REMOTE SENSING, GEOGRAPHICAL INFORMATION SYSTEMS, AND SPATIAL MODELING FOR ANALYZING PUBLIC TRANSIT SERVICES

DISSERTATION

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By

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Public transit service is a promising transportation mode because of its potential to address urban sustainability. Current ridership of public transit, however, is very low in most urban regions, particularly those in the United States. This woeful transit ridership can be attributed to many factors, among which poor service quality is key. Given this, there is a need for transit planning and analysis to improve service quality. Traditionally, spatially aggregate data are utilized in transit analysis and planning. Examples include data associated with the census, zip codes, states, etc. Few studies, however, address the influences of spatially aggregate data on transit planning results. In this research, previous studies in transit planning that use spatially aggregate data are reviewed. Next, problems associated with the utilization of aggregate data, the so-called modifiable areal unit problem (MAUP), are detailed and the need for fine resolution data to support public transit planning is argued. Fine resolution data is generated using intelligent interpolation techniques with the help of remote sensing imagery. In particular, impervious surface fraction, an important socio-economic indicator, is estimated through a fully constrained linear spectral mixture model using Landsat Enhanced Thematic Mapper Plus (ETM+) data within the metropolitan area of Columbus, Ohio in the United States. Four
endmembers, low albedo, high albedo, vegetation, and soil are selected to model heterogeneous urban land cover. Impervious surface fraction is estimated by analyzing low and high albedo endmembers. With the derived impervious surface fraction, three spatial interpolation methods, spatial regression, dasymetric mapping, and cokriging, are developed to interpolate detailed population density. Results suggest that cokriging applied to impervious surface is a better alternative for estimating fine resolution population density. With the derived fine resolution data, a multiple route maximal covering/shortest path (MRMCSP) model is proposed to address the tradeoff between public transit service quality and access coverage in an established bus-based transit system. Results show that it is possible to improve current transit service quality by eliminating redundant or underutilized service stops. This research illustrates that fine resolution data can be efficiently generated to support urban planning, management and analysis. Further, this detailed data may necessitate the development of new spatial optimization models for use in analysis.
Dedicated to my mother, father, and wife
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Portions of this research are published or submitted to the following journals. Chapter 3, ‘Remote sensing for fine resolution data generation’ is an expanded version of two papers, one published in *Remote Sensing of Environment*, the other submitted to *Computers, Environment, and Urban Systems*. Both of them are coauthored with Alan Murray. Moreover, Chapter 4, ‘Transit service quality improvement’ is an expanded version of a paper submitted to *Environment and Planning B*, coauthored with Alan Murray.

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CHAPTER 1

INTRODUCTION

1.1 Background

Energy deficiency and environmental deterioration have become serious problems affecting human beings (Newman and Kenworthy 1999). Fossil fuel consumption, air pollution, accumulating greenhouse gases, and congestion are impacting quality of life and economic development in urban areas (Black 1996, 1997). For instance, air pollution adversely affects human health, vegetation growth, and urban infrastructure. Furthermore, it has serious consequences, such as acid rain, photochemical smog, ozone layer depletion, and enhanced greenhouse effect (Air pollution 2001). In order to solve these problems, sustainable development was proposed in the 1970’s and subsequently implemented in various ways in countries around the world (Brundtland Report 1987; World Commission on Environment and Development 1989). Moreover, because transportation contributes much to energy and environmental problems, “sustainable transportation” is a concept of great interest for addressing these problems (Replogle 1991; Commission of the European Communities 1992; World Bank 1996). Black (1996) characterized sustainable transportation as “…satisfying current transport and mobility needs without compromising the ability of future generations to meet these needs”.
Researchers have suggested that current automobile-dependent transportation systems in the United States are not sustainable (Black 1996, 1997; Transportation Research Board 1997; Newman and Kenworthy 1999). In particular, automobiles are recognized as being responsible for a major share of world oil consumption, a resource that is non-renewable (Transportation Research Board 1997). Hubbert (1965) questioned the availability of oil and predicted that global oil production would peak around 2000. Although scientists have tried to develop alternatives, new fuels have proven to be less efficient than oil (Transportation Research Board 1997). Of equal concern to oil resources is the serious environmental problem caused by vehicle emissions (Newman and Kenworthy 1999; Black 1996, 1997). For example, the U.S. transportation sector produces about 5 percent of annual CO\(_2\) that is built up in the atmosphere (Transportation Research Board 1997).

Table 1.1 shows that automobile-dependent transportation systems in U.S. cities have the highest quantity of emissions per individual (4536 kg/person for CO\(_2\) and 252 kg/person for others polluted gases). In other words, this high quantity of emissions per person reflects how people in U.S. cities are more dependent on automobiles than others around the world.

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Congestion is another condition affecting sustainable transportation (Black 1996, Transportation Research Board 1994). Levels of congestion have increased rapidly in the last decade, creating travel delays and wasting fuel due to vehicles being stuck in traffic. The costs associated with congestion are estimated to be over $40 billion a year (Transportation Research Board 1994). Increasing the capacity of congested roads is the traditional method for reducing congestion. However, studies have shown that in developed countries, increasing capacity only induces more travel, and subsequently perpetuates congestion (Transportation Research Board 1994, 1995). If congestion continues, or worsens, the result will be more time spent in traffic and reduced regional mobility. Furthermore, due to the rapid increase of congestion, automobiles emit excess pollutants into the atmosphere, negatively impacting the natural environment (Transportation Research Board 1994).

Realizing the severity of unsustainable transportation practices, particularly in developed countries, people have proposed many methods to solve this problem. Blowers (1993) summarizes four major classes: (1) new technologies and alternative fuels; (2) regulatory mechanisms to control emissions; (3) tax increases favoring energy-efficient transport modes; (4) planning approaches lessening the need for automobile travel. Evidence suggests that new technologies for improving fuel efficiency only stimulate greater vehicle use, resulting in more environmental pollution and increased consumption of fuels (Newman and Kenworthy 1999). Although other gases or liquid fuels such as hydrogen and biofuel have been developed, none of these appear promising for replacing
oil (Transportation Research Board 1997). Regulatory mechanisms have been applied for more than thirty years. The Clean Air Act Amendment of 1990 (CAAA) and complementary provisions of the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) set the standards for automobile emissions to preserve air quality (Transportation Research Board 1995). However, this has not been effective in reducing congestion or reducing atmosphere pollutants (Transportation Research Board 1997). Tax increases favoring energy-efficient transport modes have been applied in the form of redistributed transportation taxes, parking fees, and road fees. However, most funds tend to be used for highways construction rather than inducing travel mode changes. Moreover, the increment of tax is also a sensitive political issue, which makes it hard to apply (Transportation Research Board 1994,1997).

Public transportation planning is seen as one of the more promising approaches for achieving urban sustainability (Newman and Kenworthy 1999). Most studies highlight that transit can reduce automobile dependence, particularly for journey to work trips (Transportation Research Board 1997). It was found in Portland, for example, that reductions of more than 10 percent of motor vehicle travel could be attributed to improved transit (Cambridge Systematics 1996). Public transit can serve a large number of people using less fossil fuel. It is also an effective means for addressing environmental problems in terms of decreasing air pollution (Transportation Research Board 1997). In addition, public transportation is a good way to lessen congestion because it provides a much higher carrying capacity than automobiles (Gray and Hoel 1992), thereby enhancing quality of life and enabling greater mobility and economic activity.
Although public transit is a promising means for achieving some degree of urban sustainability, transit patronage in urban regions of United States comprises less than 10 percent of all work trips (Charles River Associates 1997). Evidence suggests that it has further decreased in the last 10 years (Newman and Kenworthy 1999). From an operational perspective, poor service quality no doubt contributes to low transit patronage. Common complaints are that transit service is too slow, too infrequent and generally inconvenient compared to automobile travel (Altshuler et al. 1979). Levinson (1983) found that bus travel time is typically 1.4 – 1.6 times higher than using private automobiles in a survey of several large U.S. cities.

Given the above, there is a need for transit planning and analysis to improve service quality. Spatially aggregate data are typically utilized in transit planning and analysis. Examples include data associated with the census, zip codes, states, etc. However, problems associated with the utilization of spatially aggregate data, the so-called modifiable areal unit problem (MAUP), may have adverse impacts on transit modeling results. Therefore, a need exists for disaggregate information to support public transit planning.

In this research, previous studies in transit planning that use spatially aggregate data are reviewed. Then, the MAUP effects associated with the utilization of spatially aggregate data are detailed and the need for fine resolution data to support public transit planning is argued. Intelligent interpolation technologies using remote sensing imagery are proposed
for generating fine resolution data. In particular, impervious surface fraction, an important socio-economic indicator, is estimated through a fully constrained linear spectral mixture model using Landsat Enhanced Thematic Mapper Plus (ETM+) data within the metropolitan area of Columbus, Ohio in the United States. Four endmembers, low albedo, high albedo, vegetation, and soil are selected to model heterogeneous urban land cover. Impervious surface fraction is estimated by analyzing low and high albedo endmembers. With the derived impervious surface fraction in residential areas as ancillary data, three spatial interpolation methods, spatial regression, dasymetric mapping, and cokriging, are developed to interpolate detailed population density. Further, these fine resolution population estimates are utilized as an input to a developed model to address the tradeoff between public transit service quality and access coverage in an established bus-based transit system.

1.2 Organization of the research

This research is organized as follows. Chapter 2 begins with a review of spatially aggregate data commonly relied upon in transit planning. Next, problems associated with using spatially aggregate data in transit planning are discussed. Then, methods to address MAUP issues in transit planning are addressed. Further, the need for disaggregate information to support transit planning is argued, and finally, potential contributions of remote sensing technologies in interpolating fine resolution data are discussed.

Chapter 3 generates fine resolution data using intelligent interpolation technologies with the help of remote sensing imagery. This chapter begins with a description of the study
area, metropolitan area of Columbus. Next, impervious surface fraction, an important socio-economic indicator, is estimated through a fully constrained linear spectral mixture model using Landsat Enhanced Thematic Mapper Plus (ETM+) data. Three intelligent interpolation methods, spatial regression, dasymetric mapping, and cokriging, are developed to interpolate detailed population density. Finally, the estimation accuracies of these methods are compared and a best interpolation method, cokriging, is suggested.

In Chapter 4, a multiple route maximal covering/shortest path (MRMCSP) model is proposed to address the tradeoff between public transit service quality and access coverage in an established bus-based transit system. Further, this model is applied to transit routes in the study area. Modeling results comparing aggregate census data and the derived fine resolution data are presented.

The final chapter, Chapter 5, summarizes the research results and gives concluding comments. Further, contributions and future research have been discussed.
CHAPTER 2

SPATIAL DATA FOR PUBLIC TRANSIT PLANNING

2.1 Introduction

Spatially aggregate data are widely utilized as an input in many public transit planning applications. One example is the traffic analysis zone (TAZ) used to represent urban trip origins (e.g. households) and destinations (e.g. employment, shopping centers, etc.). The TAZ helps to account for locations that generate or attract trips and is defined prior to classical transportation modeling (O’Neill 1991). These predefined TAZs are an essential input to the four-step travel demand modeling process of trip generation, trip distribution, modal split, and network assignment (Miller and Storm 1996; Wirasinghe and Kumarage 1998; Navick and Furth 2002). Further, the interaction between each TAZ pair is considered a principal input to operational transit planning, including transit route and stop design, timetable setting, vehicle scheduling, and crew assignment (Mandl 1980; Ceder 2001, 2003a,b). Besides their use in traditional transit modeling, spatially aggregate data have been utilized in geographical information system (GIS)-supported transit analysis. In particular, census data as well as TAZs have been widely applied in transit access coverage evaluation (Hsiao et al. 1997; Murray et al. 1998; Murray 2001), accessibility assessment (Huang and Wei 2002; Wang and Minor 2002), service area

Although popularly utilized in transit planning and analysis, spatially aggregate data are likely to have adverse influences on modeling results (Miller 1999a). Few studies, however, have explicitly addressed data aggregation issues in the context of transit planning. One exception is the early work of Daganzo (1980a,b), who explored the possibility of applying traffic assignment algorithms to a disaggregate TAZ system. Geographical research has examined the potential effects of data aggregation in trip generation and distribution models (Openshaw 1977; Batty and Sikdar 1982a) and attempted to derive approaches for dividing TAZs into sub-zones in order to minimize aggregation effects (Anderson 1991, Horowitz 2001). Similarly, in GIS-supported transit planning, Murray et al. (1998) highlights that the use of aggregate data (e.g. census block group) potentially introduces modeling errors. Thus, aggregate data is commonly used in transit planning and analysis, yet there are likely substantial impacts that coarse data can have on analytical results (Murray et al. 1998; Horner and Murray 2003). Moreover, in most public transit studies aggregation effects are typically not recognized, so utilized aggregate data are assumed detailed enough to produce accurate modeling results.

Given the above, a need exists for exploring potential effects associated with the use of spatially aggregate data in public transit planning and analysis. Further, we would like to
assess the need for fine resolution data to support transit studies. In this research, spatial aggregation effects, the so-called modifiable areal unit problem (MAUP), are highlighted in the context of transit modeling. In addition, methods for eliminating the MAUP and the need for spatially disaggregate data are discussed. This chapter begins with a review of spatially aggregate data commonly relied upon in transit planning. Next, problems associated with using spatially aggregate data in transit planning are discussed. Then, methods to address MAUP issues in transit planning are addressed. Finally, a discussion and concluding comments are given.

2.2 Spatially aggregate data in traditional transit planning

2.2.1 Traffic analysis zone (TAZ) data

Spatially aggregate data, the TAZ in particular, are an essential input to traditional transit planning, including travel demand modeling and transit operational planning (O’Neill 1991). TAZs are defined to represent trip origins and destinations. In order to accurately represent actual trip information, the boundaries of TAZs are delineated with several criteria including (You et al. 1997a): (1) homogeneity of socioeconomic characteristics; (2) spatial contiguity of TAZs; (3) compactness in zonal shape; and (4) similarities in the generation and attraction of trips. Moreover, in practice TAZ boundaries are preferred to follow existing census boundaries, transportation networks, and physical barriers (O’Neill 1991; You et al. 1997a, b).
2.2.2 Applications of TAZ data in transit demand models

With a predefined TAZ system, public transit demand between each TAZ pair can be explained and predicted using the classical four-step process: trip generation, trip distribution, modal split, and network assignment (Miller 1999a). In particular, regression and categorical analysis of the socioeconomic characteristics associated with each TAZ are generally conducted to identify trip generation locations and associated modal splits (O’Neill 1991). In the trip distribution step, an origin-destination trip matrix for a predefined TAZ system is typically estimated using gravity-based models (O’Neill 1991; Taaffe et al. 1996; Wirasinghe and Kumarage 1998). TAZ based transit demand is a byproduct of this process and is validated using passenger counts and transit surveys to calibrate estimates (Van Zuylen and Willumsen 1980; Cascetta 1984; Spiess 1987; Barua et al. 2001; Navick and Furth 2002).

In summary, a predefined TAZ system is a prerequisite for four-step travel demand models. An output is origin-destination transit demand estimates for each TAZ pair. Further, TAZ-based transit demand estimates are utilized in operational transit planning.

2.2.3 Applications of TAZ based transit demand in operational transit planning

Given TAZ-based public transit origin-destination flows, operational planning uses these estimates in transit route and stop design, timetable setting, vehicle scheduling, and driver assignment (Ceder 1987, 2003a,b; Carraresi et al. 1996; Nuzzolo 2003). In particular, with a pre-determined origin-destination transit demand matrix, Mandl (1980) evaluated
and optimized urban public transit routes with average transportation cost as an objective. Further, Soehodo and Koshi (1999) designed public transit routes and frequencies with elastic demand by optimizing generalized social costs. Similarly, Ceder (2001, 2003a,b) developed an operational procedure in public transit planning for transit network design and vehicle and crew scheduling using passenger demand (O-D matrix for each TAZ pair) as one of the important inputs. In summary, spatially aggregate data, especially TAZs, have served as an important input for the entire traditional transit modeling process (You et al. 1997a).

### 2.3 Application of aggregate data in GIS-supported public transit planning

Although traditional transit modeling has been regularly applied in practice, many criticisms have been raised regarding its use and appropriateness. Firstly, traditional transit models are trying to satisfy transit demand and maximize total throughput. However, this is not a major objective for providing transportation services, especially public transit. In contrast, an individual’s accessibility to activities, which can be easily evaluated using GIS functions, is considered an essential objective of transportation services (Morris et al. 1979; Miller 1999b). Moreover, traditional transit models typically oversimplify actual geographic representations of trip information and transportation network (Nyerges 1995). In contrast, GIS provides abilities to acquire, manage, analyze, and visualize geographic information. Therefore, GIS-supported public transit planning is better capable of representing geographic information, such as the transit network and locations of potential transit riders. Following the rapid developments of GIS applications
in transit planning, we detail the usage of spatially aggregate data in GIS-supported transit planning in this section.

2.3.1. Accessibility measurement

Instead of satisfying travel demand and maximizing total throughput in traditional four-step travel demand modeling, accessibility studies attempt to evaluate and maximize individual opportunities to reach activities across space and time (Weibull 1980; Miller 1999b). With the exception of space-time accessibility measurement using individual trip diary information, spatially aggregate data are generally applied in most accessibility measurements (Kwan 1998). Hansen (1959) was one of the first to define a general accessibility measure:

\[ A_i = \sum_j a_j d_{ij}^{-\alpha} \]  

(2.1)

where \( A_i \) is the accessibility for zone \( i \); \( a_j \) is the attraction of zone \( j \); \( d_{ij} \) is the distance between zone \( i \) and \( j \); and \( \alpha \) is a parameter indicating the influence of distance. Based on this specification, many related accessibility measures have been derived (Morris et al. 1979; Hanson 1997; Kwan 1998). A common characteristic of accessibility measures is that aggregate zonal data are utilized to represent attractions and destinations. For example, in transit studies, TAZ data has been applied in measuring spatial patterns of transit and automobile accessibility to supermarkets in Syracuse, New York (Grengs 2001). Similarly, Wang and Minor (2002) explore the relationship between transit accessibility and crime in Cleveland, Ohio using TAZ data. In addition, with census tract
data as a basic spatial unit, Huang and Wei (2002) developed a new transit based accessibility measure to explore spatial mismatch in Milwaukee, Wisconsin.

2.3.2 Access studies

Measuring accessibility is always data intensive because it requires information about an individuals’ origin, destination and associate travel time via transit (Murray and Davis 2001). A less data intensive approach is to evaluate which areas are covered by public transit, which is referred to as transit access. Spatially aggregate data are always utilized in access studies. In particular, with census data at the collection district level (roughly equivalent to the U.S. census block), Murray et al. (1998) evaluate public transit access in the South East Queensland region of Australia. Other studies have also analyzed transit access coverage strategically (Cha and Murray 2001; Murray 2001). As well, approaches have been developed to extend current transit access coverage (Murray 2003). All of these studies have relied on census data at different zonal levels. Moreover, public transit access evaluated using spatially aggregate data has been considered an essential criterion for exploring employment rates (Sanchez 1999), evaluating service provision (Hsiao et al. 1997), and measuring service equity (Murray and Davis 2001). In almost all studies related to transit access, spatially aggregate data, mostly census data with associated socioeconomic characteristics, are utilized, supported by GIS.

2.3.3 GIS-based transit route and stop design

In addition to finding use in public transit accessibility and access assessment, spatially aggregate data have been employed for representing potential ridership demand in
designing transit routes and locating service stops. In transit route design, census data are invariably relied upon as centroids representing potential zonal demand. For example, using census tract data Ramirez and Seneviratne (1996) developed a model to plan a new transit route that minimized total travel distance and maximized potential ridership. Moreover, Current et al. (1985) developed a maximal covering/shortest path (MCSP) model to design a new route with objectives of maximizing total population access coverage and minimizing total travel time. Extensions of the MCSP have been proposed to address various aspects of route design in new service areas, including tours (Current and Schilling 1989, 1994) and multiple routes (Boffey and Narula 1998; Hachicha et al. 2000). Implied in this work is the existence of spatially aggregate data to be utilized for demand representation.

For analysis in an existing transit route structure, spatially aggregate data are also used to evaluate stop placement. For example, with transit demand redistributed to census blocks, Furth and Rahbee (2000) developed a dynamic programming model to locate bus stops along a route. Murray (2001) applied the location set covering problem (LSCP) to minimize the number of stops required to maintain existing access coverage using census data. In addition, Murray and Wu (2003) modeled the tradeoff between accessibility and access in deciding optimal bus stop spacing using population and employment at the census block level to represent potential transit demand. Similarly, using census block group data Horner and Grubesic (2001) developed an accessibility measure applied to rail terminal siting in Columbus, Ohio. Overall, transit route and stop design extensively relies on aggregate data to represent potential transit demand.
2.3.4 Transit ridership forecasting

Besides designing new transit routes and service stops, spatially aggregate data are also central in estimating and forecasting transit ridership. In particular, Hunt et al. (1986) developed a geodemographic model in which transit ridership is predicted using population and employment information extracted from census tracts and TAZs. Azar and Ferreira (1995) estimated transit ridership using a regression model applied to socioeconomic characteristics of census zones. Using census tract data Peng et al. (1997) developed a route level transit ridership prediction model that considers transit demand, supply, and complimentarity and competition between routes. In transit ridership-forecasting models census information is utilized as an important input for subsequent analysis and ridership prediction.

2.4 Problems associated with aggregate data

As detailed above, spatially aggregate data are generally utilized in both traditional and GIS-supported transit planning. Few studies, however, explicitly address data aggregation problems in transportation modeling, particularly public transit planning (Miller 1999a; Horner and Murray 2003). Nevertheless, geographic research documents a range of spatial data aggregation problems, referred to the Modifiable Areal Unit Problem (MAUP). The MAUP typically occurs when the boundaries of aggregate zonal data are not data driven, but rather reflect ease of enumeration or reporting (Openshaw 1984). MAUP can be divided into two components: scale effects and unit effects. Scale effects relate to the influences of data aggregation on modeling results. Unit effects refer to the
sensitivities of results to different zonal arrangements (Miller 1999a). In this section, potential MAUP effects in transit planning are discussed.

2.4.1 Traditional transit modeling

In travel demand modeling, MAUP effects may often affect modeling results (Miller 1999a). Take, for example, trip distribution. As mentioned previously, gravity-based models are generally utilized in distributing trips and estimating travel demand between each TAZ pair. However, Ord and Cliff (1976) show that a distributional bias exists in such an estimate because interzonal flows are affected by TAZ size. That is, smaller zones may result in higher zonal flows because of shorter distances travel to reach zonal boundaries. Moreover, trip distribution models fail to measure intra-zonal trips and poorly represent inter-zonal trips when centroid-to-centroid distances are used as a surrogate of spatial interaction costs (Kuiper 1986; Willson 1990). For example, Daganzo (1980a,b) points out that trips located at the edges of a TAZ are misrepresented when the centroid of the TAZ is used to represent the locations of all trip-ends in traditional travel demand modeling. Moreover, Batty and Sikdar (1982a,b,c,d) point out the significant effects of zonal aggregation in estimating model parameters and assessing goodness-of-fit in trip distribution models. Besides the scale effects of spatially aggregate data, Openshaw (1977) found that different zonal arrangements also have a significant effect on parameter estimation in distributing trips. Finally, MAUP biases are certain to exist in trip generation and distribution estimation, which will no doubt be propagated through travel demand models (Zhao and Kockelman 2002) and other operational transit planning and analysis.
2.4.2 GIS supported transit studies

In addition to the MAUP effects in traditional transit planning, spatially aggregate data also have considerable influences on GIS supported transit planning. In this section, several GIS-supported transit applications, such as accessibility measurement, access studies, and transit route and stop designs, are reviewed.

2.4.2.1 Accessibility measurement

In transit accessibility studies using aggregate data it is typically assumed that population and employment activities are evenly distributed within a zone, with centroid-to-centroid distance representing the interaction between two zones (Hansen 1959; Huang and Wei 2002). However, in reality, the distribution of population and employment activities within a zonal unit may vary significantly (Martin 1996) and the use of zonal data may mask actual underlying population and employment distributions (Moon and Farmer 2001), creating difficulties for accessibility assessment. Moreover, problems also arise in the use of centroid-to-centroid distances to represent interactions between zones. With census tract data as an example, Hillsman and Rhoda (1978) suggest that centroid-to-centroid distances between two tracts are likely to be as much as 8% from the true distance.

2.4.2.2 Transit access and service area delineation

As detailed in section 3, census zones are typically used in public transit access studies to represent the location of potential transit ridership. Of interest in assessment is whether
areas have suitable access, where suitable access is defined as an individual being able to walk to a transit stop under normal conditions. A distance of 400 meters from a stop is typically stipulated as a suitable access coverage standard (Peng et al. 1997; Murray et al. 1998). Evaluating access involves an assessment of the proximity of an area to a transit stop relative to the suitable coverage standard. As such, the size of the zone may introduce estimation errors when zones are large in comparison to the distance standard. In the greater Columbus, Ohio region (Franklin County), for example, the mean area of a census block is 80,692 square meters (see figure 2.1). This represents a radius of 160 meters if a circular block shape is assumed (see figure 2.2). If a 400 meter standard is assumed for this region, as stipulated by the Central Ohio Transit Authority (COTA) and done in Murray and Wu (2003), then an average census block is approximately 16% of the stop service area. This indicates that a census block is comparable to the suitable access standard, thus potential errors may raise in access evaluation. Moreover, the maximum area of a census block is 7.6 square kilometers, which equates to a radius of 1.6 kilometers for a circle. This is about four times the size of the 400 meter access area. Clearly the use of aggregate data has significant potential to introduce errors. Further, in transit studies that use TAZs, potential errors are even more pronounced. The mean area of a TAZ in Columbus is about 1.2 square kilometers (see figure 2.3), which equates to a radius of 624 meters for an associated circle (see figure 2.4). Further, the maximum area of a TAZ is 19.1 square kilometers, or a circular radius of 2.5 kilometers. The average radius of a TAZ is much larger than a stipulated 400 meter access standard, making access evaluation problematic in this case. Unfortunately, the situation reflected in Columbus is not unlike that of most urban regions in the U.S. Therefore, careful
consideration is needed when spatially aggregate data, such as census data and TAZs, are used to evaluate transit access or delineate service areas.

Figure 2.1 Census blocks in Franklin County, Ohio
Figure 2.2 Size comparison of an average census block and a transit stop service area

Figure 2.3 Traffic analysis zones (TAZs) in Franklin County, Ohio
As an alternative to census zones, parcel data is likely the most disaggregate data available to public, if and when it is accessible. In Columbus, as an example, the average area of a parcel is about 3,616 square meters. This would represent a circular radius of 34 meters. Compared to a 400 meter access distance, parcel data seems to be detailed enough to support transit access evaluation. However, parcel data does not contain information about people living or working in these areas nor associated socioeconomic characteristics. Such information is essential in transit planning and analysis. Moreover, the size of parcels varies significantly in an urban area. In Columbus, the largest parcel has a circular radius of 1.4 kilometers, much larger than the commonly relied on 400
meter access distance standard. Thus, parcel data is not generally adequate for transit access evaluation and service area delineation either.

2.4.2.3 **GIS-based transit route and service stop design**

With spatially aggregate data representing potential transit demand, transit route and service stop design has been implemented with the support of GIS and location models (Ramirez and Seneviratne 1996; Murray 2001). However, MAUP effects associated with spatially aggregate data introduce potential errors to modeling results. In particular, spatial aggregation errors are known to exist in location-allocation models (Hillsman and Rhoda 1978), yet similar models are used for siting transit stops (see Murray and Wu 2003). Goodchild (1979) points out that aggregation errors have dramatic influences on actual facility location. Spatial aggregation is also a significant issue in coverage modeling, a much relied upon modeling approach in designing transit routes and service stops (Ramirez and Seneviratne 1996; Murray et al. 1998). In particular, Daskin et al. (1989) and Current and Schilling (1990) suggest that the binary representation of distance in covering models compounds aggregation errors. Further, studies have been conducted to explore the relationship between modeling errors and data aggregation, and conclude that data aggregation does give rise to modeling errors and the more aggregate the data, the larger the errors (Fotheringham et al. 1995; Francis et al. 1996, 1999; Murray and Gottsegen 1997). In addition to scale effects, Fotheringham et al. (1995) point out that zonal definitions also have influences on modeling results. In summary, for location modeling that uses spatially aggregate data, MAUP effects are significant. Thus, one
would certainly anticipate influences on modeling results in transit route and stop designs when location models are applied.

2.5 Addressing MAUP issues in transit planning

Given the expectation that MAUP effects associated with the use of spatially aggregate data in transit planning and analysis are significant, it is critical that the nature and magnitude of potential effects be evaluated. Tobler (1989) argues that MAUP effects are not inherently associated with spatially aggregate data, but rather with the use of inappropriate methods/models. He advocates that spatial models should generate consistent results, independent of scale or unit definition. Thus, there may well be a need to search for frame independent models as suggested by Tobler (1989) in the context of transit planning.

Clearly, it is essential that transit planning models be assessed for frame independence. If they are independent, scale or unit definition would not be an issue. If a frame independent model is not available, the use of the most disaggregate data available may aid in the assessment of MAUP effects. That is, disaggregate data are not directly utilized in transit modeling, but rather used to help identify and eliminate aggregation errors prior to the modeling process. In particular, disaggregate data have been utilized to assess zoning system effects (Batty 1976; Batty and Sikdar 1982a), design optimal zoning system (O’Neil 1991; You et al. 1997a,b), and eliminate distance measurement errors (Rodriguez-Bachiller 1983; Current and Schilling 1987; 1990; Okabe and Miller 1996). Although popularly applied, this method requires spatially disaggregate data of some
form. Often times such disaggregate data are not publicly available. Moreover, disaggregate data, like parcels, may not be suitable for detailed transit planning. As such, there is a need to generate spatially disaggregate data that may be applied to transit planning and analysis.

Ideally, fine resolution, spatially disaggregate data could eliminate MAUP effects in transit planning. Fotheringham et al. (1995) suggest that small grid cells with spatially interpolated attributes could eliminate modeling errors associated with variations in zonal size. Alternatively, rather than aggregate zonal demand, continuous demand representations have been of great interest to researchers because it could eliminate aggregation problems (Miller 1996; Church 2002). As a proxy to a continuous representation, disaggregate raster representations have been applied in solving shortest path problems (Goodchild 1977).

Along the lines of Goodchild (1977) and Fotheringham et al. (1995), recent work in using remotely sensed imagery gives rise to the belief that it may be possible to obtain fine resolution spatial data for a range of planning applications, including transportation studies. Remote sensing data has been used to derive detailed information associated with socio-economic activities (Chen 2002; Harris and Longley 2000). However, challenges remain along many fronts. In particular, remote sensing imagery does not explicitly provide urban and socio-economic information, but rather reflectance or irradiation of ground materials. Thus, there is a need for image processing techniques to extract detailed socio-economic information from remote sensing imagery. Another challenge is
associated with geographical generalizabilities. Often, relationships between imagery and socio-economic activities are application and area specific. As such, there remains a need for a modeling approach that accommodates geographical instabilities. Further, the generation of fine resolution data requires ancillary data like census information, which may not be available in some developing countries. Finally, classic statistical techniques are not necessarily appropriate for linking census and acquired imagery due to the spatial interactions among different geographical locations. Thus, spatial statistical approaches are needed for more accurately interpolating fine resolution data.

Even if the above issues are sufficiently addressed, the generation and use of more spatially disaggregate data may not be a panacea as it is likely to raise appropriateness and computational issues. In particular, some models in transit planning are not likely to be solved effectively if enhanced disaggregate data is used. One reason is associated problem size. Whereas currently solved models may have hundreds or thousands of decision variables, fine resolution data may produce models with hundreds of thousands or millions of decision variables. As such, linear and non-linear optimization techniques may not be capable of solving resulting problems. Further, fine resolution data may necessitate new spatial models as it could enable new questions to be addressed.

2.6 Conclusions

In this chapter, the application of spatially aggregate data in traditional and GIS-supported transit modeling has been reviewed. Moreover, MAUP effects associated with
the use of spatially aggregate data were discussed and techniques for eliminating MAUP effects in public transit planning were detailed.

One emphasis of this chapter was the current reliance on aggregate data in transit planning and analysis. In fact, TAZs are often utilized in traditional travel demand models and in operational transit planning. Further, census zonal data are generally applied in various GIS-supported transit studies related to access and accessibility measurement, ridership prediction, transit route and stop design, among others. Another emphasis of this chapter was that MAUP effects associated with the use of spatially aggregate data are varied and significant in transit planning. In classic travel demand modeling, for example, it is anticipated that MAUP effects exist in trip generation and distribution estimation, and are propagated through all later modeling and planning steps, including transit route and stop design, timetable setting, and crew assignment. However, the nature of these effects is largely unknown. MAUP effects are also likely in GIS-supported transit analysis. Finally, this chapter discussed potential techniques for eliminating the MAUP in public transit planning. One method is to develop frame independent spatial models in which modeling results are consistent when changes in spatial resolution or unit definition occur. If a frame independent model is not available, it is essential that fine resolution data be used in transit planning. Of particular promise is the use of remote sensing combined with advanced GIScience techniques for generating detailed socio-economic data at a fine scale. However, one should anticipate new problems arising with the emergence of greater resolution data.
CHAPTER 3

REMOTE SENSING FOR FINE RESOLUTION DATA GENERATION

In public transit planning and analysis, population density is an important consideration because it reflects potential daily trips originating from an area (Benn 1995). In particular, population densities below approximately 4000 persons per square mile often exhibit a low demand for public transit (Downs 1992; Transportation Research Board 1996, 1997). Although population data is critical, it is typically only available in aggregate forms, such as census blocks or block groups in the United States or enumeration districts in the United Kingdom (Rhind 1991). This aggregate data often cannot sufficiently represent the underlying geographical distributions fundamental to many planning studies (Bracken and Martin 1989, 1995; Martin and Bracken 1991; Martin and Williams 1992; Goodchild et al. 1993; Moon and Farmer 2001). As an example, a primary inquiry in public transit planning is whether individuals reside within a suitable walking distance, typically 400 meters, of a service stop (Murray 2001). Census information does not provide sufficient detail to satisfy many of the associated application demands in transportation planning because of the intentional spatial masking employed. The result is errors in estimating public transit access coverage, which may

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1 Portions of this chapter have been published or submitted in the following journals: *Remote Sensing of Environment* and *Computers, Environment, and Urban Systems*, coauthored with Alan Murray.
inadvertently lead to fallacious conclusions or inappropriate interpretations (Murray et al. 1998). Further, there are well-known scale and unit specification issues, the modifiable areal unit problem (MAUP), that must be addressed when statistical or spatial models are applied in the context of planning and decision making (Openshaw 1977; Current and Schilling 1990; Fotheringham et al. 1995; Murray and Gottsegen 1997; Francis and Lowe 1999).

In order to address the shortcomings of aggregate census data, researchers have developed interpolation approaches for transforming areal population counts to grid-based population density estimates. These interpolation methods can be divided into two classes: simple interpolation and intelligent interpolation (Okabe and Sadahiro 1997). Simple interpolation methods include all data transferring approaches that do not use supplementary data. Many simple interpolation methods have been detailed in the literature, including polygon overlay (Markoff and Shapiro 1973; Lam 1983; Goodchild et al. 1993), pycnophylactic interpolation (Tobler 1979, 1999; Rase 2001), spread functions (Bracken and Martin 1989, 1995; Martin 1989, 1996; Martin and Bracken 1991), point-in-polygon (Burrough 1986; Okabe and Sadahiro 1997), and Theissen/Voronoi approaches (Robinson and Zubrow 1997). In contrast to these simple methods, intelligent interpolation involves integration with supplementary data (Langford et al. 1991; Okabe and Sadahiro 1997). Often land use and land cover data is utilized, given that it is highly correlated with population density (Wright 1936; Flowerdew and Green 1989; Langford et al. 1991; Langford and Unwin 1994). Other supplementary data sources include nighttime satellite imagery using the visible near-IR band (Sutton et al.
1997; Dobson, et al. 2000), Ordnance Survey GB’s Address-Point and Code-Point data (Harris and Longley 2000), and housing distribution data (Moon and Farmer 2001).

While some possibilities exist for obtaining spatially detailed population density information, such data are not generally available for use or are prohibitively costly (Harris and Longley 2000). Nighttime satellite imagery is too coarse for detailed studies given its 1 km spatial resolution (Sutton et al. 1997). Moreover, although intelligent interpolation methods using land use/cover data have proven to have superior estimation accuracy compared to simple interpolation methods (Fisher and Langford 1995; Sadahiro 1999), limited land use types lose much biophysical information in satellite images (Jensen 1983). As a result, they tend to be too coarse for estimating population density. On the other hand, impervious surface fraction, which can also be estimated from remotely sensed data, maintains detailed information on urban morphology (Ji and Jensen 1999). Therefore, it is likely better suited for estimating population density.

This chapter develops techniques for fine resolution population density estimation by applying intelligent interpolation methods using impervious surface fraction as ancillary data. In particular, with impervious surface fraction in delineated residential areas as supplementary data, three intelligent interpolation methods (spatial regression, dasymetric mapping, and cokriging) are used to derive fine resolution population estimates (see figure 3.1). The organization of this chapter is as follows. Section 3.1 describes the study area of this research. Next, impervious surface fraction, an important socio-economic indicator, is estimated through a fully constrained linear spectral mixture model using Landsat Enhanced Thematic Mapper (ETM+) data. Then, impervious
surface in residential areas is delineated in section 3.3. Further, three interpolation methods, spatial regression, dasymetric mapping, and cokriging, are developed to derive fine resolution population density. Finally, section 3.5 provides a comparison of these methods.

![Diagram](image.png)

Figure 3.1 Intelligent interpolation for fine resolution population density estimation
3.1 Study Area

An area of 81 km$^2$ was selected for impervious surface generation within the metropolitan area of Columbus, Ohio in the United States. This region is one of the fastest growing areas in the Midwest United States and it is expected to continue growing over the next 25 years (Horner & Grubesic 2001). This selected region includes most of the representative land cover classes: central business district (CBD), high-density residential, low-density residential, vegetation, exposed soil, and water (see figure 3.2). A Landsat 7 ETM+ scene (level-1G product for path 19, row 32) taken on July 8, 1999 was used in this study. The geometric error of these data is within 30 meters (sub-pixel) after precision correcting using ground control points (Irish 1998). Eight Digital Orthophoto Quarterquadrangles (DOQQs) for this region were downloaded from the Ohio Geographically Referenced Information Program (OGRIP 1999). These DOQQs were based on black and white National Aerial Photography Program (NAPP) photographs acquired between 1993 and 1999. They have one meter resolution and have geometric error less than 12 meters (US Department of Interior 1996). These DOQQs are suitable for ground truthing in accuracy assessment associated with impervious surface estimation using Landsat ETM+ data.
Figure 3.2 Columbus metropolitan area in Franklin County, Ohio. The lower right corner shows a ETM+ image acquired on July 8, 1999 for the study area.
A portion of this area was chosen for fine resolution population generation. This region is 47.4 km² and is divided into 36 tracts, 125 block groups, and 2445 blocks in the 2000 Census (see figure 3.3). The 2000 Census data were acquired from the ESRI website in the shapefile format (United States Census Bureau 2002). National Land Cover Data (NLCD), produced from Landsat TM imagery between 1987 and 1994, was acquired from Multi-Resolution Land Characteristics Consortium (MRLC 2002). This data gives historical information for this study area and is used for guiding training data selection in residential land use classification. Further, parcel data and address-based employment

Figure 3.3 Study area for fine resolution population generation
(Green indicates tract boundary, blue indicates block group boundary, black indicates block boundary)
data were obtained from the Franklin County Auditor and the Mid-Ohio Regional Planning Commission respectively. These data include detailed local information about land uses, buildings, and employment. They are used for delineating apartment-based residential areas which cannot easily be classified from the Landsat imagery.

3.2 Impervious Surface Fraction Estimation

3.2.1 Introduction

Impervious surface is any material prohibiting the infiltration of water into soil. As a major component of urban infrastructure, impervious surface has become a primary variable in urban planning and environmental management (Ridd 1995; Ji and Jensen 1999). Impervious surface fraction, calculated as the proportion of impervious surface over a small area, has been found to reveal more information about built-up areas than land use and land cover classification (Ji and Jensen 1999). For population estimation, as an example, impervious surface in residential areas generally corresponds to housing, which serves as an indicator of people.

Ridd (1995) proposed the vegetation-impervious surface-soil model (V-I-S) for parameterizing biophysical composition of urban environments. In this model, urban land use and land cover classes can be modeled by the fraction of vegetation, impervious surface, and soil. Ridd (1995) suggests that the V-I-S model might be a basis for better understanding urban environments, both physical geography (e.g. urban heat islands, run-
of modeling, and urban change detection) and human geography (e.g. population density estimation, and quality of life assessment). However, the V-I-S model is only considered conceptually, with limited applications because of the difficulties in impervious surface estimation (Madhavan et al. 2001). One exception is Ward et al. (2000) and Phinn et al. (2002) who applied the V-I-S model to an urban environment in Australia. Ridd (1995) calculated impervious surface fraction through comparison of digitized aerial photographs with classified satellite imagery. However, digitizing aerial photographs is tedious and costly. Ward et al. (2000) developed a classification approach for mapping vegetation and soil cover with moderate accuracy, but did not report results for impervious surface estimation. Phinn et al. (2002) estimated impervious surface distribution using a constrained spectral mixture analysis method. Small (2001) estimated urban vegetation distribution using a three-endmember linear mixture model, but expressed difficulties associated with impervious surface estimation. Deguchi and Sugio (1994) estimated impervious area by applying a clustering algorithm to SPOT HRV imagery, but with very coarse spatial units. Ji and Jensen (1999) estimated impervious surface fraction based on subpixel analysis and layered classification but their results are represented as eight 10% intervals due to the limitations of subpixel processing. In this research, impervious surface distribution, together with vegetation and soil distribution, is derived directly from Landsat ETM+ data using spectral mixture analysis (SMA). The fractions of four endmembers (vegetation, soil, low albedo, and high albedo) are calculated using a linear spectral mixture model in section 3.2.2-3.2.5. Impervious surface fraction estimation from these four endmembers is detailed in section 3.2.6 and
accuracy assessment is described in section 3.2.7. Finally, potential applications of this model and further research directions are discussed in section 3.2.8.

3.2.2 Radiometric calibration

The digital numbers (DNs) of the ETM+ image were converted to normalized exo-atmospheric reflectance measures following the methods proposed by Markham and Barker (1987). The calibration parameters used were obtained from Landsat 7 ETM+ sensor pre-launch calibration data and the ETM+ data header (Irish 1998). We assumed homogeneous atmospheric conditions within the image, so no atmospheric corrections were performed. A sample of calibrated at-sensor reflectance for representative land cover types is shown in figure 3.4.

![Figure 3.4 Normalized exo-atmospheric reflectances for representative land cover types calibrated using methods proposed by Markham and Barker (1987).](image-url)
3.2.3 Spectral mixture analysis

Spectral mixture analysis (SMA) was utilized for calculating land cover fractions within a pixel and involves modeling a mixed spectrum as a combination of spectra for pure land cover types, called endmembers (Roberts et al. 1998). SMA can be sub-classified into linear spectral mixture analysis and nonlinear spectral mixture analysis according to the complexity of scattering. If each photon interacts with a single land cover type within the field of view, the mixing can be considered linear and the modeled spectra is the linear summation of the spectrum of each land cover type multiplied by the surface fraction they cover (Settle and Drake 1993, Roberts et al. 1993, Adams et al. 1995, Roberts et al. 1998, Van Der Meer and De Jong 2000, Sabol et al. 2002). The surface fraction of each land cover type can be calculated using an inverse least squares deconvolution model and endmember spectra. However, if scattered photons interact with multiple land cover types, such as multiple scattering by vegetation and soil, nonlinear spectral mixture analysis should be applied (Roberts et al. 1993, Zhang et al. 1998, Gilabert et al. 2000). Although multiple scattering may be significant, it is assumed to be negligible in most urban applications (Rashed et al. 2001, Small 2001, 2002, Phinn et al. 2002). In this research, we only consider linear spectral mixtures.

The linear spectral mixture model describes the surface composition in each pixel of an image using two to six endmembers (for an ETM+ image). Each endmember represents a pure land cover type. The linear mixture model is:
\[ R_b = \sum_{i=1}^{N} f_i R_{i,b} + e_b \] (3.1)

Where \( R_b \) is the reflectance for each band \( b \) in the ETM+ image, \( N \) is the number of endmembers, \( f_i \) is the fraction of endmember \( i \), \( R_{i,b} \) is the reflectance of endmember \( i \) in band \( b \), and \( e_b \) is the unmodeled residual. Associated with determining \( R_b \), \( \sum_{i=1}^{N} f_i = 1 \) and \( f_i \geq 0 \) are required. The sensitivity and applicability of these constraints have been discussed by others (Settle and Drake 1993, Van Der Meer and De Jong 2000, Heinz and Chang 2001, Small 2001). Model fitness is normally assessed by the residual term \( e_b \) or the RMS over all image bands \( M \):

\[ RMS = \left( \frac{\sum_{b=1}^{M} e_b^2}{M} \right)^{1/2} \] (3.2)

The fraction of each endmember can be obtained by applying a least squares technique in order to minimize the unmodeled residual error \( e_b \), given the constraints on \( f_i \). As stated by Small (2001), the linear mixture model may not be appropriate for applications in which only subtle spectral differences exist in all sampled bands. Moreover, the validity of the model also depends on the selection of endmembers. There is a trade-off between the number of endmembers and model fitness. More endmembers can explain more spectral variation, thereby increasing model fitness. However, too many endmembers make the mixture model sensitive to endmember selection and may not be generally
applicable. In many applications, about three to four endmembers are chosen for simple linear mixture models (Roberts et al. 1993, Small 2001).

3.2.4 Endmember selection

An optimal approach for selecting endmembers is to use laboratory-based measurements of endmember’s spectra, referred to as “reference endmember”. Although substantial problems exist in correcting for atmospheric conditions in satellite sensor data (Settle and Drake 1993), recent research by Smith et al. (1990), Adams et al. (1995), and others, overcomes this by considering the mixed spectra as a linear combination of endmembers derived from an image (image endmembers). Each image endmember is a combination of reference endmembers, including atmospheric scattering and absorption. More discussion about reference endmembers and image endmembers can be found in Van Der Meer and De Jong (2000). In our study of Columbus, detailed ground cover spectral information is not available. Thus, image endmembers were chosen and derived from the ETM+ image.

One approach for choosing image endmembers is selecting representative homogeneous pixels from satellite images through visualizing spectral scatter plots of image band combinations (Rashed et al. 2001). A principal component (PC) transformation was also used to guide image endmember selection because it puts almost 90% of the variance on the first two or three components and minimizes the influence of band to band correlation (Smith et al. 1985). However, noise variance in one band may be larger than signal variance in another band in terms of unequal scaling in different bands (Small 2001). Therefore, PC transformation cannot necessarily order components according to signal
information. Unlike PC transformation, the maximum noise fraction (MNF) transformation orders components according to signal to noise ratios (Green et al. 1988). MNF transformation can be considered cascaded PC transformations given the following steps: (1) a PC transformation is performed to diagonalize the noise covariance matrix; (2) the noise covariance matrix is converted to an identity matrix by scaling the transformed dataset; and (3) a second PC transformation is conducted on the scaled dataset (Lee et al. 1990). In MNF transformation, steps (1) and (2) are to transform the noise covariance matrix of the dataset to an identity matrix. Step (3) is to conduct a PC transformation on the transformed dataset with the identity noise covariance matrix. Among these steps, a difficult task is to estimate the error covariance matrix. Some sensor calibration measurements or ground reflectance measurements may provide the error covariance matrix (Lee et al. 1990). However, these measurements are not generally available.

Green et al. (1988) provided a minimum/maximum autocorrelation factors (MAF) procedure to estimate the noise covariance matrix directly from images. This procedure assumes that noise is spatially uncorrelated while signal is highly correlated over space. In this research, the image noise covariance matrix was estimated by applying the MAF procedure. By conducting cascaded PC transformations, we obtained MNF components from the ETM+ reflectance images (see figure 3.5). The first three MNF components provide information for the original ETM+ image. In particular, the first two MNF components clearly illustrate spatially coherent contrasts differentiating CBD, residential
Figure 3.5 MNF components of ETM+ image
areas, vegetation, and water. In addition, the third MNF component is essential in identifying soil among other land cover types. Higher order MNF components, however, show diminishing spatial coherence and provide little information. This result is comparable to the results obtained by Small (2001).

The clear delineation of feature spaces corresponding to the first three MNF components (figure 3.6) suggests that the reflectance spectra of the ETM+ image might best be represented by a four-endmember linear mixing model. Following the procedure proposed by Smith et al. (1985), we selected the extreme pixel clusters which bound almost all other pixels in shown feature spaces as endmembers. The four endmembers were identified according to the feature spaces and their associated interpretations obtained from the original reflectance data. These endmembers are (1) high albedo (e.g. concrete, clouds, and sand), (2) low albedo (e.g. water and asphalt), (3) vegetation (e.g. grass and trees), and (4) soil. Theoretically, if all of the pixels are within the triangles formed by endmembers, the mixture model can be considered an ideal linear model. In this study, there is a slight outward curvature along the edge of the soil and high albedo endmembers in the scatter plot of MNF component 1 and 3 (figure 3.6). This implies some nonlinear mixtures among these endmembers. Moreover, the selection of high albedo endmember is difficult because it does not cluster well in feature spaces. We selected this endmember from highly reflected roofs in the CBD because impervious surface is most important in this study. The endmember spectra are shown in figure 3.7.
Figure 3.6 Feature space representation of the first three MNF components
3.2.5 Fraction image calculation

The endmember fractions (figure 3.8) were calculated by solving a fully constrained four-endmember linear mixing model using the Landsat ETM+ reflectance data. The vegetation fraction image correlates with known vegetated areas within the original ETM+ image. That is, the vegetation fraction is near zero in the CBD, while increasing to 30-50% in high-density residential areas, and 50-80% in low-density residential areas, and near 100% in vegetated areas (figure 3.8c). Moreover, the soil fraction image is also consistent with the soil distribution in the study area because the soil fraction in the CBD and residential areas is lower than 20-30% but higher than 70% in some parts of the urban fringe (figure 3.8d). Fraction images of low albedo and high albedo cannot be directly interpreted from the image. However, their relationship with impervious surfaces...
will be built using a two-endmember linear mixture model in next section. The RMS for every image pixel was calculated in order to assess the performance of this model (figure 3.9). The mean RMS over the image is 0.0057, which suggests a generally good fit (less than 0.02). Figure 3.9 also shows that this model represents residential, vegetation, soil, vegetation, and soil.
and water cover types very well. However, performance is not as good for modeling some high albedo materials, such as high reflectance roofs, clouds, and sand.

3.2.6 Impervious surface estimation

The high albedo and low albedo endmembers cannot be directly interpreted as impervious surfaces. Moreover, impervious surfaces cannot be an endmember due to their spectral variability. Thus, building a relationship between high and low albedo and impervious surfaces is essential in this study. Through the analysis of relationships between impervious surfaces and the four endmembers, we found that impervious surfaces are likely on or near the line connecting the low albedo and high albedo

Figure 3.9 Spectral mixture analysis RMS

3.2.6 Impervious surface estimation

The high albedo and low albedo endmembers cannot be directly interpreted as impervious surfaces. Moreover, impervious surfaces cannot be an endmember due to their spectral variability. Thus, building a relationship between high and low albedo and impervious surfaces is essential in this study. Through the analysis of relationships between impervious surfaces and the four endmembers, we found that impervious surfaces are likely on or near the line connecting the low albedo and high albedo
endmembers in the feature spaces. In other words, most impervious surfaces might be represented by low and high albedo endmembers as follows:

\[ R_{\text{imp},b} = f_{\text{low}} R_{\text{low},b} + f_{\text{high}} R_{\text{high},b} + e_b \]  

(3.3)

\( R_{\text{imp},b} \) is the reflectance spectra of impervious surfaces for band \( b \), and \( f_{\text{low}} \) and \( f_{\text{high}} \) are the fractions of low albedo and high albedo respectively. \( R_{\text{low},b} \) and \( R_{\text{high},b} \) are the reflectance spectra of low albedo and high albedo for band \( b \), and \( e_b \) is the unmodeled residual.

Associated with determining \( R_{\text{imp},b} \) is the requirement \( f_{\text{low}} + f_{\text{high}} = 1 \) and \( f_{\text{low}}, f_{\text{high}} \geq 0 \).

In order to test the validity of this two-endmember model, the CBD (see figure 3.10a), which consists of relatively homogeneous impervious surfaces, was selected from ETM+ reflectance image. An unsupervised classification was conducted to mask water and vegetated areas. The rest of the pixels were considered to be pure impervious surfaces. A two-endmember linear mixture model was conducted in the CBD and the RMS was reasonably small (with a mean of 0.02) over all of the impervious surface pixels (see figure 3.10b). The fitness of this two-endmember linear mixture model can also be seen from the feature space diagram (figure 3.11), which shows that most of the impervious surface pixels in the CBD are on or within a small distance of the line connecting low and high albedo.
Figure 3.10 Two-endmember linear mixture analysis in the CBD of Columbus, Ohio: (a) ETM+ reflectance image in the CBD; (b) RMS for two-endmember linear mixing model in the CBD.

Figure 3.11 Feature space representation of MNF component 1 and 2 for impervious surfaces in CBD area.
Following the above discussion, a pure impervious surface land cover type might be modeled by low and high albedo endmembers through a fully constrained linear mixture model. That is, vegetation and soil endmembers have little or no contribution to impervious surface estimation. Therefore, given three land cover types (vegetation, impervious surface, and soil) on the ground, the impervious surface fraction can be calculated by adding low and high albedo fractions. However, some low reflectance materials (e.g. water and shade) and high reflectance materials (e.g. clouds and sand) adversely affect impervious surface estimation (Small 2001). Therefore, these materials should be identified and masked to ensure that only vegetation, impervious surface, and soil exist in the image. Water can be easily masked through an unsupervised classification (figure 3.12). Topographical shade can be removed by topographical correction (Sabol et al. 2002) and vegetation shade can be identified through detailed study of urban vegetation canopy structure (Gilabert et al. 2000). In this research, the effects of topographical and vegetation shade were ignored because they are not significant in this study region. Clouds and associated shadows can be delineated by screen digitizing and removed through unsupervised or supervised classifications (Lillesand et al. 1998). Although sand cannot be easily removed from the image through traditional classification techniques due to the spectral similarity of sand with high reflectance impervious surfaces (Lillesand et al. 1998), it might be separated through the incorporation of textural analysis (Irons and Petersen 1981, Gong and Howarth 1990, Berberoglu et al. 1999, Karathanassi et al. 2000, Stefanov et al. 2001), contextural techniques (Lobo 1997; Stuckens et al. 2000), and post-processing with ancillary data (Harris and Ventura 1995, Flanagan and Civco 2001). In this research, we assume that...
sand does not have a significant effect on the estimation of impervious surface. However, in urban change studies, these effects could be substantial because sand and soil are prevalent on the urban fringe.

![Figure 3.12 Result of unsupervised classification of water](image)

After image pre-processing, every pixel can be considered as a combination of three land cover types: vegetation, soil, and impervious surface. While impervious surface cannot be a single endmember due to its complexity, its fraction in each pixel can be calculated by adding the fractions of low albedo and high albedo endmembers. The impervious surface fraction shows a spatial coherence in the image (figure 3.13). That is, the impervious surface fractions are high (over 75%) in the CBD, middle (50-75%) in high-density residential areas, low (20-50%) in low-density residential areas, and near zero in rural areas.
3.2.7 Accuracy assessment

In order to assess accuracy of impervious surface estimation, a random sampling method was applied. For estimating classification accuracy, there is a consensus among researchers that a minimum of 50 samples for each category is reasonable, both statistically and in practical terms, using random or stratified random sampling schemes (Congalton 1991). Deguchi and Sugio (1994) used the whole population to test the estimation accuracy of impervious surface, but only 17 units existed in their population. As a compromise between statistical rigor and practical limitations, 100 samples in the image were chosen. A sampling unit of 3 by 3 pixels was used to avoid the effects of geometric errors of ETM+ and DOQQ image. For every sampled 3 by 3 TM pixel, the corresponding DOQQ image was digitized and the impervious surface fraction was

Figure 3.13 Fraction image of impervious surface
calculated from the digitized map. These DOQQs and ETM+ images have been co-
registered to NAD83 datum and UTM projection. The acquisition dates of these DOQQs
are between 1994 and 1995, which are about four to five years earlier than the TM image.
There are possible contemporaneous problems using these DOQQs in assessing the
accuracy (Flanagan and Civco 2001). However, these problems should not significantly
affect our results because urban infrastructure did not change dramatically during this
period. Results show that the overall estimation RMS is 10.6% for all samples (see Figure
3.14a), which is comparable to the 10% digitizing errors for impervious surfaces from
aerial photographs (Deguchi and Sugio 1994). The outlier on the upper left corner in
Figure 3.14a represents large estimation errors associated with sand. The residual
analysis (Figure 3.14b) shows that this model seems to

![Figure 3.14 Results of impervious surface estimation accuracy assessment: (a)
accuracy assessment of the impervious surface estimation; (b) residual analysis of
the impervious surface estimation.](image)

53
overestimate slightly impervious surface fraction in less developed areas (0-20%), while underestimating it in the CBD (over 80%). This is reasonable since the fully constrained linear mixture model requires that endmember fractions are positive and sum to 1. Further analysis could focus on applying the same linear mixture model but relaxing one or both constraints.

3.2.8 Summary of impervious surface estimation

Thus far, impervious surface distribution, together with vegetation and soil cover, have been directly derived from a Landsat ETM+ reflectance image by applying a fully constrained linear mixture model. The quantification of vegetation, impervious surface, and soil fraction is an important extension to traditional urban land use and land cover mapping. The ternary V-I-S model, especially the axis of V-I (Figure 3.15), shows the linkage between the V-I-S compositions and urban land use types. Such urban land use types include commercial, residential, industrial, and transportation (Anderson et al. 1976). Jensen (1983) suggests that much biophysical information from satellite sensors is lost in using these limited land use types. One example is estimating socio-economic factors, such as population and employment densities. Although population density can be estimated through regression models using certain land use types (Langford et al. 1991), such estimation is typically based on coarse spatial resolution (1 by 1 km grid). In transportation planning, especially public transit, it is essential to have detailed population estimates for distances characterized as suitable for walking in normal conditions, typically 400 meters (Murray 2001). Therefore, 1 km population density data
are unsuitable. Of significance here is that detailed population density estimates can be obtained using the V-I-S compositions derived from remotely sensed data. Research has shown that population density is closely related to impervious surface in urban residential areas. In particular, Anderson and Anderson (1973) stated that population density can be estimated by using streets and rooftops. Further, Treitz et al. (1992) identified different urban residential densities using impervious surfaces. Incorporating such information with census data is likely to offer great potential in estimating population density with higher accuracy.
Figure 3.15 Linking impervious surface and vegetation fractions to land use types (Revised from Ridd, 1995).
3.3 Residential impervious surface fraction delineation

While impervious surface exists in all built-up areas, impervious surface in residential areas generally corresponds to the location of people. Therefore, we first need to extract residential areas from the entire study area. As detailed in the previous section, residential areas can be delineated by applying classification methods to either derived vegetation-impervious surface-soil (V-I-S) images (Ridd 1995; Rashed et al. 2001) or original satellite images (Chen 2002). In this study, a maximum likelihood classification method was developed to classify the original ETM+ image into six classes: commercial and transportation, low density residential, medium density residential, soil, water, and vegetation (see figure 3.16). For every class, training samples were selected based on the NLCD data, DOQQ data, and original ETM+ image. In particular, low density residential samples were selected from scattered houses neighboring grassland and medium density residential samples were chosen from continuous building units with little surrounding grassland. After classification, these six classes were grouped into two major categories: residential and non-residential. The accuracy of the residential land use classification was checked using DOQQs for ground truthing. Four hundred samples were generated using a stratified random sampling scheme. The sampling unit is 3 by 3 in order to avoid geometric errors. The overall classification accuracy of the residential land use is 86% and the kappa coefficient is 0.7169 (see table 3.1), which is comparable to the results obtained by Lo (1995) and Chen (2002).
Table 3.1 Residential land use accuracy assessment (Maximum Likelihood classification)

<table>
<thead>
<tr>
<th>Classified image</th>
<th>Non-residential</th>
<th>Residential</th>
<th>Commission errors (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-residential</td>
<td>194</td>
<td>21</td>
<td>9.77</td>
</tr>
<tr>
<td>Residential</td>
<td>35</td>
<td>150</td>
<td>18.9</td>
</tr>
<tr>
<td>Omission error</td>
<td>15.3</td>
<td>12.3</td>
<td></td>
</tr>
</tbody>
</table>

Overall accuracy = 86.00%, overall kappa statistics = 0.7169
Mesev (1998) pointed out that residential land use classification could be improved by using ancillary data in a post-classification process. In particular, he suggested that census data is helpful in detecting potentially misclassified residential pixels (Mesev 1998). In this study, we found that population density information for each census block is helpful for identifying potential misclassified pixels. Firstly, census blocks with zero population density were analyzed. In our study area, 628 blocks (out of 2445) have zero population (see figure 3.17a). It is obvious that all of the pixels within these zero population blocks should be classified as non-residential. That is, the residential pixels within these blocks are misclassified and should be corrected. Figure 3.17b shows that many misclassified pixels are along main roads and others are in non-residential built-up areas sharing similar spectral signatures with residential built-up areas.

Figure 3.17 Post-classification to identify misclassified residential pixels using zero-population census blocks. The residential pixels within these zero population census blocks are considered misclassified.
High population density census blocks were also analyzed. If a pixel is within a high population density block, but classified as non-residential, this pixel is potentially misclassified and subject to further analysis using ancillary data or fieldwork. Parcel data and address-based employment data were utilized to examine these pixels. Most of these misclassified pixels were found to contain group-quarter populations (Plane and Rogerson 1994, pp142), which include students in university apartments (upper left portion in figure 3.18a), people in shelters, institutions, and nursing homes (middle portion in figure 3.18a), etc. It is difficult to classify this type of land use based only on remotely sensed data because it has similar spectral signatures to commercial land use.

---

Figure 3.18 Post-classification to identify misclassified residential pixels using high population density census blocks, parcel data, and employment data
Moreover, most of these areas are also classified as commercial land use in parcel data because of their mixed commercial and residential land uses. This mixed land use phenomenon was discussed in Lo (1995) and found to be a major problem in population estimation. In this study, we separated this land use type from others with the help of employment data and parcel data (see figure 3.18b).

After delineating different residential land uses through classification and post-classification, we combined them together to obtain a single residential land use class (see figure 3.19a). The accuracy of residential land use classification after post-classification adjustment was checked using the same set of samples mentioned previously. As expected, the overall classification accuracy is improved to 90.00% and the overall kappa coefficient increases to 0.7942 (see table 3.2). Table 3.2 also shows that the commission error for the residential class decreases from 18.9% to 9.32%, which means the overestimates of residential area have been partially corrected by this post-classification process. After obtaining the residential land use class, impervious surface fractions for residential pixels (see figure 3.19b) were separated from the entire impervious surface fraction image (figure 3.13) using ERDAS Imagine spatial modeler.
<table>
<thead>
<tr>
<th>Classified image</th>
<th>Reference image</th>
<th>Commission errors (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-residential</td>
<td>Non-residential</td>
<td>10.46</td>
</tr>
<tr>
<td>Residential</td>
<td>Residential</td>
<td>9.32</td>
</tr>
<tr>
<td>Omission error</td>
<td>6.55</td>
<td>14.62</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>90.00%</td>
<td>overall kappa statistics = 0.7942</td>
</tr>
</tbody>
</table>

Table 3.2 Residential land use accuracy assessment after post-classification (Maximum Likelihood classification)

Figure 3.19 Residential impervious surface fraction delineation after maximum likelihood classification and post-processing
3.4 Fine resolution data generation using intelligent interpolation

With impervious surface fraction in the delineated residential areas as supplementary data, it is now possible to interpolate population estimates in these areas. Three interpolation methods, regression analysis, dasymetric mapping and cokriging, are proposed to estimate population density. Regression analysis involves estimating population density through a regression model that establishes a relationship between population counts or density and variables derived from remotely sensed data (Langford et al. 1991; Goodchild 1993; Chen 2002; Harvey 2002). Alternatively, dasymetric mapping allocates population to each land use type based on the assumption that population density for a single land use is constant and can be estimated through surveys (Fisher and Langford 1995). Cokriging is a geostatistical method that accounts simultaneously for spatial autocorrelation in population density and impervious surface fraction and the cross-correlation between these spatial variables. In this research, spatial regression, dasymetric mapping, and cokriging are applied in combination with the newly developed supplementary data, residential impervious surface fraction. In particular, a spatial regression model is described in section 3.4.1. Next, section 3.4.2 details an extended dasymetric mapping method. Finally, cokriging is reported in section 3.4.3.

3.4.1 Spatial regression

Many researchers have proposed regression-based models to estimate population density using supplementary data derived from satellite imagery. These models can be divided
into two classes. The first involves exploring relationships between population counts in each census zone and a number of scale dependent variables (e.g. pixel counts) from remotely sensed data for that zone (Langford et al. 1991; Sutton et al. 1997; Chen 2002). The other category of regression-based models focuses on the relationship between population density and a few scale-invariant variables (e.g. mean of reflectance in a specific band) from remotely sensed data (Lo 1995; Webster 1996; Harvey 2002). One potential problem with these regression models is the non-constant variance of residuals (heteroscedasticity), especially when the variance of the respondent variable is not stable (Hamilton 1992, pp53). In particular, population density may be described by a Poisson function (see figure 3.20a) and its variance is likely to be proportional to its mean value.

![Histograms](image.png)

Figure 3.20 Histogram of (a) population density and (b) square root of population density at the block level. It shows that population density may be described by a Poisson distribution, while the square root transformation is a reasonable approximation of a normal distribution.
In order to stabilize the variance of population density and linearize the relationship between population density and residential impervious surface fraction, a square root transformation of population density was performed. Other transformations, such as logarithmic, could also be valuable, however, the square root transformation has proven to perform better in estimating population (Harvey 2002). Figure 3.20b shows that the distribution of the square root of population density is near normal and its variance is approximately constant. In this study, we excluded zero population density census blocks because no interpolation is necessary for these blocks.

The other potential problem with linear regression models in this context is that they assume only first order variation and that regression residuals are spatially independent. However, this assumption is unlikely to be correct in many geographical applications (Griffith 1993; Griffith and Can 1996). In this study, both the square root of population density (with Moran’s I of 0.4726) and residential impervious surface fraction (with Moran’s I of 0.6155) show moderate, but statistically significant, positive spatial autocorrelation. Therefore, instead of assuming residual independence, more complex models that include spatial autocorrelation effects are necessary. We performed a simultaneous autoregressive (SAR) model, which is widely applied in spatial statistics (Griffith 1993), to explore the relationship between the square root of population density and residential impervious surface fraction. Moreover, we chose the area of each census block as a weighting factor to reduce the effects of zonal area. The utilized model is as follows:
\[
\sqrt{P} = \beta_1 \delta + \beta_0 + \rho W U + \varepsilon
\] (3.4)

where \( \sqrt{P} \) is the square root of population density in each census zone; \( \delta \) is the mean residential impervious surface fraction for each zone; \( \beta_1 \) and \( \beta_0 \) are regression coefficients; \( W \) is a proximity matrix created from census block data; \( U \) is a zero-mean vector of errors; \( \varepsilon \) is a vector of independent random errors with constant variance; and \( \rho \) is the interaction parameter describing the significance of second order variation. In this model, the estimated population density of a census zone not only depends on the impervious surface fraction mean of its own zone, but also relates to the mean of neighboring zones through the proximity matrix \( W \) and interaction parameter \( \rho \). Details of the SAR model are given in Bailey and Gatrell (1995, pp276) and Griffith (1993). We structured and solved this model using the S+SpatialStats module (Venables and Ripley 1999) for S-Plus 2000 and ESRI ArcView software. The results (see table 3.3) show that the residential impervious surface fraction is a statistically significant factor in explaining the distribution of the square root of population density.

\[
\begin{array}{cccc}
\beta_0 & 0.4493 & 0.0313 & 14.3665 & 0.0000 \\
\beta_1 & 3.2733 & 0.0874 & 37.4714 & 0.0000 \\
\end{array}
\]

\( \rho = 0.05554 \)

Table 3.3 Regression results for population density against residential impervious surface fraction using the SAR model
The population estimation accuracies were tested for each census level (block, block group, and tract) using the root mean square error ($E_{RMS}$) and coefficient of variation ($V$) developed by Fisher and Langford (1995), defined as follows:

$$E_{RMS} = \left[ \frac{1}{m} \sum_{j=1}^{m} (P_j - \hat{P}_j)^2 \right]^{1/2} \quad (3.5)$$

$$V = \frac{1}{P} \sum_{j=1}^{m} E_{RMS} = \frac{1}{P} \sum_{j=1}^{m} |P_j - \hat{P}_j| \quad (3.6)$$

where $P$ is the total population in the study area; $m$ is the number of total census blocks; $P_j$ is the population count of block $j$; and $\hat{P}_j$ is the estimated population count for block $j$.

For the entire study area, population estimation accuracy was checked using relative estimation error ($R$):

$$R = (\hat{P} - P) / P \quad (3.7)$$

where $\hat{P}$ is the estimation of total population in the study area. The estimation errors of the SAR model for each census level are shown in table 3.4. It shows that the residential impervious surface fraction is a major factor influencing population density. In particular, the coefficient of variation is relatively small for small areas (42.4% for the block level and 22.7% for the block group level). These results are better than those given in Lo (1995) where relative errors of 60-100% were reported for small areas. For the entire study area, the relative estimation error is comparatively large (-10.4%) considering results given in Lo (1995) and Harvey (2002). This error is likely due to the
underestimates of population in multiple story residential buildings, for which the population density is higher than 10 persons per pixel.

<table>
<thead>
<tr>
<th>Target zones</th>
<th>Average population</th>
<th>Root mean square error ($E_{\text{RMS}}$)</th>
<th>Coefficient of variation ($V$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block (2445)</td>
<td>40.99</td>
<td>50.9</td>
<td>42.4%</td>
</tr>
<tr>
<td>Block group (125)</td>
<td>801.74</td>
<td>266.8</td>
<td>22.7%</td>
</tr>
<tr>
<td>Tract (36)</td>
<td>2825.84</td>
<td>718.4</td>
<td>20.2%</td>
</tr>
<tr>
<td>Total study area</td>
<td>100,200</td>
<td>-10.4%</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.4 Absolute and relative estimation errors of the SAR model

Applying the SAR model, population density was estimated for the entire study area (see figure 3.21). There is a distinguishable variation in the geographical distribution of population in the study area. That is, high-density, household-based populations reside in the southern and northwestern part of the study area and low-density, household-based populations live in the eastern portion of Columbus. Moreover, the scattered group-quarter populations mostly reside in the CBD (middle portion) and university apartments (northwestern portion).
3.4.2 Dasymetric mapping

While regression-based methods have been widely applied, population counts are not preserved in census units. That is, these methods may add or subtract population from a census unit in the interpolation process. In order to overcome this problem, dasymetric mapping was proposed by Wright (1936) and later applied by others (Langford and Unwin 1994; Fisher and Langford 1995; Moon and Farmer 2001) as an intelligent
interpolation approach for estimating population density. A major difference between the regression-based method and dasymetric mapping is that the former is fitted for population globally, while the later is locally adjusted (for every small zone) (Fisher and Langford 1995). Dasymetric mapping has proven to be generally more accurate than regression-based intelligent interpolation and simple interpolation models (Fisher and Langford 1995; Sadahiro 1999).

Dasymetric mapping is an approach that allocates population in a census unit to every grid cell (e.g. 30 by 30 m) within that unit based on observed land use types (Plane and Rodgerson 1994). A basic assumption is that population density for each land use type is constant and can be estimated through surveys or calculations. In this study, we extend the traditional dasymetric mapping method for allocating people to each pixel using its impervious surface fraction. That is, instead of presuming population density is constant for each land use type, we assume that population density is a linear function of residential impervious surface fraction. This method is likely to be a special case of geographically weighted regression (see Brunsdon et al. 1996, 1999; Fotheringham et al. 1998) in which regression parameters are localized. This allocation is as follows:

\[ P_j = \beta_j \times \delta_j \]  

(3.8)

where \( P_j \) is the population density of census block \( j \); \( \delta_j \) is the mean impervious surface fraction of block \( j \); and \( \beta_j \) is a localized regression parameter to be estimated. After obtaining parameter \( \beta_j \), it can be used to calculate the population count for each pixel within block \( j \). As mentioned before, the estimation error of this dasymetric mapping
method in each census district level is zero since it preserves the total population counts in census units.

Figure 3.22 shows the population distribution estimated using this extended dasymetric mapping method. It illustrates a similar geographical pattern to that shown in figure 3.21.

However, a major difference is that the population density surface in figure 3.22 is not as smooth as that in figure 3.21. This is because dasymetric mapping preserves the total population count of every census block, emphasizing small-scale variation. As such, there is no error associated with these estimates with respect to known census counts, in contrast to the estimations using spatial regression.
3.4.3 Cokriging

In comparison to regression analysis and dasymetric mapping, cokriging simultaneously accounts for spatial autocorrelation in population density and impervious surface fraction and the cross-correlation between these spatial variables. Moreover, it is suitable when the variable to be estimated (e.g. population density) is under-sampled while other supplementary variables are abundant (e.g. impervious surface fraction). Cokriging is a geostatistical method originating from mining applications (Journel and Huijbregts 1978; Cressie 1993) and widely applied in soil science (Webster and Burgrss 1980; Vauclin, et al. 1983, Webster 1985). Geostatistical methods were introduced in remote sensing in the late 1980s (Curran 1988; Woodcock et al. 1988). Now geostatistics are commonly applied in soil science, biogeography, climatology, and environmental studies (Oliver et al. 1989a, 1989b; Atkinson et al. 1992, 1994). A review of geostistical methods and associated applications may be found in Cressie (1993), Curran and Atkinson (1998), and Curran (2001). Although widely applied in physical geography, cokriging has rarely been utilized in estimating socio-economic conditions, such as population densities. In this section, population density is estimated using a cokriging method in which impervious surface fraction is taken as a secondary variable to improve estimation accuracy.

3.4.3.1 Cokriging theory

As an extension to two or more variables in ordinary kriging, cokriging is based on regionalized variable theory (Journel and Huijbregts 1978; Oliver et al. 1989a). According to this theory, any regionalized variable $z(x)$ can be considered a realization of
a random function $Z(x)$, which is a combination of a deterministic component, $m(x)$, and random fluctuation, $\varepsilon(x)$:

$$z(x) = m(x) + \varepsilon(x)$$  \hspace{1cm} (3.9)

where $x$ denotes the geographical coordinates in one, two, or three dimensions; $m(x)$ indicates a geographical trend or drift; and, $\varepsilon(x)$ is the spatially dependent random errors with mean zero. In most applications, the deterministic component, $m(x)$, is assumed to be locally constant,

$$m(x) = \mu$$  \hspace{1cm} (3.10)

and for any given distance and direction $h$, the variance of differences between $z(x)$ and $z(x+h)$ is finite and independent of $x$:

$$\text{var}[z(x) - z(x+h)] = E[\{z(x) - z(x+h)\}^2] = 2\gamma(h)$$  \hspace{1cm} (3.11)

where vector $h$, the lag, is a given separation distance and direction, and $\gamma(h)$ is the variogram. $\gamma(h)$ has been found to be an important tool in modeling spatial autocorrelation (Journel and Huijbergts 1978). Moreover, if two or more variables are needed, a cross variogram is defined as follows:
Based on regionalized variable theory, it is necessary to estimate an under-sampled variable using cokriging. This method ensures unbiased estimates with minimum and known variance (Curran 2001). If we consider estimating a variable \( u \) in a block \( B \) with sampling points of \( u \) and a second variable \( v \), our estimate will be:

\[
\hat{z}_u (B) = \sum_{i=1}^{N_u} \lambda_{u,i} z_u (x_{u,i}) + \sum_{j=1}^{N_v} \lambda_{v,j} z_v (x_{v,j})
\]  

(3.13)

in which \( N_u \) and \( N_v \) are the number of sampling points for variable \( u \) and \( v \); \( x_{u,i} \) and \( x_{v,j} \) are the locations of sampling points for variable \( u \) and \( v \), respectively; and, \( \lambda_{u,i} \) and \( \lambda_{v,j} \) are the weights to be calculated.

In order to ensure unbiasedness, the following constraints must be satisfied (see Aboufirassi and Marino 1984):

\[
\sum_{i=1}^{N_u} \lambda_{u,i} = 1
\]  

(3.14)

\[
\sum_{j=1}^{N_v} \lambda_{v,j} = 0
\]  

(3.15)

The first constraint indicates that at least one observation of the primary variable \( u \) is necessary for cokriging. Moreover, constraint (3.15) ensures that the summation of the
weights for the secondary variable $v$ is zero. Subject to these constraints, we minimize the estimation variance:

$$
\sigma^2_u(B) = E[(z_u(B) - \hat{z}_u(B))^2]
$$

(3.16)

This is an optimization problem in which $\lambda_{ui}$ and $\lambda_{vj}$ are the decision variables and $\sigma^2_u(B)$ is the objective function. Standard Lagrangian techniques can be applied to solve this problem. This results in the following:

$$
\sum_{j=1}^{N_u} \lambda_{ui} \gamma_{uu}(x_{ui}, x_{uk}) + \sum_{j=1}^{N_v} \lambda_{vj} \gamma_{uv}(x_{vj}, x_{vj}) + \psi_u = \bar{\gamma}_{uu}(B, x_{uk}) \quad k = 1, N_u 
$$

(3.17)

$$
\sum_{j=1}^{N_u} \lambda_{ui} \gamma_{uv}(x_{ui}, x_{vl}) + \sum_{j=1}^{N_v} \lambda_{vj} \gamma_{vv}(x_{vj}, x_{vl}) + \psi_v = \bar{\gamma}_{uv}(B, x_{vl}) \quad l = 1, N_v 
$$

(3.18)

$\gamma_{uu}(x_{ui}, x_{uk})$ is the semi-variogram of variable $u$ between site $i$ and $k$, $\gamma_{uv}(x_{ui}, x_{vj})$ is the cross semi-variogram between variable $u$ and $v$ at site $k$ and $j$. Finally, $\bar{\gamma}_{uv}(B, x_{vl})$ is the cross semi-variogram between variable $u$ and $v$ at block $B$ and site $l$.

Using this method, there are $N_u+N_v+2$ equations and $N_u+N_v+2$ variables, which can be easily solved by linear algebra. After obtaining the parameters $\lambda_{ui}$ and $\lambda_{vj}$, $\hat{z}_u(B)$ may be estimated using equation (3.13). The cokriging variance can be obtained as a byproduct of the cokriging process as follows:
\[
\sigma_u^2(B) = \sum_{i=1}^{N} \lambda_{ui} \bar{\gamma}_u(B, x_i) + \sum_{j=1}^{N} \lambda_{vj} \bar{\gamma}_v(B, x_j) - \psi_u - \bar{\gamma}_u(B, B)
\]  
(3.19)

Matrix formulations of these equations can be found in Myers (1982), McBratney and Webster (1983), and Aboufirassi and Marino (1984). Details on solving this problem using Lagrangian techniques are given in Vauclin et al. (1983) and Atkinson et al. (1992).

### 3.4.3.2 Variogram estimation

From equations (3.14), (3.15), (3.17), and (3.18), it is clear that parameters \( \lambda_{ui} \) and \( \lambda_{vj} \) are dependent on the variograms associated with variables \( u \) and \( v \), their cross-variogram, and block size. In this study, block size is defined to be the same as the TM image resolution (30 m by 30 m). Therefore, once the variograms and cross-variogram have been derived, cokriging is a straightforward process (Atkinson et al. 1992, 1994). In practice, the variograms are typically estimated using sampling points as follows:

\[
\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{z(x_i) - z(x_i + h)\}^2
\]  
(3.20)

where \( z(x_i) \) are known values of variable \( u \) or \( v \) at sampling point \( x_i \), and \( N(h) \) is the number of sampling point pairs separated by lag \( h \). Similarly, the cross variogram can be estimated as follows:
After obtaining the variogram and cross-variogram, a theoretical model is needed to fit them. Such a model needs to be positive definite and coregionalized to ensure the cokriging variance is non-negative. More discussion about choosing theoretical functions can be found in McBratney and Webster (1986) and Curran (1988). In this study, we chose a model satisfying the positive definite and coregionalized requirements, the details of which are discussed later in this section.

3.4.3.3 Interpolating population density using cokriging

In this study population density is considered the primary variable to be estimated. In addition, residential impervious surface fraction is considered a secondary variable used to increase estimation accuracy. One issue is that reported census statistics are not based on a sampling point, but rather on an areal unit like a block. The centroid of a census block may be used as the sampling point for the assignment of population density. However, this method is not realistic because there may not actually be people at the centroid of a block. Martin (1989) solved this problem by using a population-weighted point as the representative point of a census block. In a similar manner, in this research the central point of the pixel whose impervious surface fraction is approximately equal to the block mean is used as a population-weighted block point. In addition, we assign impervious surface fraction of the pixel and average population density of the block to
this sampling point. After obtaining the impervious surface fraction and population density on these samples, the characteristics of the data are explored. If they are not secondary stationary, i.e. have the same mean and variance, the accuracy of the estimated experimental variogram and associated cokriging will be degraded (Cressie 1993). The histograms for population density (see Figure 3.23a) and impervious surface fraction (see Figure 3.24) were captured based on the sampling points. It is clear that population density is highly positively skewed and may be approximated by a Poisson function with its variance proportional to its mean value (Bailey and Gatrell 1995; Harvey 2002). A square root transformation was performed on population density to stabilize its variance. The histogram of the transformed population density (see Figure 3.23b) shows that its distribution is near normal and its variance is approximately constant. The histogram of impervious surface fraction is slightly negatively skewed, but may be considered approximately normal. Thus, no transformation was conducted on impervious surface fraction. We excluded zero population density census blocks because no interpolation is necessary for these blocks.
Figure 3.23 Histogram of (a) population density and (b) square root of population density at sampling points. It shows that population density may be described by a Poisson distribution, while the square root transformation is a reasonable approximation of a normal distribution.

Figure 3.24 Histogram of impervious surface fraction at sampling points.
In this study, the primary variable $u$ is the square root of population density, and the secondary variable $v$ is impervious surface fraction. Experimental variograms and cross variograms were calculated using equations (3.11) and (3.12). Gstat software was utilized to fit these variograms to theoretical functions (Pebesma and Wesseling 1998). The weighted least squared method and visualization were applied in modeling the experimental variograms (Cressie 1985). Directional variograms were also computed and no obvious anisotropies were found. Therefore, the variograms were assumed to be isotropic and were fitted using an exponential model of the following form:

$$\gamma(h) = \begin{cases} 
C_0 + C_1 \{1 - e^{(-h/r)}\} & \text{for } h > 0 \\
0 & \text{for } h = 0
\end{cases}$$

(3.22)

Here $C_0$ is the nugget representing unexplained variance and $r$ defines the spatial scale of the variation. In practice, the sill is $C_0 + 0.95C_1$ at the point of $3r$. In this study, the parameters were calculated for the variograms of the square root of population density and impervious surface fraction, and also for their cross-variogram (see Table 3.5 and Figure 3.25).
<table>
<thead>
<tr>
<th></th>
<th>$C_0$</th>
<th>$C_1$</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population density</td>
<td>0.196</td>
<td>0.176</td>
<td>1000</td>
</tr>
<tr>
<td>Impervious surface</td>
<td>0.007</td>
<td>0.0089</td>
<td>1000</td>
</tr>
<tr>
<td>Population density – impervious surface</td>
<td>0.012</td>
<td>0.030</td>
<td>1000</td>
</tr>
</tbody>
</table>

Table 3.5 Coefficients of the theoretical variogram and cross variogram functions
Figure 3.25 Variograms of (a) square root of population density, (b) residential impervious surface fraction, and (c) the cross-variogram between square root of population density and impervious surface fraction. Exponential functions with $r=1000$ are chosen to model these variograms.
After obtaining the variograms of impervious surface fraction, square root of population density, and their cross-variogram, a block cokriging was performed to interpolate population density (see Figure 3.26) using Gstat software embedded in IDRISI (Harmon 2002). Figure 3.26 shows a clear geographical pattern of population distribution in the study region. In particular, few people live in the CBD except group-quarter populations. High-density household-based populations are adjacent to the CBD in the southern and northwestern portions of the study region. Moreover, low-density household-based populations reside relatively far away from the CBD (in the eastern and southern portions).

![Figure 3.26 Estimated population density using developed cokriging method. The height indicates the value of population density for each TM pixel. The average population density is 4.28, with a maximum of 52, and a minimum of 0.](image-url)
3.4.3.4 Accuracy assessment

Using the cokriging variance approach defined in equation (3.19) for the square root of population density, the mean cokriging variance is 23.5% (minimum of 21.3% and maximum of 50.3%). Figure 3.27 shows the distribution of cokriging variance in the study area. In particular, cokriging variance is high along the study area boundary because few samples are used in estimating population density in this portion of the region.

Figure 3.27. Cokriging variance of the square root of population density estimation. The average cokriging variance is 0.235, with a maximum of 0.503, and a minimum of 0.213.
It is possible to examine population count estimation accuracies at each census zonal level using the root mean square error ($E^{RMS}$) and coefficient of variation ($V$) to evaluate the absolute and relative error as defined in equations (3.5) and (3.6). The overall regional assessment of population count estimation accuracy can be carried out using the relative estimation error ($R$) defined in equation (3.7).

The results (see Table 3.6) show that the cokriging method gives good estimation accuracy. In particular, the coefficient of variation is relatively low at the census block level (34.7%), low at the block group and tract levels (15.2% and 10.2% respectively), and near zero for the entire study area (-0.3%). This result is comparable to or better than the results reported in Lo (1995) and Harvey (2002).

<table>
<thead>
<tr>
<th>Target zones</th>
<th>Average population</th>
<th>Root mean square error ($E^{RMS}$)</th>
<th>Coefficient of variation ($V$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block (2445)</td>
<td>40.99</td>
<td>45.3</td>
<td>34.7%</td>
</tr>
<tr>
<td>Block group (125)</td>
<td>801.74</td>
<td>215.0</td>
<td>15.2%</td>
</tr>
<tr>
<td>Tract (36)</td>
<td>2825.84</td>
<td>411.0</td>
<td>10.2%</td>
</tr>
<tr>
<td>Total study area</td>
<td>100,200</td>
<td>-0.3%</td>
<td>-0.3%</td>
</tr>
</tbody>
</table>

Table 3.6 Absolute and relative estimation errors of the cokriging model
3.4.3.5 Population density adjustment

The cokriging approach gives unbiased estimates for the square root of population density with minimum variance. However, the population count estimation errors evaluated at the census block level are still somewhat large (34.7%). As discussed in previous studies (Langford and Unwin 1994; Fisher and Langford 1995, Martin 1996), interpolation methods should preserve population counts in each reporting zone. One option is adding a volume-preserving constraint in the cokriging model. However, this will make the model more complex since it has a quadratic objective function and a quadratic regional constraint. In fact, it is not clear that this resulting model can be solved, exactly or heuristically. An alternative option is to rescale the population estimates on every pixel to satisfy this zonal constraint:

\[ P_{ij}^* = \frac{\hat{P}_j}{\hat{P}_i} \times \frac{P_i}{\hat{P}_i} \]  

(3.23)

Here \( P_{ij}^* \) is the rescaled population estimates of pixel \( j \) in census block \( i \), \( \hat{P}_j \) is the population estimates through the cokriging, and \( P_i \) and \( \hat{P}_i \) are the population counts of block \( i \) (census count and cokriging estimates, respectively). This rescaled population density (see Figure 3.28) generally maintains the estimates obtained using cokriging, but emphasizes local variation as well. For example, the cokriging method tends to underestimate population counts in multi-story and high-rise buildings (the middle
portion of Figure 3.26). In contrast, the rescaling approach adjusts these inaccuracies and obtains more accurate population density estimates.

Figure 3.28. Adjusted population density that preserves zonal population counts. The height indicates the value of population density for each TM pixel. The average population density is 4.40, with a maximum of 143, and a minimum of 0.

3.5 Comparisons of interpolation methods

In section 3.4, three intelligent interpolation methods, spatial regression, dasymetric mapping, and cokriging, were developed for generating fine resolution population estimates using impervious surface fraction in the delineated residential areas as
supplementary data. In particular, the SAR model establishes the relationship between the square root of population density and residential impervious surface fraction while considering spatial autocorrelation effects. Alternatively, the extended dasymetric mapping method allocates people to each pixel with the help of impervious surface fraction. In comparison, cokriging estimates population density by accounting simultaneously for spatial autocorrelation in population density and impervious surface fraction and the cross-correlation between these spatial variables.

The SAR model has advantages over traditional linear regression models for estimating population density using residential impervious surface fraction since regression residuals are spatially autocorrelated. Results show that residential impervious surface fraction has a significant contribution in explaining the variation of population density. Moreover, this model has relatively good accuracy in large area population estimation. For instance, the relative population estimation error is about 20% at the block group and tract levels, and 10% for the entire study area. However, as expected, the estimation error (40-45%) is relatively large at the block level.

As an extension to traditional dasymetric mapping, residential impervious surface fraction was utilized to allocate population counts in a block to each pixel within that block. Because it utilizes detailed information of residential built-up area, this extended approach improves the accuracy population density estimation. Moreover, there is no estimation error associated with the utilized dasymetric mapping approach at census district levels since population counts in each census unit are preserved. However, it may be biased in estimating population density at the pixel level. Moreover, unlike regression
analysis, it cannot be applied in areas where census data are not available. In addition, dasymetric mapping is a relatively subjective method in distributing population in a small area.

Compared to spatial regression and dasymetric mapping, cokriging is clearly a better approach in deriving detailed population estimates. In particular, the relative population estimation error for the entire study area is –0.3%, which is much better than the results obtained using the SAR model (10% estimation error). Further, the estimation errors at the census block group and tract levels (15.2% and 10.2% respectively) are about 10% lower than those calculated using regression analysis (22.7% and 20.2% respectively). At the census block level, the estimation error is about 8% lower than that reported for the SAR model (see Table 3.6). These results demonstrate that cokriging applied to residential impervious surface fraction is a superior alternative to regression based interpolation approaches.

One reason explaining why cokriging performs well is that it addresses spatial autocorrelation and cross autocorrelation associated with the distribution of people in urban areas. Instead of ignoring spatial dependence, which was done in dasymetric mapping, it models the spatial autocorrelation of population and impervious surface fraction through variograms, and applies them in population interpolation. Moreover, unlike other interpolation methods, it provides estimation variance (see equation 3.19 and Figure 3.26) at the TM pixel level (30 by 30 meter). This estimation variance is an
important tool for assessing population estimation error, without aggregating to census reporting zones.
CHAPTER 4

TRANSIT SERVICE QUALITY IMPROVEMENT

4.1 Introduction

Previous chapters addressed the MAUP effects associated with spatially aggregate data and argued the need for fine resolution data to support transit planning. Further, fine resolution data were generated using intelligent interpolation technologies with the help of remote sensing imagery. Now we can examine transit issues effectively by utilizing the derived fine resolution data.

Poor transit service quality is seen as a key factor that contributes to low transit patronage. Common complaints are that transit service is too slow, too infrequent and generally inconvenient compared to automobile travel (Altshuler et al. 1979). Levinson (1983) found that bus travel time is typically 1.4 – 1.6 times higher than using private automobiles in a survey of several large U.S. cities. Studies show that better service quality can be achieved through reducing the number of stops, and/or increasing bus stop spacing (Furth and Rahbee 2000; Saka 2001; Murray and Wu 2003). However, access

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2 A modified version of this chapter has been submitted for publication consideration, coauthored with Alan Murray.
coverage is certainly important in public transit planning as this is the means by which service is provided to riders. In fact, Larwin (1999) highlights the role of access coverage, reflecting the fact that riders cannot use a service that they cannot get to. Recent research by Murray (2003) has focused explicitly on expanding access coverage.

Given the above, transit agencies must consider ways of improving both public transit access and service quality if ridership is to be increased (Larwin 1999; Murray and Wu 2003). While both components are important, studies show that service quality can be significantly improved without sacrificing current transit access coverage. In particular, Murray (2001) conducted a strategic analysis using the location set covering problem (LSCP) in order to assess how many stops in a system were actually needed to maintain current levels of coverage. Intentionally ignoring transit route structure, Murray (2001) found that only 10 percent of existing bus stops were necessary to provide equivalent service coverage. Operationally, linear programming models have been proposed to improve operational performance along a transit route by appropriately spacing stops (Wirasinghe and Ghoneim 1981; Furth and Rahbee 2000; Saka 2001; Murray and Wu 2003). Few studies, however, have explicitly addressed the tradeoff between service quality and access coverage. One exception is the work of Murray and Wu (2003) in which the tradeoff between accessibility and stop spacing was analyzed. Moreover, previous studies either ignore transit route structure or only consider a single route in the analysis of service quality. While it is reasonable to improve transit service quality route by route, interactions among different routes are necessarily neglected.
A need exists for a modeling approach that integrates transit service quality and access coverage in an existing, multiple route transit system. In this chapter, the multiple route maximal covering/shortest path (MRMCSP) model is developed to address the tradeoff between public transit service quality and access coverage. We begin by reviewing previous studies analyzing public transit access and service quality. Next, the MRMCSP is formulated. Application results for the public transit system in Columbus, Ohio are then presented. The chapter ends with discussion and concluding comments.

4.2 Background

Public transit access coverage has been considered an important standard in evaluating transit systems (Benn 1995). In fact, maximizing the number of areas having suitable access to transit is often an explicit operational policy objective of urban regions (Nelson and O’Neil 1983; Murray 2001). Access may be interpreted as the opportunity for potential riders to get from where they are to the transit service (Murray et al. 1998). Often 400 meters (quarter mile) is stipulated as a suitable access standard for an individual to walk under normal conditions (Demetsky and Lin 1982; Peng et al. 1997). A person is considered covered by public transit if they have suitable access to a transit stop. A number of studies have evaluated current transit access coverage in an existing system (Murray et al. 1998; Cha and Murray 2001; Murray 2001) and approaches have been proposed for extending transit access coverage (Murray 2003). With an objective of maximizing potential ridership coverage and minimizing associated costs, the maximal covering/shortest path (MCSP) model (Current et al. 1985) also represents an approach for extending access, though this has not been proposed or applied in the context of an
existing transit route. Different versions of one-route, two-route, and multiple-route MCSP models have been used in designing routes for new service areas (Current and Schilling 1989, 1994; Boffey and Narula 1998; Hachicha et al. 2000). While evaluating and improving access is an important issue in transit planning, this research focuses on improving service quality of an existing transit system in addition to maintaining transit access coverage to the greatest extent possible.

Service quality refers to the convenience associated with an individual traveling within a transit system. This may be measured as travel time, transit speed, the number of transfers, etc. required to get from an origin to a destination (Levinson 1983; Furth and Rahbee 2000). Transit travel time has been widely utilized as an evaluation standard of service quality. Levinson (1983) details that total travel time for a transit vehicle includes dwell, acceleration, cruise, and deceleration time. The less the travel time, the better the performance. With a goal of minimizing total travel time via transit, many models have been proposed and solved through continuum approximations or linear programming in order to decide an optimal spacing of bus stops along a transit route (Wirasinghe and Ghoneim 1981; Saka 2001). However, these approaches typically do not address the actual geography of a street network or stop locations (Furth and Rahbee 2000). One exception is the work of Furth and Rahbee (2000) in which travel demand is redistributed to the blocks of parallel streets and cross-streets in each stop’s service area. However, it is not clear whether such a redistribution is spatially appropriate (Horner and Murray 2003; Murray and Wu 2003).
An alternative performance enhancing approach is minimizing the number of stops along a transit route (Murray 2003). Removing redundant bus stops will no doubt decrease the delay associated with bus deceleration, dwell, and acceleration, thereby decreasing total travel time and increasing riders’ accessibility via transit (Murray 2003; Murray and Wu 2003). Along these lines, Murray and Wu (2003) developed two spatial optimization models for addressing improved transit accessibility.

Existing approaches for addressing transit service quality typically are not capable of addressing multiple routes in an established transit system. However, integrated route structure is essential (Pendyala et al. 2002) and most urban areas must contend with an existing transit system for which only incremental changes are possible. Given this, there is a need for a model which addresses both transit service quality and access coverage in an established multiple route transit system.

4.3 Modeling transit service quality and access coverage

This section presents a model that allows for a tradeoff between service quality and access coverage in the selection of stops to maintain in an existing transit system. Total system travel time has been utilized to represent public transit service quality. The multiple route maximal covering/shortest path (MRMCSP) model developed in this research may be thought of as an extension of the maximum covering/shortest path (MCSP) model proposed by Current et al. (1985). One major difference is that the MRMCSP is applied in an established transit system, while the MCSP is applied to identify a new transit route devoid of existing structure. Moreover, unlike the MCSP,
directed links between stops have been utilized in the MRMCSP to eliminate potential sub-tours. A similar directed network-flow model was applied in planning forest harvests (ReVelle and Snyder 1996) and for siting monitoring stations along a stream (ReVelle and Hearn 2002). However, these models only consider a single objective. In contrast, the MRMCSP considers both multiple transit routes and multiple objectives. Utilized notation is defined as follows:

\( i, j, k = \) index of existing bus stops (sets denoted \( I, J, K \));
\( r = \) index of existing transit routes (set denoted \( R \));
\( m = \) index of ridership service areas;
\( o, d = \) index of origin, \( O \), and destination, \( D \), terminals for transit routes;
\( l_{ij} = \) transit travel distance between stop \( i \) and \( j \);
\( v_{ij} = \) cruise speed between stop \( i \) and \( j \);
\( \delta_i = \) total delay time at stop \( i \) associated with bus acceleration, deceleration and door opening and closing;
\( t_{ij} = \) total travel time between stop \( i \) and \( j \) without intermediate stops;
\( a_m = \) potential ridership demand in service area \( m \);
\( \text{dist}_{mj} = \) shortest travel time or distance from service area \( m \) to stop \( j \);
\( S = \) suitable service access standard;
\( N_m = \{ j \mid \text{dist}_{mj} \leq S \} \);
\( y_{rm} = \begin{cases} 
1 & \text{if service area } m \text{ is covered by route } r, \\
0 & \text{otherwise}; 
\end{cases} \)
\[ z_{odij} = \begin{cases} 
1 & \text{if directed arc from stop } i \text{ to } j \text{ is included in path from origin } o \text{ to destination } d, \\
0 & \text{otherwise}; 
\end{cases} \]

\[ x_j = \begin{cases} 
1 & \text{if stop } j \text{ is selected to remain in the system}, \\
0 & \text{otherwise}. 
\end{cases} \]

Minimize \( Z_1 = \sum_o \sum_d \sum_i \sum_j t_{ij} z_{odij} \) (4.1a)

Maximize \( Z_2 = \sum_m \sum_r y_{rm} \) (4.1b)

Subject to:

\[ \sum_{j \in N_u} x_j \geq y_{rm} \quad \forall r, m \] (4.2)

\[ \sum_j z_{odij} = 1 \quad \forall o \in O, d \in D \] (4.3)

\[ \sum_j z_{oidd} = 1 \quad \forall o \in O, d \in D \] (4.4)

\[ \sum_j z_{odij} - \sum_k z_{adjk} = 0 \quad \forall o \in O, d \in D, j \in J, j \notin O, j \notin D \] (4.5)

\[ \sum_j z_{odij} = x_j \quad \forall o \in O, d \in D, j \in J \] (4.6)

\[ x_i = (0, 1) \quad \forall i \] (4.7)

\[ z_{odij} = (0, 1) \quad \forall o, d, i, j \]

\[ y_{rm} = (0, 1) \quad \forall r, m \]

The objectives of the MRMCSP structure the minimization of total transit system travel time between all terminal pairs and maximize the total potential ridership provided
suitable access coverage by transit routes. Constraints (4.2) account for a service area coverage by route. Constraints (4.3) and (4.4) ensure that the origin and destination terminals begin and end routes, respectively. Constraints (4.5) are connectivity requirements. Constraints (4.6) track whether stop \( j \) is sited. Finally, binary decision variables are imposed in Constraints (4.7).

As noted previously, the MRMCSP extends the MCSP proposed by Current et al. (1985). One major difference with the MRMCSP is that multiple transit routes with multiple origin and destination terminals are addressed, including transfers among different routes. Another major difference with the MRMCSP is constraint structure. The MCSP is difficult to solve because of resultant sub-tours, which must be dealt with by adding sub-tour elimination constraints (Current et al. 1985). Further, the number of potential sub-tours increases rapidly with problem size. In contrast, sub-tours do not arise in the MRMCSP because of the use of directed links. Further discussion of the efficiency of such modeling structure can be found in ReVelle and Snyder (1996).

An important element in the MRMCSP is the estimation of travel time in objective (4.1a). Travel time between stops \( i \) and \( j \), \( t_{ij} \), is determined based on three different conditions:

\[
\begin{cases} 
1/2\delta_j + \frac{I_{ij}}{V_{ij}} + 1/2\delta_j & \text{if stops } i \text{ and } j \text{ are on the same route} \\
\infty & \text{if stops } i \text{ and } j \text{ are on different routes, and not transfer stops} \\
tr_{ij} & \text{if stops } i \text{ and } j \text{ are transfer stops on different routes}
\end{cases}
\]
where \( t_{ij} \) is the transfer time between stops \( i \) and \( j \). Structured in equation (4.8), \( t_{ij} \) is direct travel time without intermediate stops between \( i \) and \( j \). Therefore, \( t_{ij} \) is half the dwell time at stop \( i \), travel time from stop \( i \) to \( j \), and half the dwell time at stop \( j \) when stops \( i \) and \( j \) are on a same route. If stops \( i \) and \( j \) are on different routes, they cannot be directly connected unless they are designed for transfer between routes.

The weighting method was applied for solving the MRM CSP in order to avoid modifying constraint structure (Zadeh 1963; Current et al. 1985). Through applying a weight, \( \omega \), this two objective problem can be transformed into a single objective model:

\[
Z = \omega * Z_1 + (1 - \omega) * Z_2
\]

(4.9)

An approximation of the noninferior solution set can be derived by systematically varying the weight, \( \omega \), and solving the associated single objective linear programming model.

4.4 Columbus Transit System Analysis

Transit service in Columbus, Ohio is examined in this research. This region has experienced rapid growth in the last ten years. Given this, the Central Ohio Transit Authority (COTA) continues to seek improvements to regional public transit services (Horner and Grubesic 2001). We focus our analysis on two routes spanning 47.4 km², partitioned into 2445 Census blocks (see Figure 4.1). This area contains approximately 100,000 people and employs some 123,800 individuals. Included in this area are most representative land use types: central business district (CBD), high-density residential
and low-density residential. Public transit routes and stops for this area were acquired from COTA. Routes 6 and 7 constitute major service areas for this region. Shown in Figure 4.1, Route 6 (49 stop pairs) starts from a high-density residential area (T1) in the west and extends about 8 kilometers to the northeast (T2). Route 7 (74 stop pairs) starts in the north (T3) and extends 10 kilometers to the southeast (T4). The headway for stops along these two routes is approximately 15 minutes. Both routes cover residential areas near the terminal points and commercial areas in the middle sections. A transfer stop for these two routes is located at the corner of N. High Street and Broad Street.

In addition to bus route and stop information, block population data from the 2000 Census and employment data from the Mid-Ohio Regional Planning Commission (MORPC 2002) were utilized as potential ridership demand in this analysis. 2000 Census data specifies the total number of people within each block. The MORPC employment data includes the addresses of employment activities and the number of people employed. Employment data was aggregated to census blocks in order to be consistent with census population data. The total number of people and total number of employees in each census block was used as a proxy for potential transit demand (Murray and Wu 2003).

Although typically utilized as demand data in spatial modeling approaches, census zonal data may be problematic in detailed transit planning (Murray et al. 1998). Census data are likely to mask the underlying population distribution because it is intentionally structured
Figure 4.1 A portion of Columbus including transit routes of interests
to aggregate individual population counts to larger zonal units (Martin 1996; Moon and Farmer 2001). In addition, scale and unit definition biases, the so-called modifiable areal unit problem (MAUP), may influence modeling results (Openshaw and Taylor 1981). To address potential transit demand spatial representation issues, detailed population data generated in Chapter 3 (see Figure 3.26) was also utilized in this analysis. Population and employment counts within each 30×30 meter grid were interpolated through cokriging using impervious surface fraction. Firstly, impervious surface fraction was derived from Landsat ETM+ imagery using spectral mixture analysis. Next, a cokriging method was applied to interpolate population and employment counts using impervious surface fraction as supplementary data. This data provides greater spatial detail on how the population is distributed and is likely better suited for modeling transit demand.

The total system travel time is calculated as the total travel time from each terminal to other terminals using public transit. In our two-route application, four terminals with six origin-destination pairs have been specified (see Figure 4.1)\(^3\). It is assumed that passengers can only transfer at the major transfer stop and the transfer waiting time is half the average headway. Total travel time is divided into three components: cruise travel time, congestion delay, and stop delay. Cruise travel time is calculated by dividing bus route length by cruise speed. Congestion on both routes is roughly equivalent, thus they were treated similarly. Stop delay time may be further subdivided into delay time associated with bus deceleration, time to open and close door, delay time associated with bus acceleration, and passenger boarding and alighting time (Furth and Rahbee 2000).

\(^3\) Unique pairs consist of T1-T2, T1-T3, T1-T4, T2-T3, T2-T4, and T3-T4.
The sum of the first three bus stop delay components is typically modeled as follows (Wirasinghe and Ghoneim 1981; Furth and Rahbee 2000; Saka 2001):

$$\delta_i = k_i + 0.5v_i \left[ \frac{1}{a_i} + \frac{1}{d_i} \right]$$  \hspace{1cm} (4.10)

where $\delta_i$ is the total delay time at stop $i$ associated with bus acceleration, deceleration, and door opening and closing; $k_i$ is the time for opening and closing doors; $v_i$ is the cruise speed; and $a_i$ and $d_i$ are the acceleration and deceleration rates respectively. In this study, $k_i$ is estimated as 3 seconds, $v_i$ is 25 mile per hour, and $a_i$ and $d_i$ are assumed to be 1.33 meters/second$^2$. These values are set based on reported empirical studies (Pline 1992; Furth and Rahbee 2000; Saka 2001) and field observations in the study region. This gives a dwell time $\delta_i$ of 11.4 seconds for each stop. The fourth bus stop delay component, total passenger boarding and alighting time, may vary for each bus stop. However, it is reasonable to assume that the total passenger boarding and alighting time is a linear function of the number of passengers (Furth and Rahbee 2000). Therefore, the total delay associated with passenger boarding and alighting in a transit system can be assumed to be a fixed value if the access coverage of potential ridership does not change significantly (Furth and Rahbee 2000). Therefore, we assume the total passenger boarding and alighting delay is fixed.
4.5 Application results

A 1.0 GHZ Pentium III personal computer running Windows NT 4.0 with 512 MB memory was utilized in this analysis. A loose-coupled modeling environment integrated GIS and spatial analysis software to address our transit planning problem. In particular, ArcView version 3.2, a commercial GIS package, was used for system travel time estimation, access coverage analysis, data management, and visualization of results. An Avenue script supported by ArcView was created to produce MRMCSP application instances for subsequent use in ILOG CPLEX 7.0, a commercial optimization package. The spatial optimization problems were solved by CPLEX and solutions were read back into ArcView for visualization and further analysis.

Using census block population and employment data representing potential demand of public transit (see Figure 4.2), the model has 10,177 decision variables and 2,629 constraints. Application results are reported in Table 4.1 for various weights, $\omega$. As expected, the MRMCSP performs well computationally, requiring only seconds to reach an optimum. This supports the noted distinction in model structure of the MRMCSP compared to the MCSP. The existing transit routes cover 145,796 potential riders. The average system travel time for the six origin-destination pairs is 32.70 minutes. The results in Table 4.1 show that current coverage can be maintained, but it is possible to decrease average travel time down to 24.14 minutes (see $\omega = 0.1$). This is 26% less than the current average travel time of 32.70 minutes. Further, the number of stops on Routes 6 and 7 decrease to 21 and 33 respectively, which are 57% and 55% less than the existing
number of stops. The spatial locations of these selected stops are shown in Figure 4.3 for $\omega = 0.1$. The average bus stop spacing increases from 163 meters up to 381 meters on Route 6, and from 135 meters up to 303 meters on Route 7.
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Table 4.1 Access coverage and average travel time tradeoff (Census blocks)
Figure 4.2 Potential ridership demand blocks
Figure 4.3 Selected stops that ensure complete coverage, but decrease average travel time by 26% (Census block demand representation)
The results discussed thus far demonstrate that system travel time can be greatly decreased through removing redundant stops without affecting access coverage of potential ridership. It is possible to further reduce travel time if access coverage can be sacrificed. The tradeoff between transit access coverage and average system travel time for each terminal pair is shown in Table 4.1 and Figure 4.4. The results illustrate that travel time can be greatly decreased if slightly less access coverage is permitted. For example, to maintain 95% of the total potential demand covered for both routes, the average system travel time can be reduced to 21.05 minutes (see $\omega = 0.94$ in Table 4.1). This is 12.8% less than the minimum travel time for a full coverage (24.14 minutes). Moreover, the number of stops on routes 6 and 7 are 11 and 18, only some 50% of the minimum number of stops required for complete coverage.

Figure 4.4 Tradeoff between access coverage and average travel time by route
(Census block demand)
In contrast to utilizing aggregate census block data, the interpolated 30×30 meter grid-based data was also used to spatially represent potential transit demand (see Figure 4.5). Results are reported in Table 4.2. The resulting model requires 22,263 decision variables and 14,715 constraints. Although more decision variables and constraints are needed, the computational complexity of this model does not increase significantly (see solution time column in Table 4.2). The modeling results differ from those obtained using census zonal data. First, the total number of potential riders covered by both routes is 143,634, slightly less than the total using census data. A more significant difference is that 32 stops on Route 6 and 51 stops on Route 7 are needed to actually cover all potential demand using the grid-based representation (see $\omega = 0.001$ in Table 4.2). Of course this represents over 50% more stops found compared to census data. The average travel time for $\omega = 0.001$ is 27.68 minutes in Table 4.2. This is 3.54 minutes higher than that suggested using census data. These results highlight problems associated with using aggregate census data in transit planning.

As done in Table 4.1, the tradeoff between average system travel time and access coverage is assessed using grid-based data in Table 4.2. The tradeoff curves are shown in Figure 4.6 are consistent with those shown in Figure 4.4. In particular, the access coverage decreases slightly when the average system travel time decreases from 32 minutes to about 21 minutes and decreases rapidly when the travel time further decreases. Taking 95% access coverage as an example, the required travel time with grid-based
representation is 21.31 minutes (see $\omega = 0.93$ in Table 4.2), which is similar to the census-based representation of 21.05 minutes for $\omega = 0.94$ in Table 4.1. Further, the grid-

Figure 4.5 Potential ridership demand by 30×30 meter grids
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Table 4.2 Access coverage and average travel time tradeoff (30×30 m grids)
based representation finds that the minimum number of stops for 95% coverage on Routes 6 and 7 are 12 and 19 respectively, similar to the results obtained with census-based representation (11 and 18 respectively).

Figure 4.6 Tradeoff curves between access coverage and average travel time for two routes (30×30 m grid based demand)
4.6 Conclusions

In this chapter the multiple route maximal covering/shortest path (MRMCSP) model was proposed to address the tradeoff between public transit service quality and access coverage in an existing multiple route transit system. Moreover, analysis was carried out using two transit demand representations, census blocks and 30×30 meter grids.

A distinction between the MRMCSP is application to multiple routes, in contrast to one route when the MCSP is applied. Another noteworthy feature of the MRMCSP is that an existing system context enables us to structure directed arcs, which is not the case for the MCSP. A benefit of this is that improved structure is added and potential routing sub-tours are eliminated. Therefore, the MRMCSP performs extremely well computationally, with only seconds required to optimally solve problems with thousands of decision variables and thousands of constraints. Such large problems cannot be solved using the MCSP.

One significant finding was that inefficiencies do exist in the public transit system in Columbus, Ohio. In particular, with census based demand representation, 26% of the travel time can be reduced while suitably covering all potential demand. Further, only 21 out of 49 stops on Route 6 and 33 out of 74 stops on Route 7 are required to fully cover existing potential demand. This means more than half of the existing stops are redundant and could be removed. Moreover, if one is willing to allow decreases in current demand
covered, a much lower travel time can be achieved. For example, with 95% census based demand coverage, the average system travel time (21.05 minutes) decreases 12.8% and requires 11 and 18 stops on Routes 6 and 7 respectively. This requires only 25% of existing stops.

Another significant finding relates to transit demand representation. With census-based and grid-based representations of potential ridership demand, the modeling results are quite different. The differences are associated with travel time and number of stops needed to fully cover potential transit demand. With the grid-based representation, the required travel time (27.68 minutes) is 14.7% higher than that (24.14 minutes) found using census data. Moreover, the number of stops required to cover all potential demand was more than 50% higher than that found using census data. This result illustrates the significant influences of demand data representation on modeled travel time and number of required stops. This suggests that the modifiable areal unit problem does exist in modeling public transit service quality and access coverage. However, using the MRMCSP enables large planning problems associated with spatially disaggregate data to be modeled without any computational difficulties.
CHAPTER 5

CONCLUSIONS

5.1 Summary

This research addressed modifiable areal unit problem (MAUP) effects associated with spatially aggregate data in public transit planning and analysis. In particular, the significance of MAUP effects in transit planning was highlighted and the need for fine resolution data to reduce these effects was noted. Further, fine resolution data were generated by applying several spatial interpolation techniques with the help of remote sensing imagery. Finally, the derived fine resolution data were utilized in the multiple route maximal covering/shortest path (MRMCSP) model applied to routes in Columbus, Ohio in order to demonstrate that public transit service quality could be improved.

An essential motivation of this research is the existence and significance of MAUP effects associated with spatially aggregate data used in transit planning and analysis. Spatially aggregate data are popularly utilized in transit planning and analysis. Examples include TAZ data utilized in travel demand modeling and census data used in GIS-supported transit planning. This research reviewed previous studies in transit planning
that use spatially aggregate data. Moreover, we detailed the MAUP effects associated with the utilization of aggregate data, and argued the need for fine resolution data to reduce MAUP effects in public transit planning.

Further, in this research we generated fine resolution data using intelligent interpolation technologies with the help of remote sensing imagery. In particular, impervious surface fraction, an important socio-economic indicator, was estimated through a fully constrained linear spectral mixture model using Landsat Enhanced Thematic Mapper Plus (ETM+) data within the metropolitan area of Columbus, Ohio in the United States. Four endmembers, low albedo, high albedo, vegetation, and soil were selected to model heterogeneous urban land cover. Impervious surface fraction was estimated by analyzing low and high albedo endmembers. Next, impervious surface in residential areas was delineated using classification and post-classification techniques. With the derived residential impervious surface fraction, three spatial interpolation methods, spatial regression, dasymetric mapping, and cokriging, were developed to interpolate fine resolution population density. In particular, a spatial regression model was proposed to estimate population density by establishing a relationship between the square root of population density and residential impervious surface fraction. Alternatively, the extended dasymetric mapping method allocates people to each pixel with the help of impervious surface fraction. Finally, cokriging generates population density by accounting simultaneously for spatial autocorrelation in population density and impervious surface fraction and the cross-correlation between these spatial variables.
Comparative results suggest that cokriging applied to impervious surface is a superior approach for estimating fine resolution population density.

With the fine resolution data generated through cokriging with impervious surface fraction, an MRMCSP model was proposed to address the tradeoff between public transit service quality and access coverage in an established bus-based transit system. Results show that it is possible to improve current transit service quality by eliminating redundant or underutilized service stops. Further, modeling results showed that MAUP effects do exist in the MRMCSP model and fine resolution data are essential for reducing effects.

5.2 Contributions

One contribution of this research is the recognition of MAUP effects in transit planning and analysis. Previous studies have not explicitly addressed MAUP effects associated with spatially aggregate data in the context of transit planning. This research, however, detailed significant MAUP effects in most transit planning applications and argued the need for fine resolution data to minimize these effects.

Another contribution is the generation of impervious surface fraction from remotely sensed data. Previously, impervious surface fraction has seen limited application in urban and transportation analysis because of the difficulties of quantification in a heterogeneous urban area. In this research, we developed a fully constrained linear spectral mixture model to estimate impervious surface fraction using Landsat Enhanced Thematic Mapper Plus (ETM+) data. In particular, heterogeneous urban land cover was modeled by four
endmembers, low albedo, high albedo, vegetation, and soil. Further, impervious surface fraction was estimated by analyzing low and high albedo endmembers. This model gives high estimation accuracy with RMS error of approximately 10 percent. Such an estimation error is comparable to manually intensive approaches, but requires considerably less work.

This research also developed various spatial interpolation technologies, spatial regression, extended dasymetric mapping, and cokriging, to generate fine resolution population estimates with the help of impervious surface fraction. An interesting aspect of this work is that residential impervious surface fraction was found to be an effective replacement for land use and land cover data typically used in modeling population density. This makes sense intuitively given that impervious surface fraction is closely related to housing development, and thus population density. Moreover, the cross variogram in cokriging clearly shows that population density and impervious surface fraction are co-regionalized variables, with only 25% variance unexplained. Another finding is that the cokriging method gives better results in deriving detailed population estimates. As an example, the relative population estimation error for the entire study area is about 10% lower than the results obtained using the SAR model. These results demonstrate that cokriging applied to residential impervious surface fraction is a superior alternative to regression based interpolation approaches.

An optimization model was developed in this research to address access and service quality. This model (MRMCSP) can be applied to multiple routes, in contrast to one route...
when the MCSP is applied. Moreover, the MRMCSP applied in an existing system context enables us to structure directed arcs, which is not the case for the MCSP. This improved model structure eliminates potential routing sub-tours. Therefore, the MRMCSP performs extremely well computationally, with only seconds required to optimally solve problems with thousands of decision variables and thousands of constraints. Another significant finding was that inefficiencies do exist in the public transit system in Columbus, Ohio. In particular, with census based demand representation, 26% of the travel time can be reduced while suitably covering all potential demand. Further, more than half of the existing stops are redundant and could be removed. This result suggests that it is possible to improve current transit service quality by eliminating redundant or underutilized service stops. Finally, this research suggests that the MAUP does exist in modeling public transit service quality and access coverage. With census-based and fine resolution representations of potential ridership demand, the modeling results are quite different. This illustrates the significant influences of demand data representation on modeling results. Further, it supports the need for fine resolution data to support transit planning and analysis.

5.3 Future Research

While this research has made a considerable contribution to the literature, potential improvements and extensions may be worth exploring. Future studies are conceivable in three areas: 1) applying impervious surface fraction in urban modeling, 2) refining spatial
interpolation models in population estimation, and 3) integrating travel behavior in public transit planning.

5.3.1. Applying impervious surface fraction in urban modeling

In traditional urban land use classification, each pixel is assigned to a single land cover type. In reality, however, most pixels contain information on multiple ground cover types (Settle and Drake 1993). Therefore, without considering spectral mixture effects, these urban land use classifications lose detailed information and degrade classification accuracy (Wang 1990, Ji and Jensen 1996), thereby adversely affecting capabilities for urban growth detection. Moreover, transitional changes within a pixel have been missed in traditional classification approaches (Ji and Jensen 1999). In contrast, impervious surface fraction maintains detailed information on urban morphology and likely has greater accuracy and stability for urban growth studies (Ji and Jensen 1999). This is consistent with the recognized applicability of the V-I-S model for urban heat island detection, run-off modeling, and environmental change detection (Ridd 1995). Therefore, one potential research area would be applying impervious surface fraction estimated from remotely sensed data for monitoring urban sprawl and examining the effects of urban sprawl on environmental sustainable development.

5.3.2. Refining spatial interpolation models in population density estimation

In applying intelligent interpolation technologies in population estimation, one potential problem is associated with residential land use classification accuracy. As stated before, it
is difficult to separate high-density residential land use from commercial land use. This may adversely influence population estimation accuracy. Although Fisher and Langford (1996) point out that population estimation accuracy is not sensitive to residential land use classification, poor classification does degrade population density estimation accuracy. In future research, technologies for integrating remotely sensed data (spectral and textural information) and spatial data in order to improve classification accuracy of residential land use would be helpful. Another improvement would be satisfying the volume preserving constraint during the interpolation process, requiring that interpolated population counts in every census zone be equal to observed counts. In this study, we satisfied this constraint by rescaling population density in every pixel after interpolation. Although the population counts in every census zone are maintained, this adjustment may introduce bias and increase estimation variance. More sophisticated models might improve population density estimation accuracy and maintain population counts in every census zone simultaneously.

5.3.3. Integrating behavior models in detailed public transit planning

In this research, a location model, the MRMCSP, was developed to address the tradeoff between transit service quality and coverage. In this model, the total population within a pre-defined service area represents as potential riders. In reality, however, transit ridership may also depend on individual behavior related to race, age, household income, car ownership, etc. Thus, a behavior model that incorporates residential socio-economic factors may improve model performance. Therefore, one future research area would be
integrating behavior and location models to address service quality and coverage in a multiple route transit system.
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