* Add *WCNTO* to *WLOW*

Add (*ASCRO*WCNTO*) to *SUMHI* Add *WCNTO* to *WHI*

next tract

Stop

Low Inc Ave *ASCRO=SUMLOW/WLOW*
Mid Inc Ave *ASCRO=SUMMID/WMID*
Hi Inc Ave *ASCRO=SUMHI/WHI*

next occupation

next decade

Report: Average Accessibility Scores by Occupation, by Income Class

Figure AF4

224

Variable Names Used in Flowchart:

INC	= tract median income value
WCNTO	= tract worker count by occupation
ASCRO	= tract level-of-service Gi* accessibility score. by occupation
SUMLOW	= sum for low income class
SUMMID	= sum for middle income class
SUMHI	= sum for high income class
WLOW	= workers in low income class
WMID	= workers in middle income class
WHI	= workers in high income class

Computing and Classifying "Footloose" and "Rooted" Census Tracts based on Functional vs. Actual Journey-to-Work Travel Times, 1990

Input:

Travel Time Cost Matrix

Functional Travel Time Cost Matrix

Tract-toTract Flow Matrix

Start

For each tract i

in relation to every tract j

Sum tract i flows = tract total flows

Sum (travel time costs, t_{ij} * flows, f_{ij}) = tract total travel time

Sum (functional time costs, ft_{ij} * flows, f_{ij}) = tract total functional time

next tract j

Tract Score = (sum tract total travel time/ tract total flows) - (sum tract total functional time/ tract total flows)

next tract i

Stop

Classify tracts "rooted" or "footloose" by natural breaks: differences < -12 = "footloose"; differences > -6 equal "rooted"

Figure AF5

225

Appendix G

GIS Implementation Flowchart
With Select Avenue Scripts and FORTRAN Source Code

Accessibility GIS Implementation

With Select Scripts and Source Code Illustrating the 1995 Gi* Statistic Accessibility Analysis

Back to ArcView

GOI
Gi95Go.Ave
Verify User Input
Build Resource File
Launch Gi* Software
Import Gi* Results
Create New Themes
Set Legend Classes/Symbols
Activate Analysis View

External Gi*
FORTRAN Executable
GiStr95.FOR

Figure AG1

Initialize Dialog Box Buttons, Lists, and Input Prompts
Gi95DialogOpen.Ave

Get a Theme
ThemeSel.Ave

Get a Z variable
ZVarSel.Ave

Get Cost Func.
CostSel.Ave

Get Beginning d value
BeginD.Ave

Get d Increment
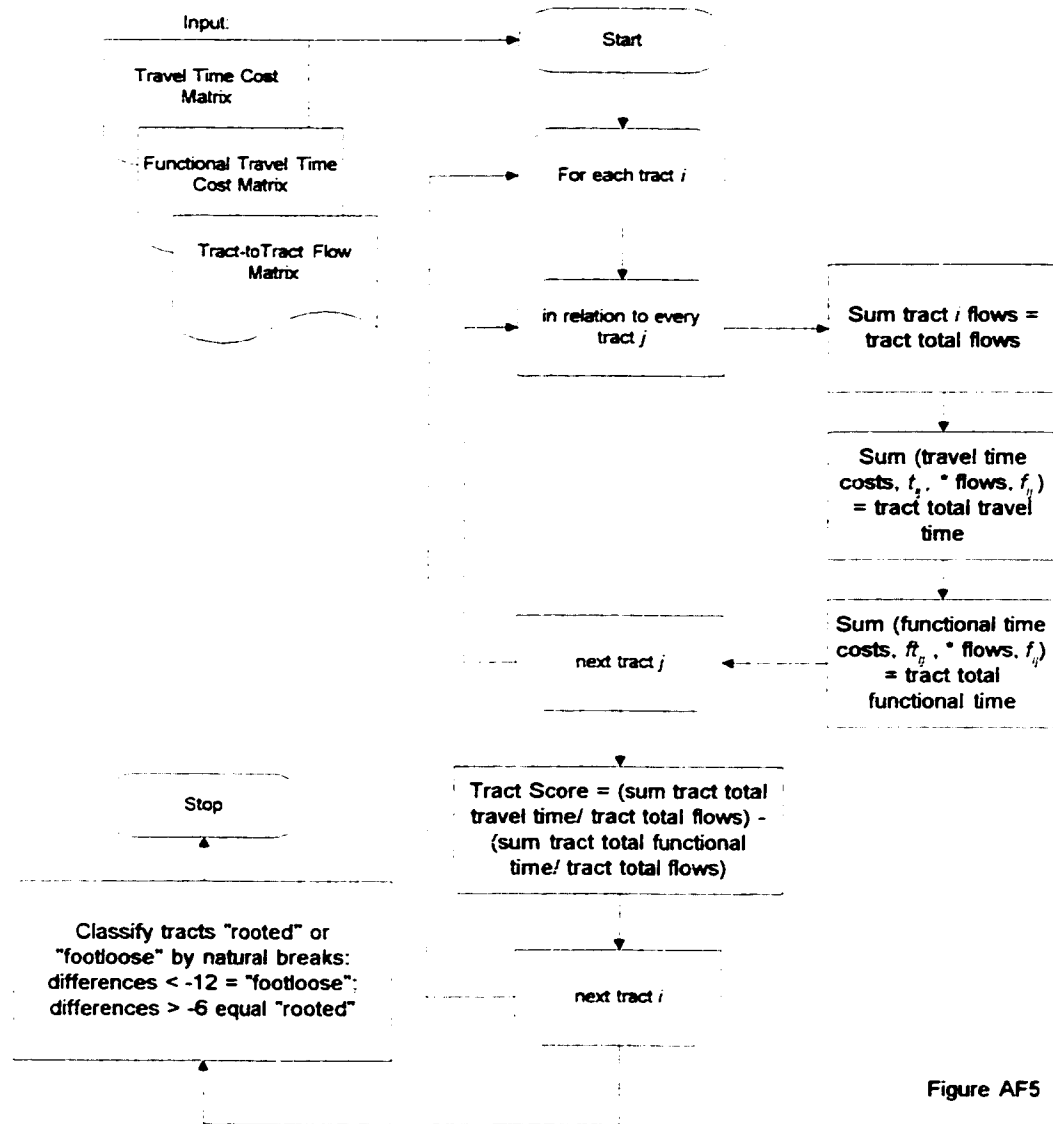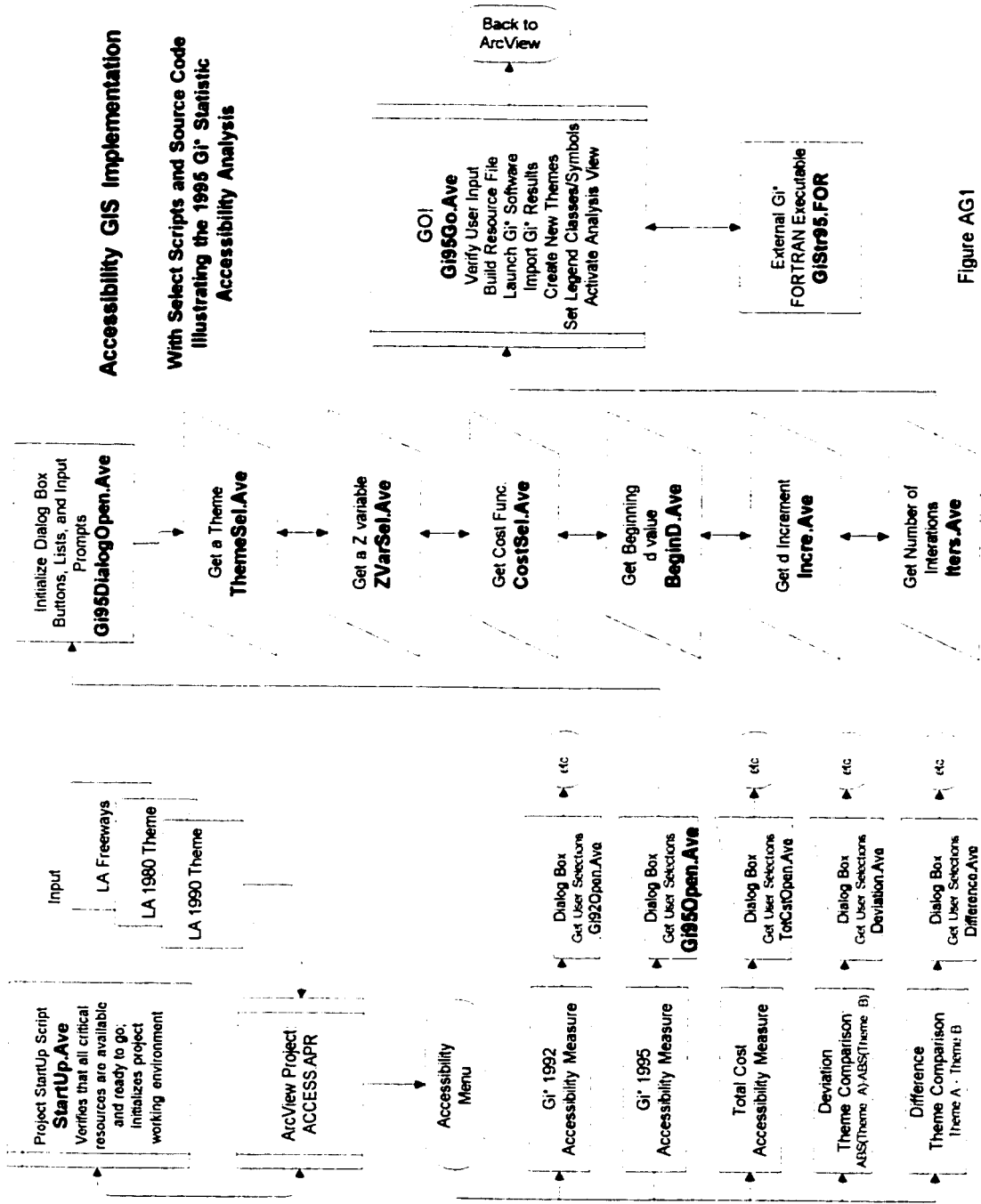**Incre.Ave**

Get Number of Iterations
Iters.Ave

Input
LA Freeways
LA 1980 Theme
LA 1990 Theme

Project StartUp Script
StartUp.Ave
Verifies that all critical resources are available and ready to go; Initializes project working environment

ArcView Project
ACCESS.APR

Accessibility Menu

Gi* 1992
Accessibility Measure

Dialog Box
Get User Selections
Gi92Open.Ave

etc

Gi* 1995
Accessibility Measure

Dialog Box
Get User Selections
Gi95Open.Ave

etc

Total Cost
Accessibility Measure

Dialog Box
Get User Selections
TotCstOpen.Ave

etc

Deviation
Theme Comparison
ABS(Theme A)-ABS(Theme B)

Dialog Box
Get User Selections
Deviation.Ave

etc

Difference
Theme Comparison
Theme A - Theme B

Dialog Box
Get User Selections
Difference.Ave

etc

227

```
'StartUp.Ave Script
'This script makes sure a View named "Analysis" exists with all
'appropriate themes and tables.  If anything is missing, it
'attemps to recreate it.
'
theProject = av.GetProject
theWorkDir = theProject.GetWorkDir
allDocs = theProject.GetDocs
rebuildView = true
for each d in allDocs
  if (d.Is(View)) then
    if (d.AsString = "Analysis") then
      rebuildView = false
      theView = d
      theWindow = theView.GetWin
      theWindow.Open
      break
    end
  end
end
'
'If the "Analysis" View does not exist, recreate it, otherwise just
'make sure it is open and ready to go.
if (rebuildView) then
  theView = View.Make
  theView.SetName("Analysis")
  theWindow = theView.GetWin
  theWindow.Open
end
'
'Now make sure all resource themes are in place.
sty80 = theView.FindTheme("LA 1980")
if (sty80 = nil) then
  theString = theWorkDir.AsString+"\T80STYA polygon"
  theSrcName = SrcName.Make(theString)
  if (theSrcName = nil) then
    msgBox.Error("Analysis View Missing 1980 Study Area Coverage","")
    exit
  end
  sty80 = Theme.Make(theSrcName)
  theView.AddTheme(sty80)
  sty80.SetName("LA 1980")
  theLegend = sty80.GetLegend
  theSymbol = theLegend.GetSymbols.Get(0)
  theSymbol.SetColor(color.getGreen)
end
'
sty90 = theView.FindTheme("LA 1990")
if (sty90 = nil) then
  theString = theWorkDir.AsString+"\T90STYA polygon"
  theSrcName = SrcName.Make(theString)
  if (theSrcName = nil) then
    msgBox.Error("Analysis View Missing 1990 Study Area Coverage","")
    exit
  end
  sty90 = Theme.Make(theSrcName)
  theView.AddTheme(sty90)
  sty90.SetName("LA 1990")
  theLegend = sty90.GetLegend
  theSymbol = theLegend.GetSymbols.Get(0)
  theSymbol.SetColor(color.getCyan)
end
```

```
freeways = theView.FindTheme("Freeways")
if (freeways = nil) then
  theString = theWorkDir.AsString+"\freeway.shp"
  theSrcName = SrcName.Make(theString)
  if (theSrcName = nil) then
    msgBox.Error("Analysis View Missing the Freeway Shapefile","")
    exit
  end
  freeways = Theme.Make(theSrcName)
  theView.AddTheme(freeways)
  freeways.SetName("Freeways")
  theLegend = freeways.GetLegend
  theSymbol = theLegend.GetSymbols.Get(0)
  theSymbol.SetColor(color.getBlack)
end
'
' Reset theme order in table of contents
'
theThemeList = theView.GetThemes
theThemeList.Shuffle(freeways,1)
theThemeList.Shuffle(sty90,2)
theThemeList.Shuffle(sty80,3)
freeways.SetVisible(false)
sty90.SetVisible(true)
sty80.SetVisible(false)
freeways.SetActive(false)
sty90.SetActive(false)
sty80.SetActive(false)
'
' Reset the View map extent
'
r = theView.ReturnExtent
if (r.IsEmpty) then
  return nil
elseif ( r.ReturnSize = (0@0) ) then
  theView.GetDisplay.PanTo(r.ReturnOrigin)
else
  theView.GetDisplay.SetExtent(r.Scale(1.1))
  av.GetProject.SetModified(true)
end
'
theView.InvalidateTOC(nil)
theView.GetDisplay.Invalidate(true)
```

'Gi95Open.Ave Script
```
'This script launches the Gi95 Dialog Box
av.FindDialog("Gi* 1995 Dialog").Open
```

```
'Gi95DialogOpen.Ave Script
'This script updates the themes list box and disables other dialog
prompts.
'It also initializes global variables.
'
self.FindByName("acc.lbx_Theme.Select").Empty
self.FindByName("acc.lbx_ZVar.Select").Empty
self.FindByName("acc.lbx_Cost.Select").Empty
self.FindByName("acc.txl_iter.Get").Empty
self.FindByName("acc.txl_incre.Get").Empty
self.FindByName("acc.txl_begin.Get").Empty
self.FindByName("acc.lbt_Gi95.GO").SetEnabled(false)
self.FindByName("acc.txl_iter.Get").SetEnabled(false)
self.FindByName("acc.txl_incre.Get").SetEnabled(false)
self.FindByName("acc.txl_begin.Get").SetEnabled(false)
self.FindByName("acc.lbt_Cancel").SetEnabled(true)
theThemeListBox.GoColumn(0)
theThemeList = {"LA 1990","LA 1980"}
theThemeListBox.DefineFromList(theThemeList)
'
'Initialize global variables:
_selectedTheme = "LA 1990"
_selectedZ      = "Jobs90"
_selectedCost   = "Euclidean Distance"
_selectedBegin  = 5
_selectedIncre  = 5
_selectedIter   = 1


'ThemeSelect.Ave
'This script stores the selected theme as a global variable, then based
'on the selection updates the Z variable list box.
'
theThemeListBox = self.GetDialog.FindByName("acc.lbx_Theme.Select")
_selectedTheme = theThemeListBox.GetCurrentValue
theThemeText = _selectedTheme
theZvarListBox = self.GetDialog.FindByName("acc.lbx_Zvar.Select")
'
'Present a list of Z variables from either the 1990 or 1980 tables.
'If the table is missing from the project, complain.
'
theProject = av.GetProject
theWorkDir = theProject.GetWorkDir
if (theThemeText = "LA 1990") then
  theTable = theProject.FindDoc("ZVars90")
else
  theTable = theProject.FindDoc("ZVars80")
end
if (theTable = nil) then
  msgBox.Error("Analysis View Missing Z Variables for 1990","")
  exit
end
theVTab  = theTable.GetVTab
allFields = theVTab.GetFields
fieldList = {}
for each f in allFields
  txt = f.AsString.UCase
  if ((txt <> "CT90") and (txt <> "CT80")) then
    fieldList.Add(f)
  end
end
theZvarListBox.DefineFromList(fieldList)
```

230

```
'ZvarSelect.Ave Script
'This script gets a Z variable to use in the accessibility
'analysis, and then fetches a list of cost files from the
'working directory.
'
theZvarListBox = self.GetDialog.FindByName("acc.lbx_Zvar.Select")
_selectedZ = theZvarListBox.GetCurrentValue
theCostListBox = self.GetDialog.FindByName("acc.lbx_Cost.Select")
costList = {}
theCostListBox.Empty
'
theProject = av.GetProject
theWorkDir = theProject.GetWorkDir
if (_selectedTheme = "LA 1990") then
  allCostFiles = theWorkDir.ReadFiles("*90.cst")
else
  allCostFiles = theWorkDir.ReadFiles("*80.cst")
end
costList = {"Euclidean Distance","Manhattan Distance"}
for each f in allCostFiles
  filnam = f.AsString.BasicTrim(theWorkDir.AsString,".cst")
  filnam = filnam.BasicProper("_")
  costList.Add(filnam)
end
theCostListBox.DefineFromList(costList)



'CostSelect.Ave
'This script gets the cost function to use in calculating accessibility,
'and enables the iteration prompts.
'
theCostListBox = self.GetDialog.FindByName("acc.lbx_Cost.Select")
_selectedCost = theCostListBox.GetCurrentValue
self.GetDialog.FindByName("acc.txl_begin.Get").SetEnabled(true)



'BeginD.Ave Script
'This script gets the beginning distance/time value for
'calculating the Gi* statistic.
'
textInput = self.GetText
aGoodNumber = textInput.IsNumber
if (aGoodNumber) then
  aNumber = textInput.AsNumber
  if ((aNumber < 0) or (aNumber > 50)) then
    msgBox.Error("Invalid Beginning Distance/Time Value","")
    self.empty
    exit
  end
  _selectedBegin = aNumber
  self.GetDialog.FindByName("acc.txl_incre.Get").SetEnabled(true)
  self.GetDialog.FindByName("acc.txl_incre.Get").Focus

else
  self.empty
end
```

```
'Incre.Ave Script
'This script gets the increment distance/time value for
'calculating the Gi* statistic.
'
textInput = self.GetText
aGoodNumber = textInput.IsNumber
if (aGoodNumber) then
  aNumber = textInput.AsNumber
  if ((aNumber < 0) or (aNumber > 40)) then
    msgBox.Error("Invalid Increment Distance/Time Value","")
    self.empty
    exit
  end
  _selectedIncre = aNumber
  self.GetDialog.FindByName("acc.txl_Iter.Get").SetEnabled(true)
  self.GetDialog.FindByName("acc.txl_Iter.Get").Focus
else
  self.empty
end
```

```
'Iters.Ave Script
'This script gets the total number of iterations to perform.
'
textInput = self.GetText
aGoodNumber = textInput.IsNumber
if (aGoodNumber) then
  aNumber = textInput.AsNumber
  if ((aNumber < 0) or (aNumber > 40)) then
    msgBox.Error("Invalid Increment Distance/Time Value","")
    self.empty
    exit
  end
  _selectedIter = aNumber
  self.GetDialog.FindByName("acc.lbt_Gi95.GO").SetEnabled(true)
else
  self.empty
end
```

```
'Gi95Go.Ave Script
'This script verifies user input, builds a resource file bases on user
'selections, runs the 1995 Gi* statistic external FORTRAN executable,
'imports the Gi* statistic results, creates a new theme for each
'iteration, sets appropriate legend classes/symbols, and activates the
' "Analysis" view so the user can explore results, create reports, produce
'maps, etc...
'
self.GetDialog.Close

' Verify user selections.
'
ch = msgBox.LongYesNo(" "+NL+
             "Selected Theme:"+tab+tab+tab+_selectedTheme.AsString+NL+
             "Selected Z Variable:"+tab+tab+_selectedZ.AsString+NL+
             "Selected Cost Function:"+tab+tab+_selectedCost.AsString+NL+
             "Beginning Increment:"+tab+tab+_selectedBegin.AsString+NL+
             "Subsequent Increments:"+tab+_selectedIncre.AsString+NL+
             "Number of Iterations:"+tab+tab+_selectedIter.AsString+NL,
             "Your Selections:",true)
```

```
if (ch = true) then
  inputOK = true
elseif (ch = false) then
  av.FindDialog("Gi* 1995 Dialog").Open
  exit
elseif (ch = nil) then
  exit
end
'
'Initialize working variables.
theProject = av.Getproject
theView = av.GetProject.FindDoc("Analysis")
theTheme = theView.FindTheme(_selectedTheme)
themeList = theView.GetThemes
theFirstTheme = themeList.Get(0)
theZ      = _selectedZ
if (_selectedCost.UCase.Contains("EUCLIDEAN")) then
  theCost = "E"
elseif (_selectedCost.UCase.Contains("MANHATTAN")) then
  theCost = "M"
else
  theCost = _selectedCost+".cst"
end
dBegin    = _selectedBegin
dIncre    = _selectedIncre
nIters    = _selectedIter
aCostName = _selectedCost.UCase
if (aCostName.Contains("DISTANCE")) then
  dstr = "d="
elseif (aCostName.Contains("TIME")) then
  dstr = "t="
else
  dstr = "r="
end
if (aCostName.Contains("FUNCTION")) then
  dstr = "f"+dstr
end
'
' Create a resource file with user selections.
'
theResourceFN = "gistr95.rsr".AsFileName
theRsrFile = LineFile.Make(theResourceFN,#FILE_PERM_WRITE)
if (theRsrFile = nil) then
  msgBox.Error("Cannot open resource file:"++theResourceFN.GetFullName,
               "Exiting")
  exit
end
if (_selectedTheme = "LA 1990") then
  theRsrFile.WriteElt("areas.inp")
  theRsrFile.WriteElt("xydat.inp")
  theJoinField = "CT90"
else
  theRsrFile.WriteElt("areas80.inp")
  theRsrFile.WriteElt("xydat80.inp")
  theJoinField = "CT80"
end
theRsrFile.WriteElt(theZ.AsString+".asc")
theRsrFile.WriteElt(theCost.AsString)
theRsrFile.WriteElt(dBegin.SetFormat("d.dd").AsString)
theRsrFile.WriteElt(dIncre.SetFormat("d.dd").AsString)
theRsrFile.WriteElt(nIters.SetFormat("dd").AsString)
theRsrFile.Close
```

233

```
' Run GiStr95
'
av.ShowMsg("Calculating Gi*...")
av.SetWorkingStatus
System.ExecuteSynchronous("gistr95.bat")
av.ClearWorkingStatus
theFN = "gistr95.out".AsFilename
if (File.Exists(theFN).Not) then
  msgBox.Error("Unable to perform analysis...","Exiting")
  av.ClearWorkingStatus
  av.ClearMsg
  exit
end

' Import the GiStr95 output.
'
av.ShowMsg("Importing Gi* accessibility scores...")
av.SetWorkingStatus
'
'Build the dbase table structure.
'
theTableFN = "GiStr95.dbf".AsFileName
theVTab   = VTab.MakeNew(theTableFN,dbase)
flist = {}
f1 = Field.Make(theJoinField,#FIELD_CHAR,9,0)
flist.Add(f1)
aStep = dBegin - dIncre
for each i in 1 .. nIters
  aStep = aStep + dIncre
  aLabel = "Gi95D"+aStep.SetFormat("dd").AsString
  f = Field.Make(aLabel,#FIELD_FLOAT,12,4)
  flist.Add(f)
end
theVTab.AddFields(flist)
'
'Populate the table with records from the external results file.
'
theImportFile = LineFile.Make(theFN,#FILE_PERM_READ)
if (theImportFile = nil) then
  MsgBox.Error("Cannot open"++theFN.AsString,"Exiting...")
  av.ClearWorkingStatus
  av.ClearMsg
  exit
end
aRecord = {}
while (theImportFile.IsAtEnd.Not)
  aRecord = theImportFile.ReadElt.AsTokens(" ,")
  rec = theVTab.AddRecord
  for each f in 0 .. nIters
    theVTab.SetValue(flist.Get(f),rec,aRecord.Get(f))
  end
end
theImportFile.Close
av.ClearWorkingStatus
theFTab = theTheme.GetFTab
toField = theFTab.FindField(theJoinField)
frField = theVTab.FindField(theJoinField)
'
```

```
' Join the dbase table to the feature theme attribute table
'
theVTab.CreateIndex(frField)
theFTab.CreateIndex(toField)
theFTab.Join(toField,theVTab,frField)
'
' Display new themes
'
av.ShowMsg("Adding new themes...")
av.SetWorkingStatus
themeList = theView.GetThemes
for each t in themeList
  t.SetActive(False)
  t.SetVisible(False)
end
theTheme.SetActive(True)
aStep = dBegin + ((nIters-1) * dIncre)
for each i in nIters .. 1 by -1
  theView.CopyThemes
  theView.Paste
  theTheme.SetActive(False)
  themeList = theView.GetThemes
  theNewTheme = themeList.Get(0)
  theNewTheme.SetActive(True)
  theNewTheme.SetVisible(False)
'
' Update the legend.
  theLegend = theNewTheme.GetLegend
  theLegend.SetLegendType(#LEGEND_TYPE_COLOR)
  theLegend.Natural(theTheme,flist.Get(i).AsString,5)
  aLegendFile = "gi.avl".AsFileName
  theLegend.Load(aLegendFile,#LEGEND_LOADTYPE_CLASSESANDSYMBOLS)
  theNewTheme.SetName("Gi*1995"++dstr.AsString+aStep.AsString++
                      _selectedTheme.AsString)
  aStep = aStep - dIncre
  theNewTheme.UpdateLegend
  theNewTheme.SetActive(False)
  theTheme.SetActive(True)
end
av.ClearMsg
av.ClearWorkingStatus
'
'Reset theme order
'
themeList.Shuffle(theFirstTheme,0)
theNewTheme.SetVisible(True)
theNewTheme.SetActive(True)
theFTab.UnJoinAll
theTheme.SetActive(False)
theView.InvalidateTOC(nil)
theView.GetDisplay.Invalidate(True)
theView.GetWin.Activate
```

235

The G$_i^*$ statistic (1992 and 1995), total cost accessibility indicator, and the difference and deviation utilities are external FORTRAN executables. The source code for the software to perform the 1995 G$_i^*$ statistic is listed below:

```
PROGRAM GISTAR95
C
C  This program performs the Getis/Ord Gi* 1995 statistic.  Input
C  filenames are obtained from a resource file: GISTAR95.RSR.
C  NOTE: *** This program assumes input units are UTM meters, and
C             reporting units are miles, if Euclidean distance or
C             Manhattan distance travel costs are selected by user.
C
       PARAMETER (MAXPTS=2400, MAXITR=25)
       CHARACTER*128 RSRCF,COSTF,XYFILE,ZFILE,AREAF,OUTF
       DOUBLE PRECISION ZSUM,ZS,ZSQ
       DIMENSION ID(MAXPTS),X(MAXPTS),Y(MAXPTS),Z(MAXPTS),
      1 ACESS(MAXPTS,MAXITR),CMATRX(MAXPTS,MAXPTS),
      2 AREA(MAXPTS)
       DATA INPT,IOUT/7,8/, MMILE /1609.0/,PI /3.141592654/
C
       OUTF =  'GISTR95.OUT'
C
C  Open resource file and read filenames.
C
       RSRCF = 'GISTR95.RSR'
       CALL OPENFL(INPT,RSRCF,'OLD')
C
C  Get input filenames and calculation parameters.
C
       READ(INPT,'(A)') AREAF
       READ(INPT,'(A)') XYFILE
       READ(INPT,'(A)') ZFILE
       READ(INPT,'(A)') COSTF
       READ(INPT,*) BEG
       READ(INPT,*) RADI
       READ(INPT,*) ITERS
       READ(INPT,*) BETA
       CLOSE (INPT)
C
C  Read input files: X,Y,Z and areas.
C
       CALL OPENFL(INPT,AREAF,'OLD')
       DO 2 I = 1, MAXPTS
          READ(INPT,*,END=3) ID(I),AREA(I)
     2 CONTINUE
       STOP '***too many points'
     3 CLOSE(INPT)
       NOBS = I - 1
       OBS  = NOBS
       CALL OPENFL(INPT,XYFILE,'OLD')
       DO 5 I = 1, NOBS
          READ(INPT,*) IID,X(I),Y(I)
          IF (IID.NE.ID(I)) STOP '***Input Files not sorted.'
     5 CONTINUE
       CLOSE(INPT)
       CALL OPENFL(INPT,ZFILE,'OLD')
       DO 10 I = 1, NOBS
          READ(INPT,*) IID,Z(I)
          IF (IID.NE.ID(I)) STOP '***Input files not sorted.'
    10 CONTINUE
       CLOSE(INPT)
```

```fortran
C       If costs come from a specified matrix, read matrix (binary format).
        JCOST = 3
        IF (COSTF .EQ. 'E') JCOST = 1
        IF (COSTF .EQ. 'M') JCOST = 2
        IF (JCOST .LT. 3) GO TO 30
        CALL OPENFL(INPT,COSTF,'U_OLD')
        READ(INPT) IVAL
        IF (IVAL .NE. NOBS) STOP 'Mismatch: NOBS, IVAL'
        DO 25 II = 1, IVAL
           READ(INPT,END=28,ERR=28)(CMATRX(II,JJ),JJ=1,IVAL)
     25 CONTINUE
     28 CLOSE(INPT)
C
C***PROCESS
C
C  Gi* (1995) statistic:
     30 STEP = BEG - RADI
        ICNT = 0
C
    100 STEP = STEP + RADI
        ICNT = ICNT + 1
C
        DO 150 I = 1, NOBS
           ZSUM = 0.0
           ZSQ = 0.0
           ZS = 0.0
           IWT = 0
C
           DO 130 J = 1, NOBS
              ZSUM = ZSUM + Z(J)
              ZSQ = ZSQ + Z(J)*Z(J)
C -           User Specified Cost Matrix
              IF (JCOST.EQ.3) THEN
                 COST = CMATRX(I,J)
C -           Euclidean Distance:
              ELSE IF (JCOST.EQ.1) THEN
                 IF (I.EQ.J) THEN
                    COST = (0.5*((AREA(I)/PI)**0.5))/MMILE
                 ELSE
                    XDIST = X(I) - X(J)
                    YDIST = Y(I) - Y(J)
                    COST = SQRT(ABS(XDIST*XDIST+YDIST*YDIST))/MMILE
                 END IF
C -           Manhattan Distance:
              ELSE
                 IF (I.EQ.J) THEN
                    COST = (0.5*((AREA(I)/PI)**0.5))/MMILE
                 ELSE
                    XDIST = X(I) - X(J)
                    YDIST = Y(I) - Y(J)
                    COST = ABS(XDIST+YDIST)/MMILE
                 END IF
              ENDIF
              IF (COST.LE.STEP) THEN
                 ZS = ZS + Z(J)
                 IWT = IWT + 1
              ENDIF
    130    CONTINUE
C
    140    X1 = ZSUM/OBS
           X2 = ZSQ/OBS - X1*X1
           WT = IWT
```
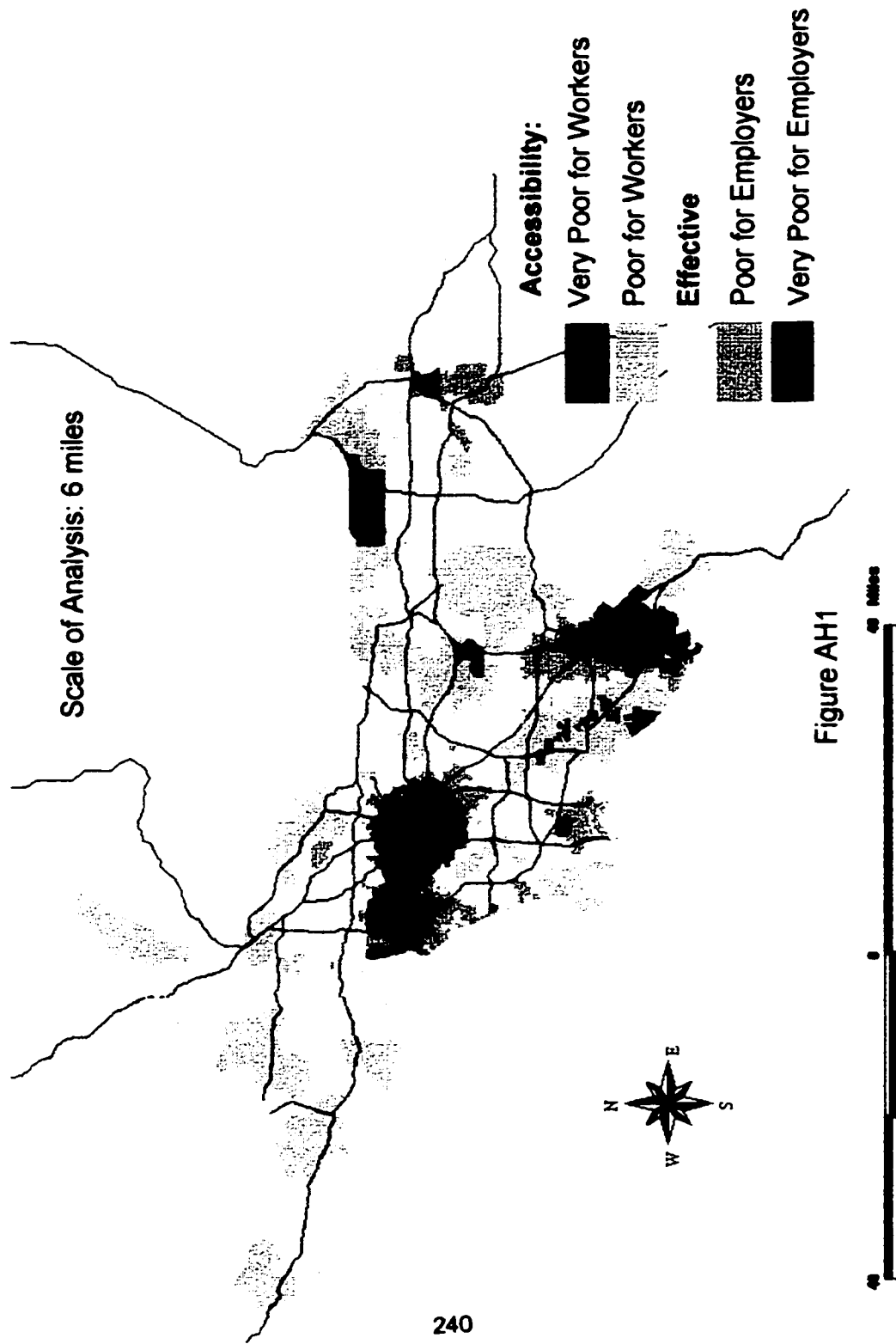
```fortran
C          Check extreme case of no neighbors at all, to avoid zero divide.
           IF (IWT.EQ.0) THEN
             ACESS(I,ICNT) = -9999.0
             GO TO 150
           END IF
C
C          Calculate Gi* value.
           ACESS(I,ICNT) = (ZS-WT*X1)/SQRT(WT*(OBS-WT)*X2/(OBS-1.0))
C
  150 CONTINUE
C
C  Another iteration?
      IF (ICNT.LT.ITERS) GO TO 100
C
C***WRAP:  Output results.
C
C  Write output.
C
      CALL OPENFL(IOUT,OUTF,'NEW')
      DO 912 I = 1, NOBS
        WRITE(IOUT,'(1X,I9.9,100(A,F12.4))')
     +                              ID(I),(',',ACESS(I,J),J=1,ITERS)
  912 CONTINUE
      CLOSE(IOUT)
C
      STOP ' '
      END
```
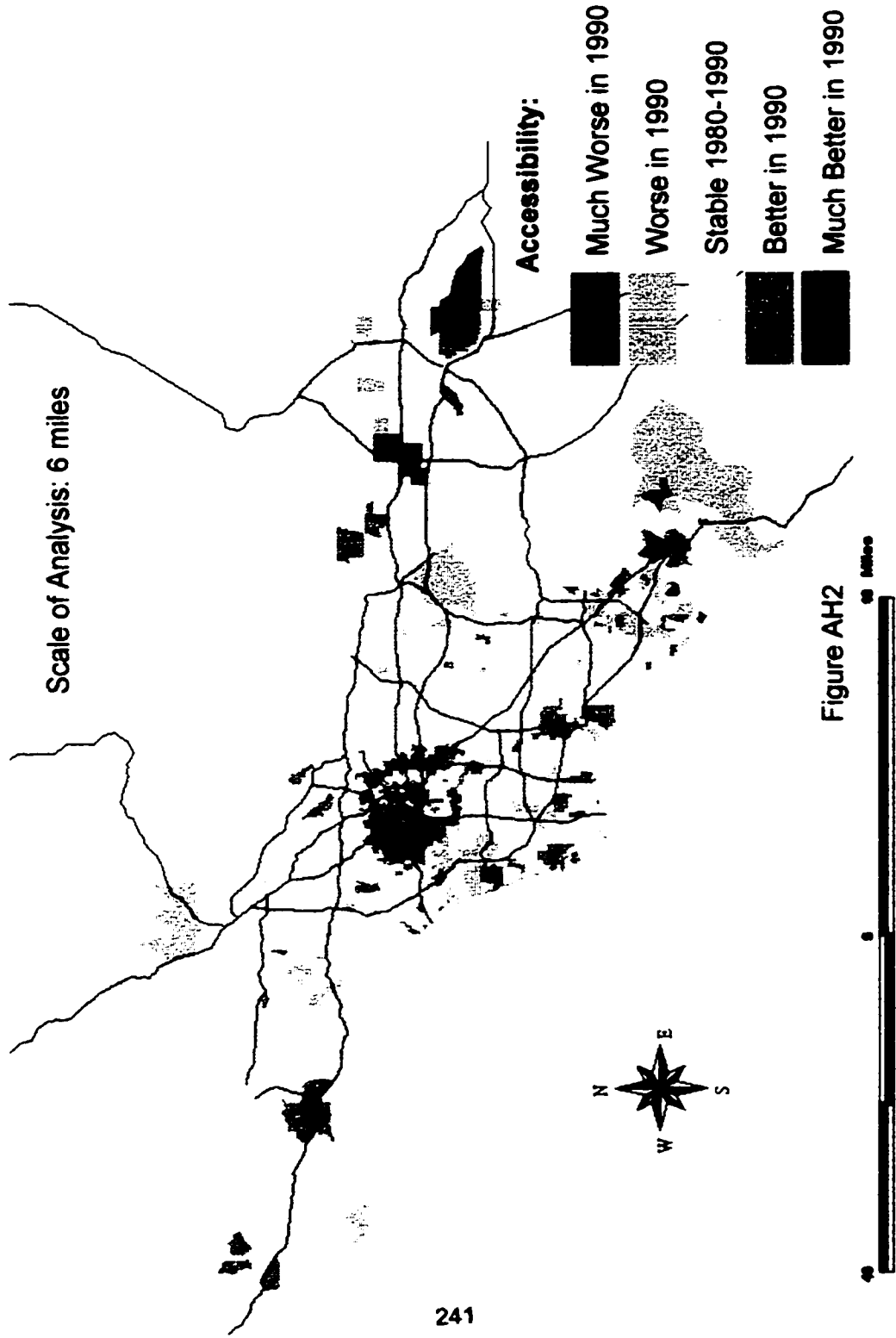
Appendix H

Additional Figures

Structural Accessibility, 1980: Technical, Sales, and Clerical Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH1

240

Change in Accessibility, 1980-1990: Technical, Sales, and Clerical Occupations

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Figure AH2

Structural Accessibility, 1990: Technical, Sales, and Clerical Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH3

242
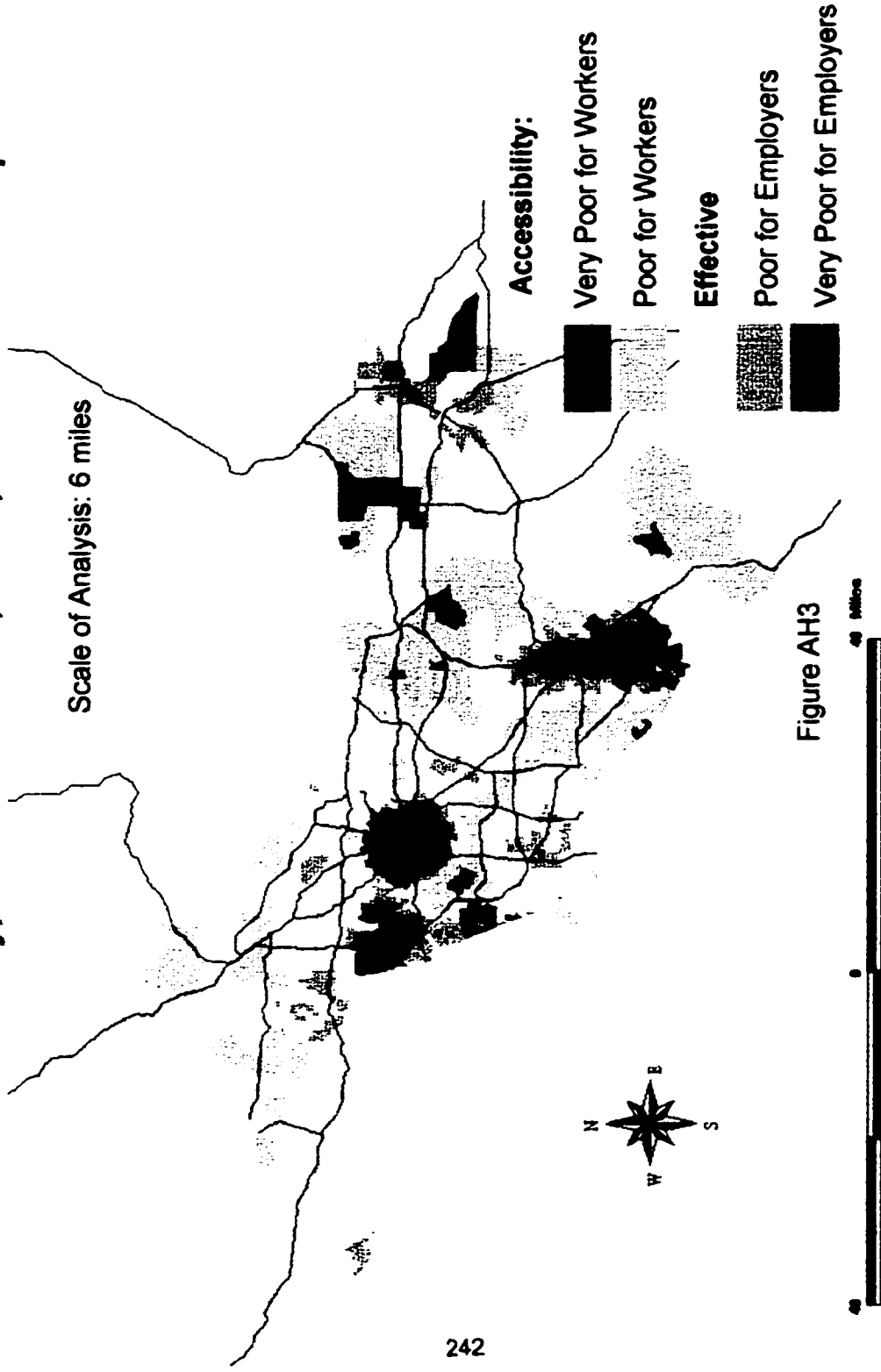
Structural Accessibility, 1980: Service Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH4

243
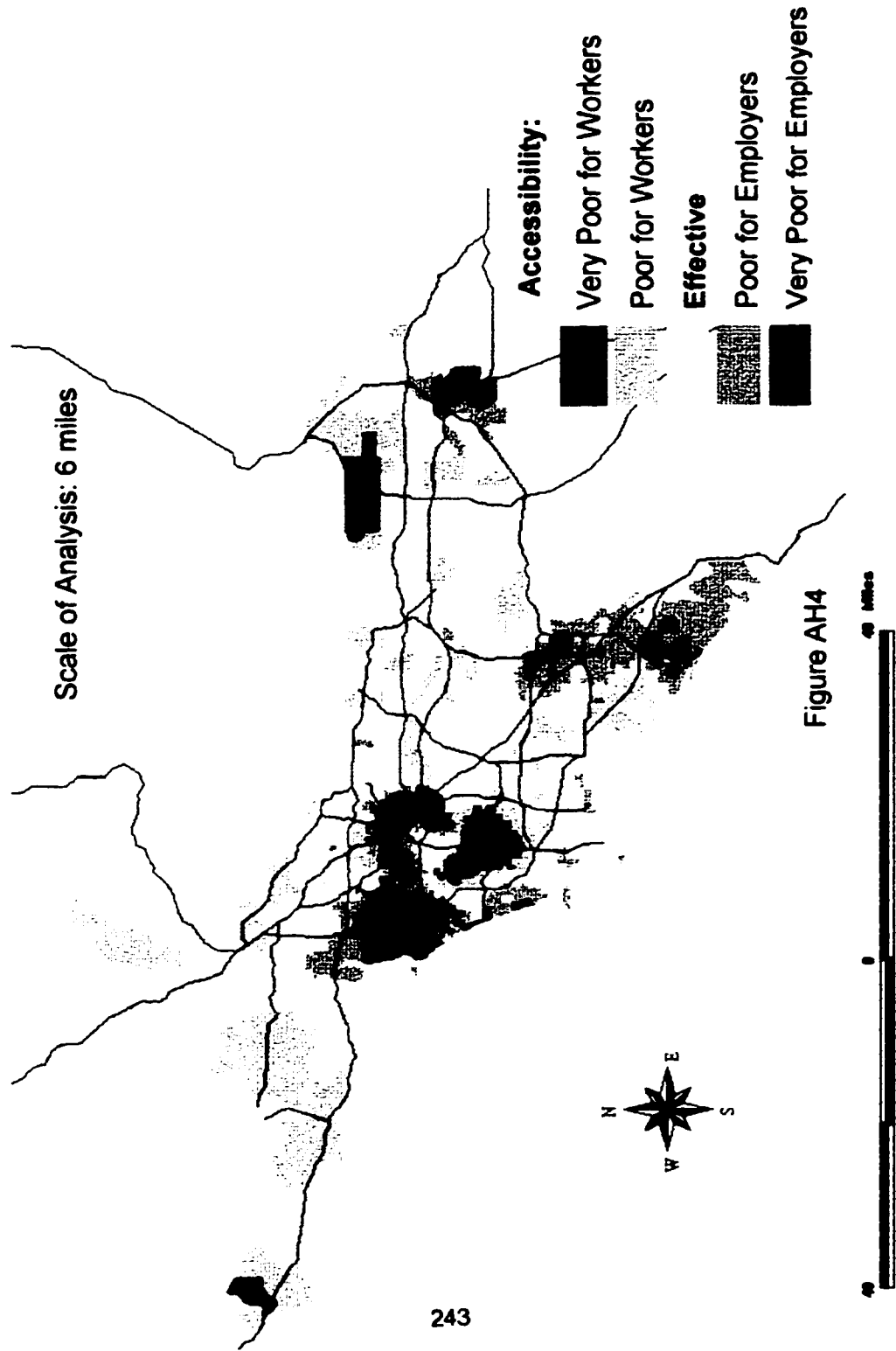
Change in Accessibility, 1980-1990: Service Occupations

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Figure AH5

244
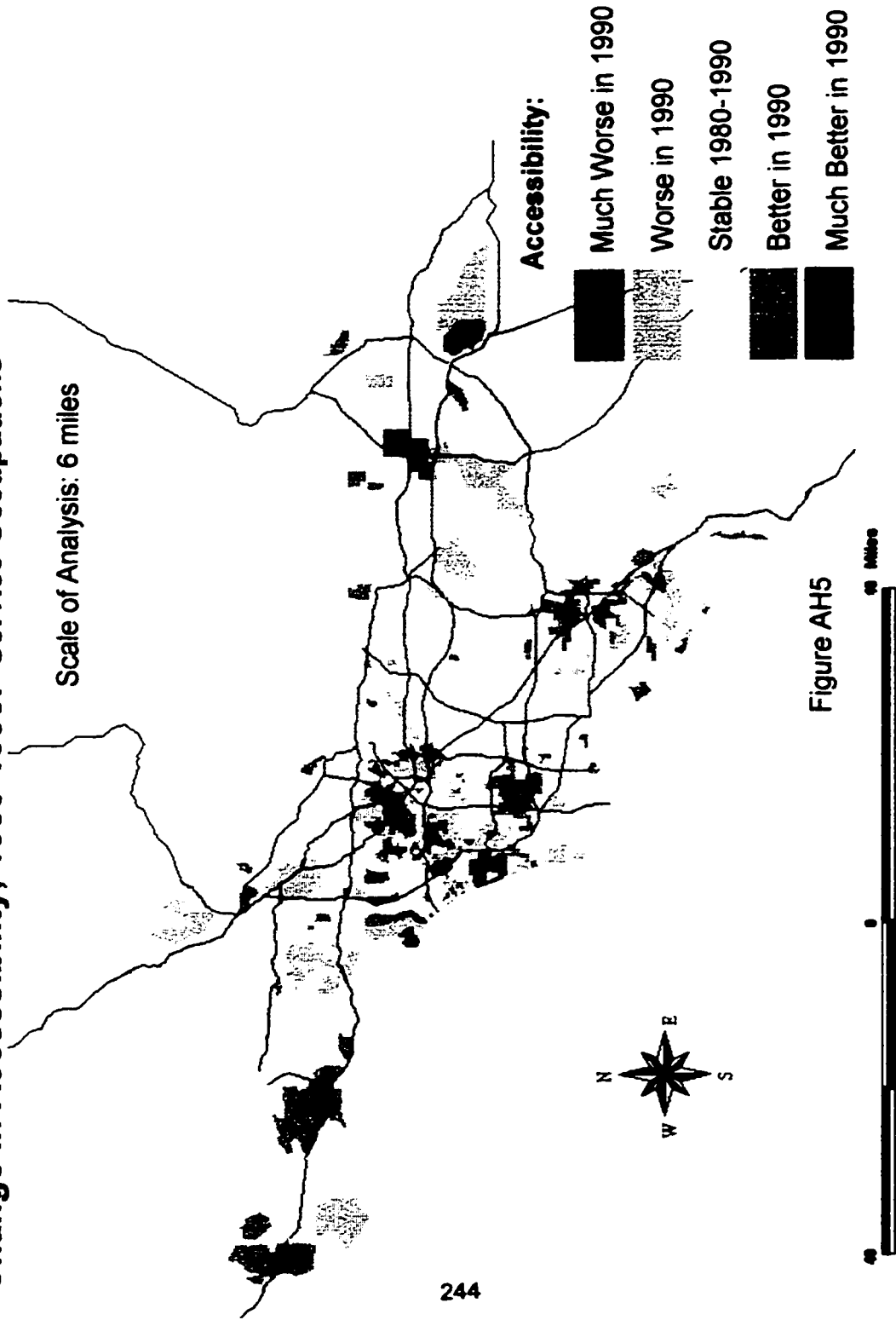
Structural Accessibility, 1990: Service Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH6

N E S W

40 Miles

245
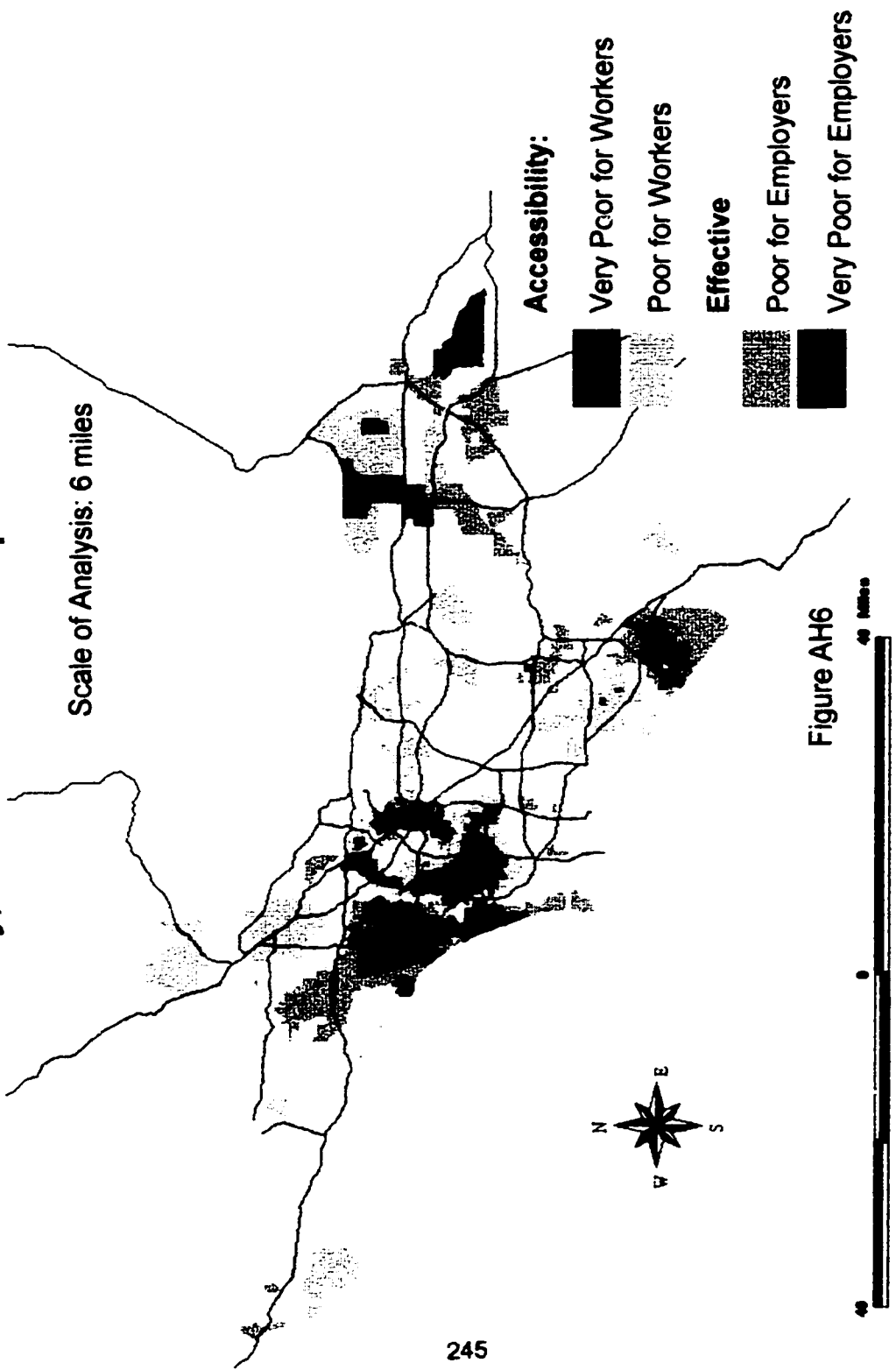
Structural Accessibility, 1980: Agricultural, Forestry, Fishing Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH7

246
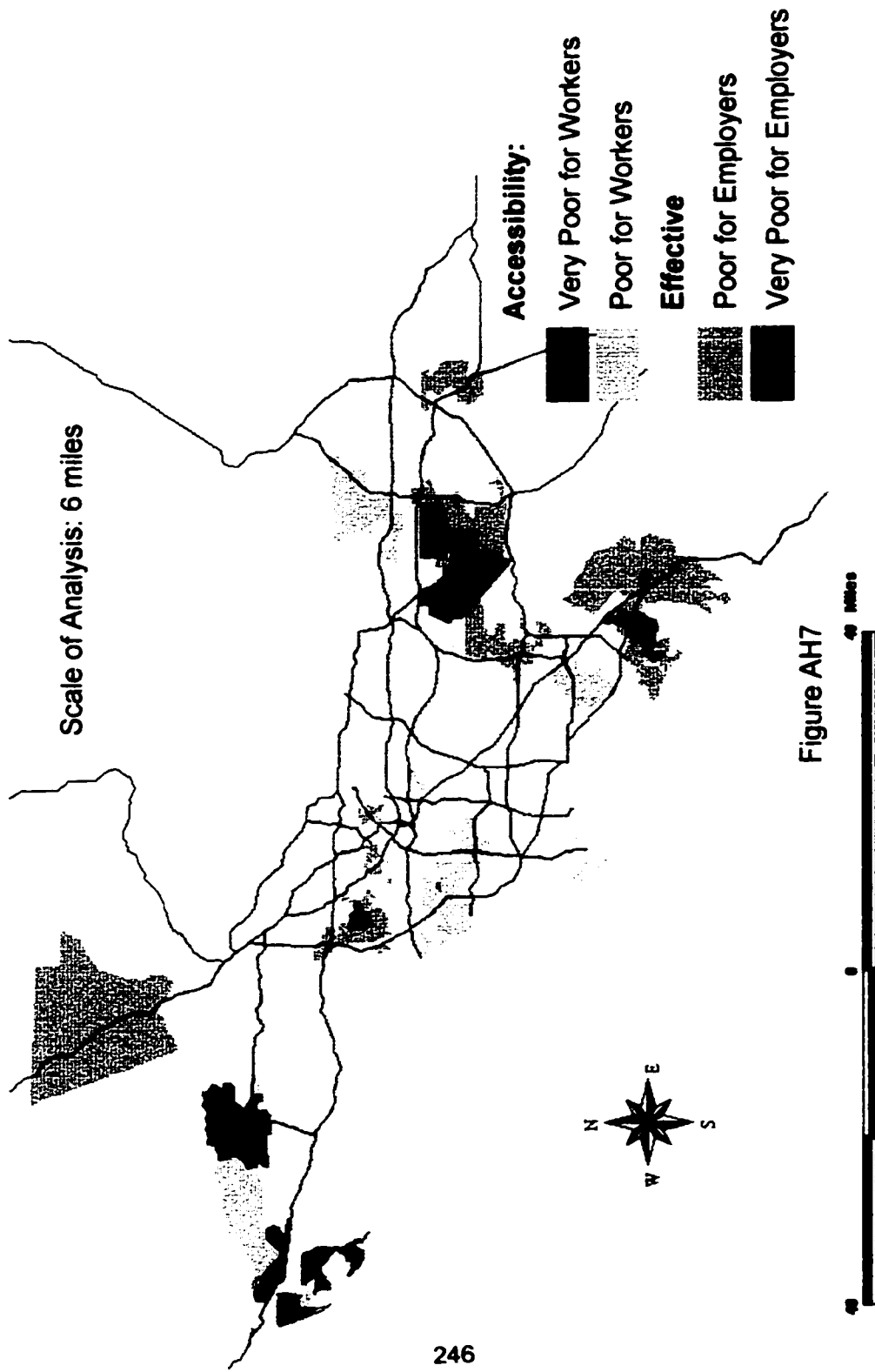
Change in Accessibility, 1980-1990: Agricultural, Forestry, Fishing Occupations

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Figure AH8

247
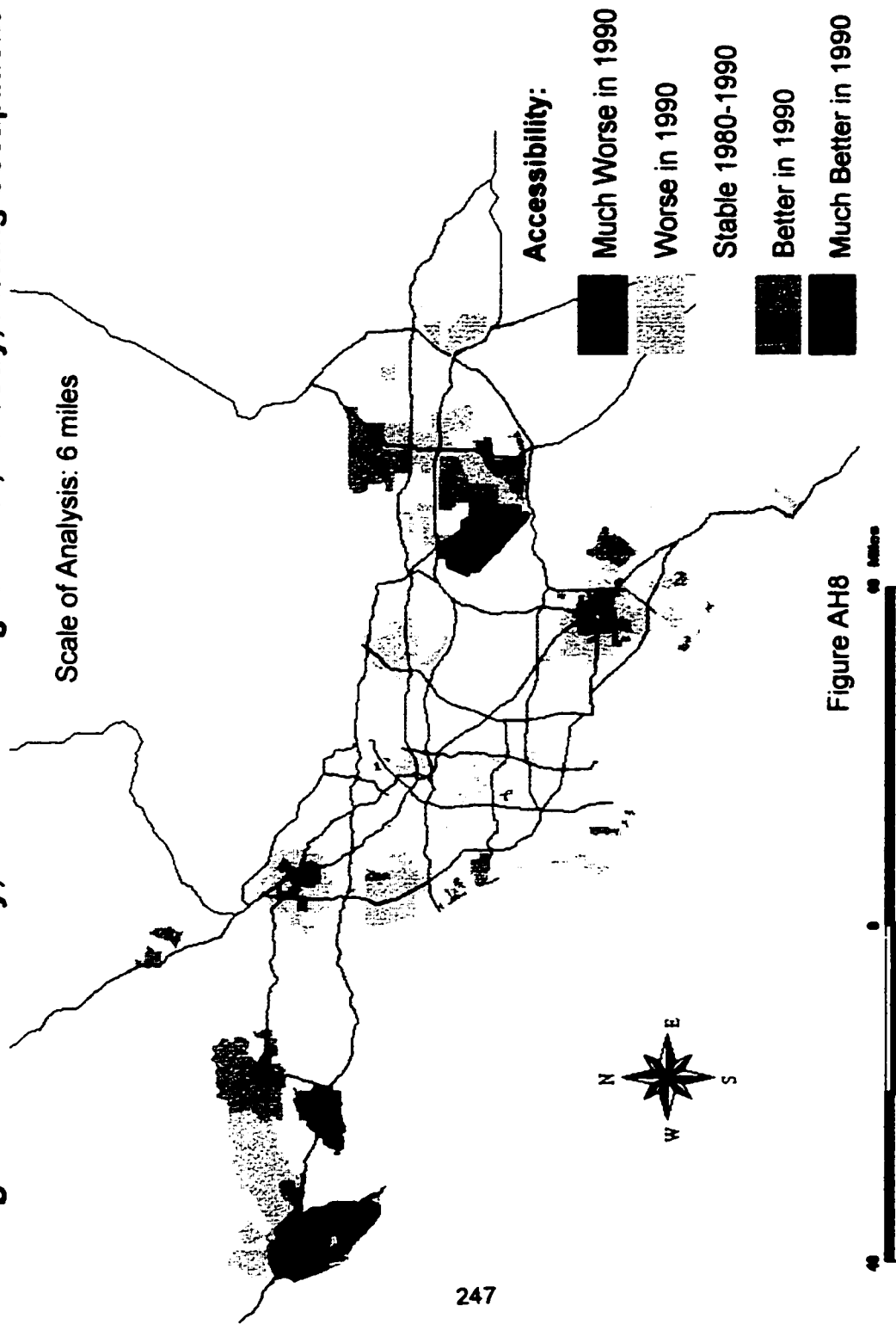
Structural Accessibility, 1990: Agricultural, Forestry, Fishing Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH9

248
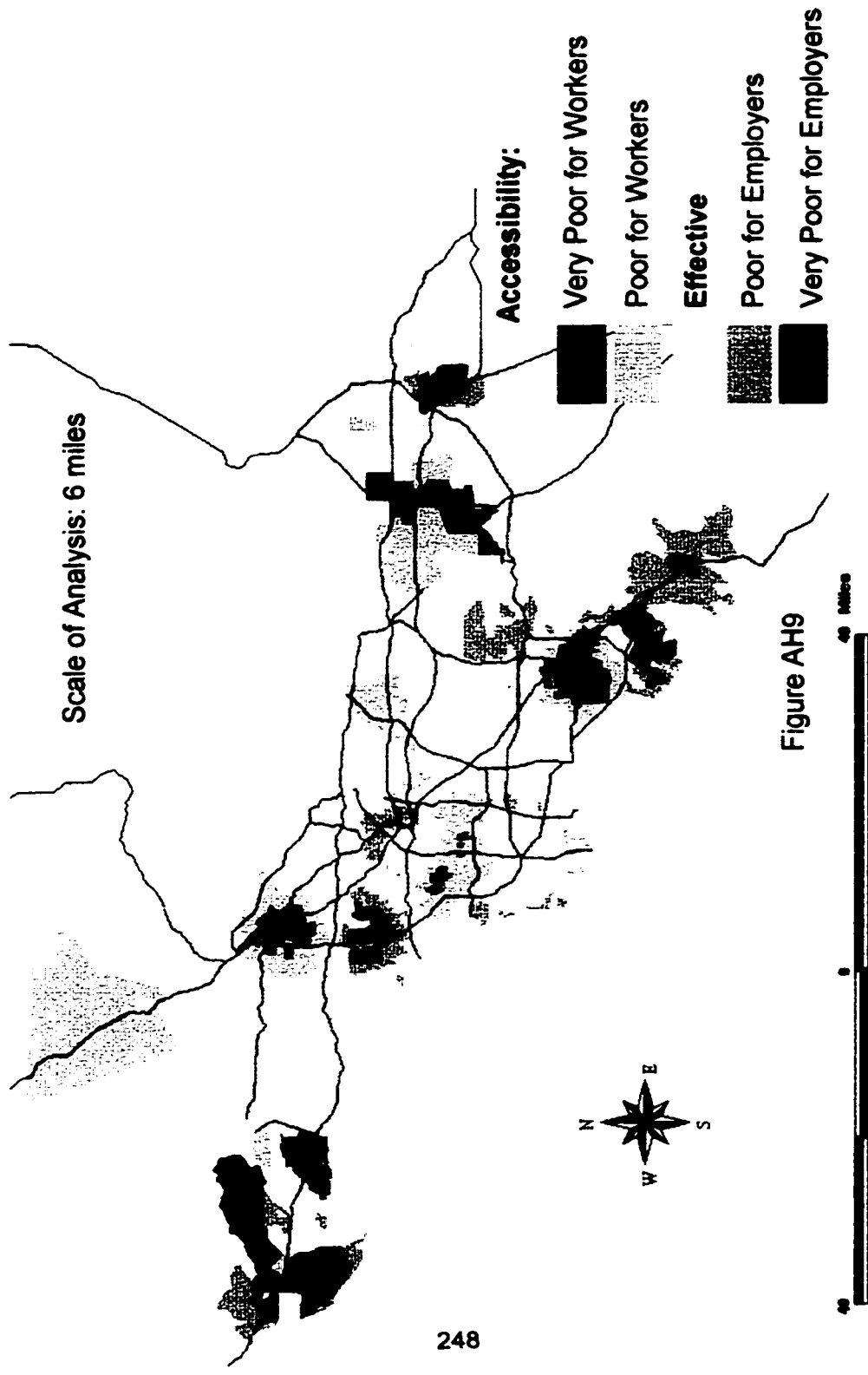
Structural Accessibility, 1980: High-Skill Blue-Collar Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH10

249
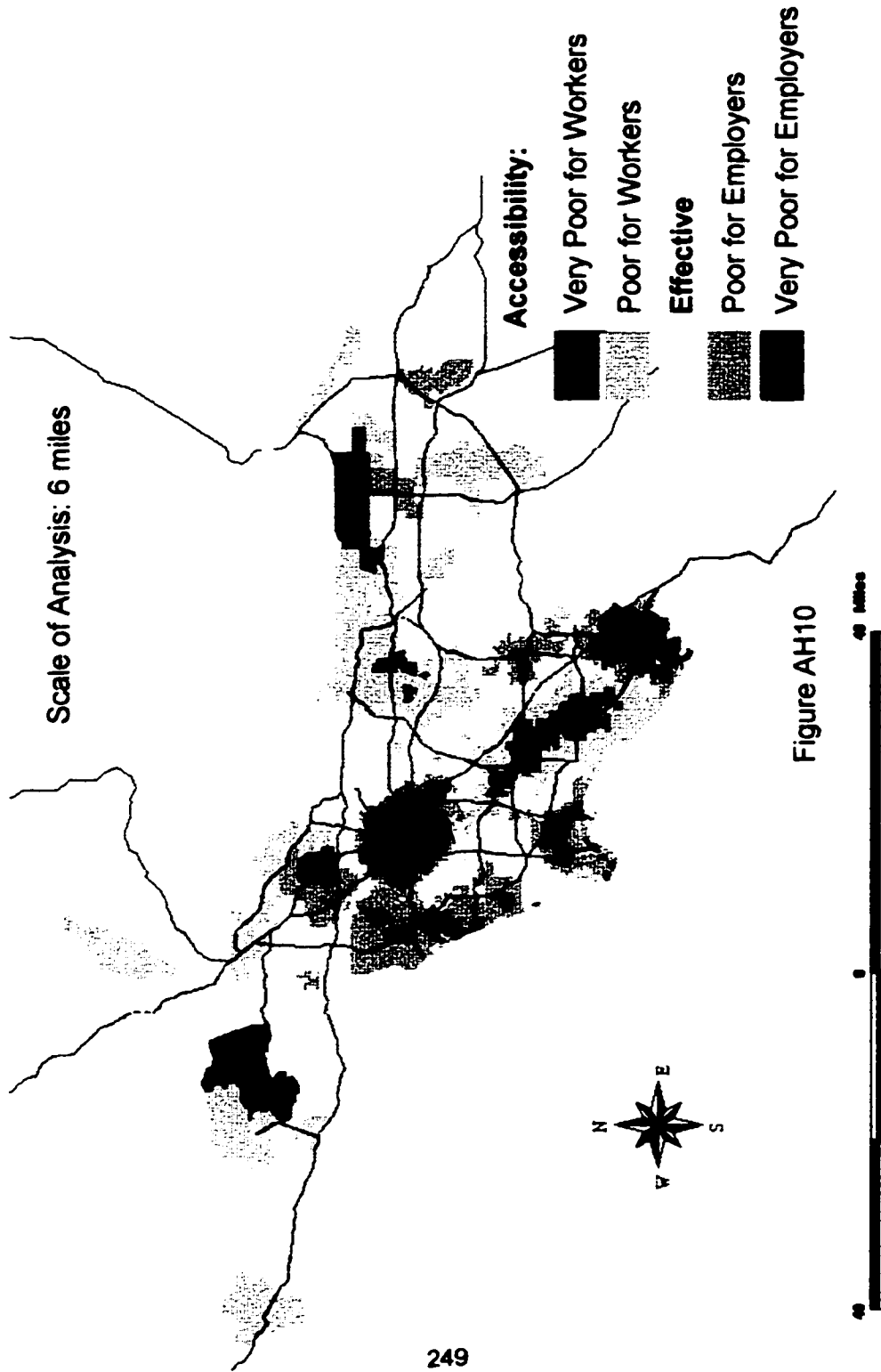
Change in Accessibility, 1980-1990: High-Skill Blue-Collar Occupations

Scale of Analysis: 6 miles

Accessibility:

Much Worse in 1990

Worse in 1990

Stable 1980-1990

Better in 1990

Much Better in 1990

Figure AH11

250
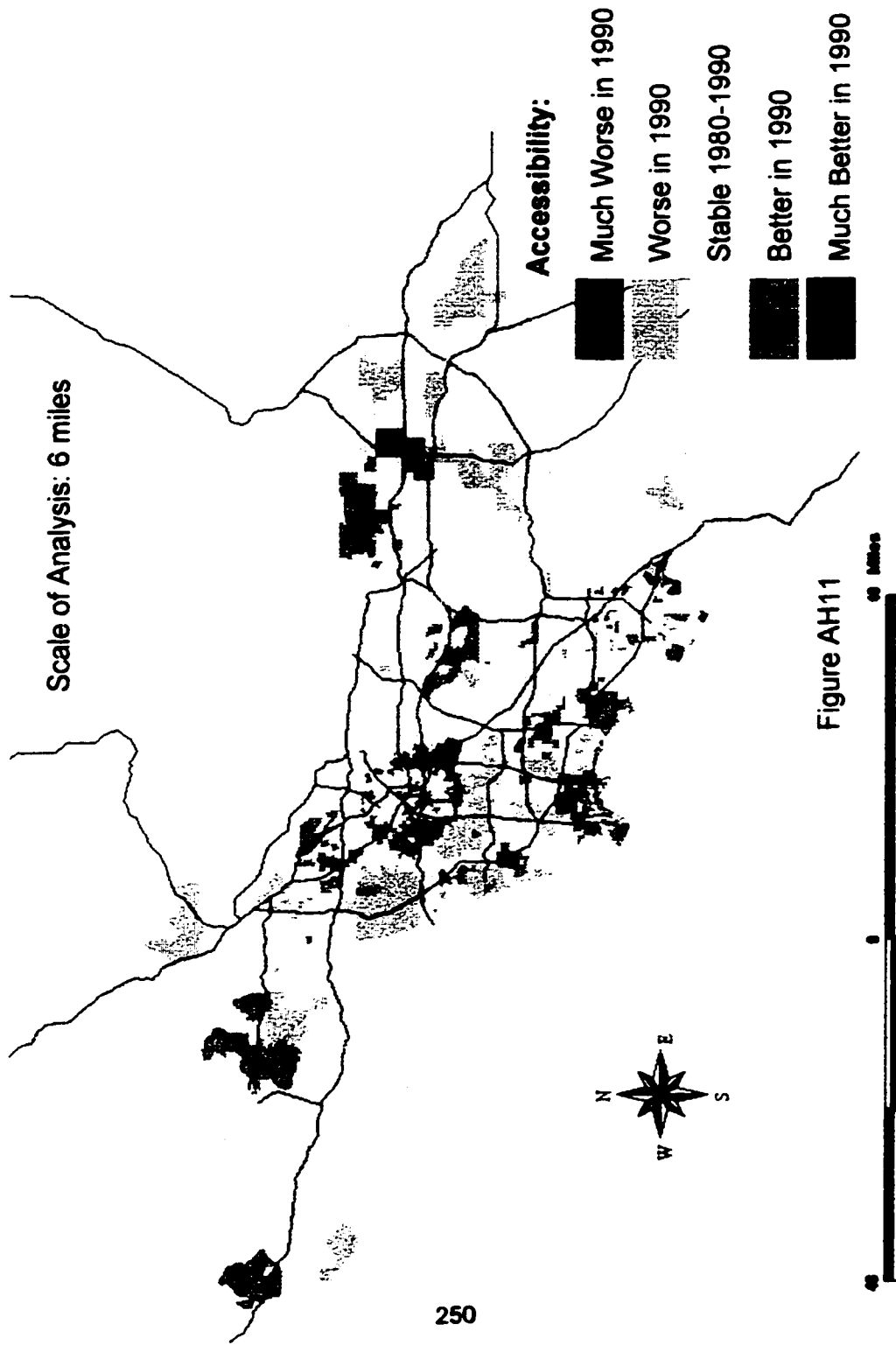
Structural Accessibility, 1990: High-Skill Blue-Collar Occupations

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH12

251

Structural Accessibility, 1990

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH13

40 Miles
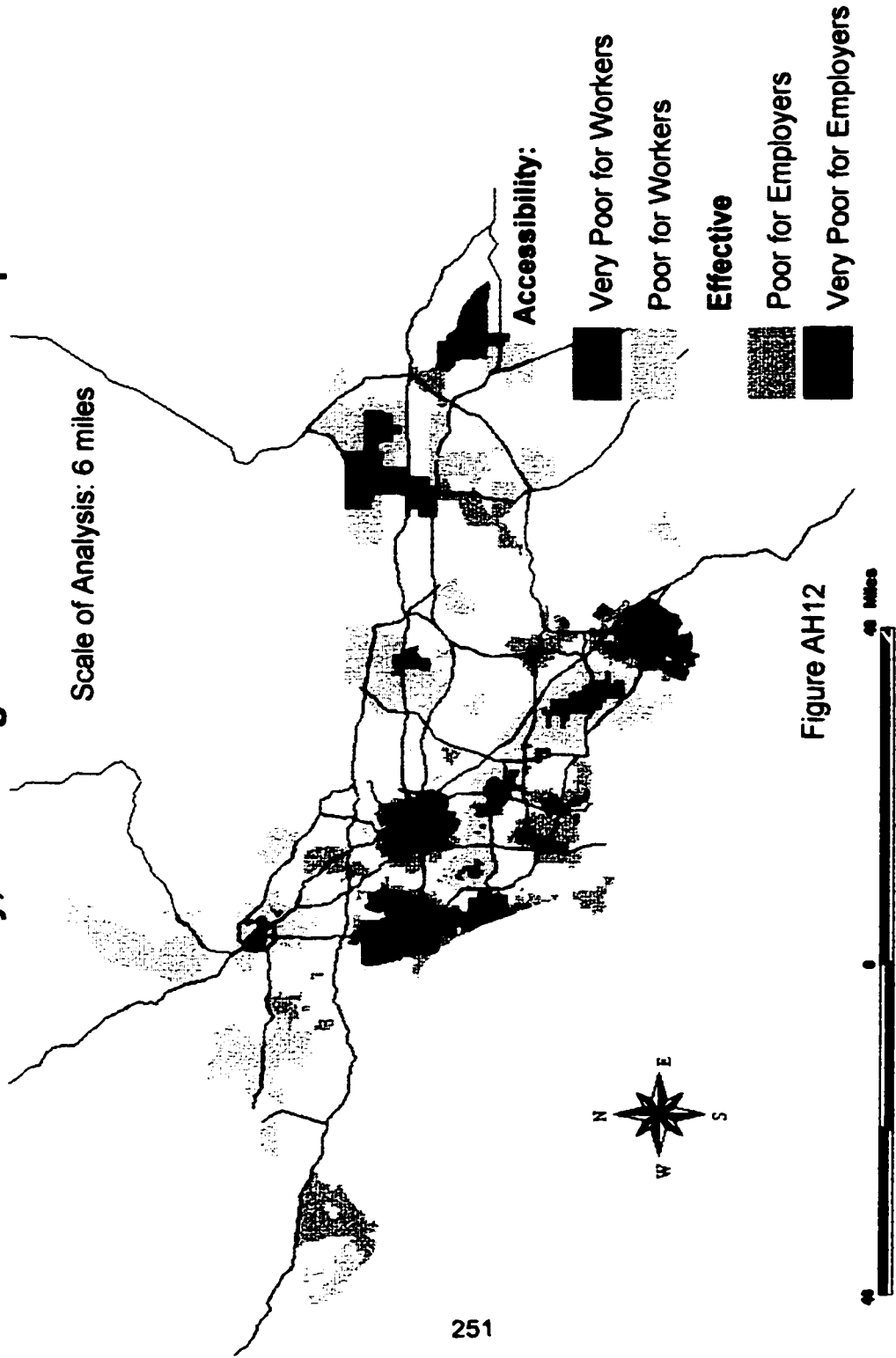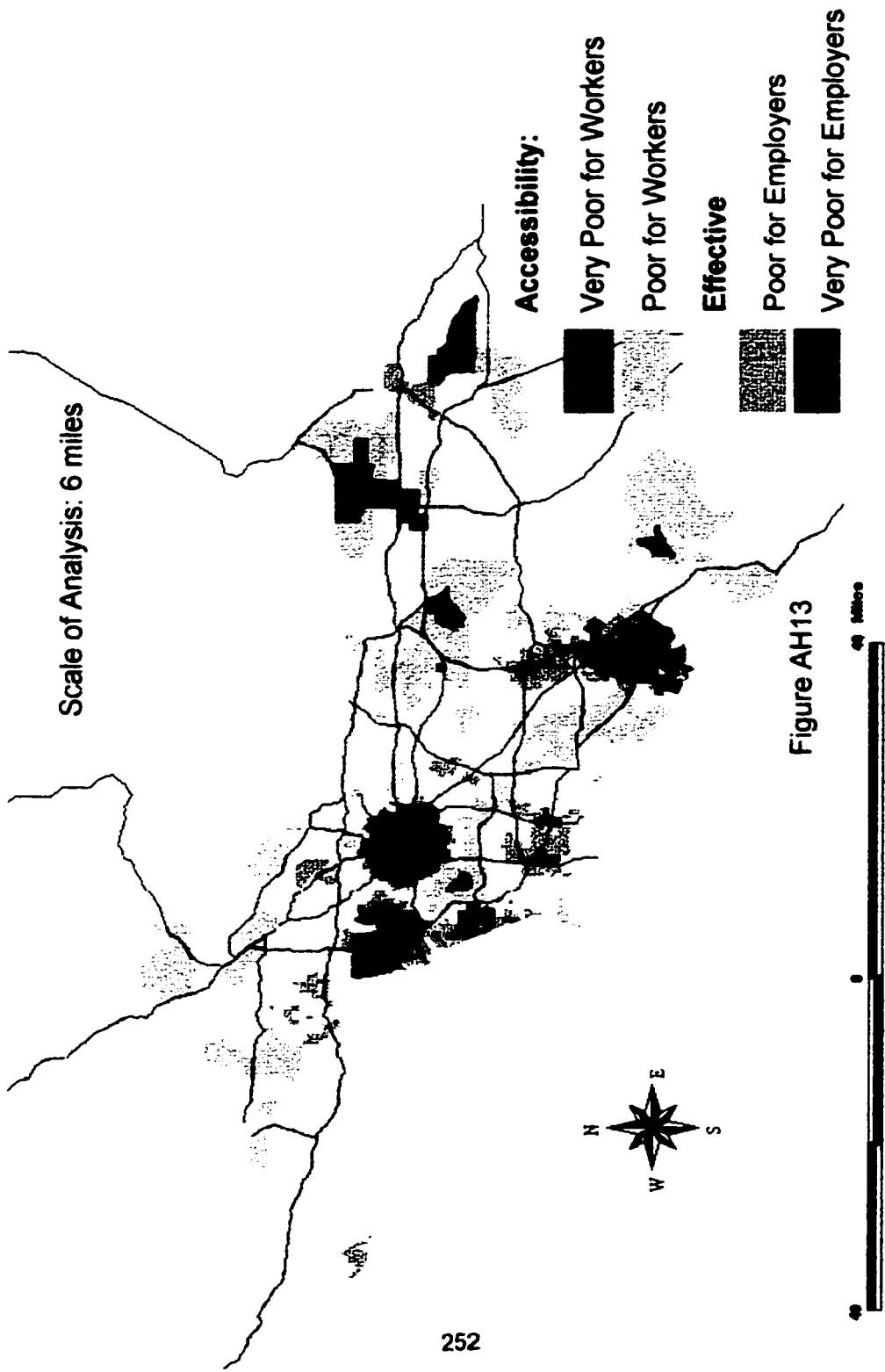
Structural Accessibility, 1990: Jobs/Workers Disaggregated by Occupation

Scale of Analysis: 6 miles

Accessibility:

Very Poor for Workers

Poor for Workers

Effective

Poor for Employers

Very Poor for Employers

Figure AH14

253