Predicting future spatial distributions of population and employment for South East Queensland – a spatial disaggregation approach

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A thesis submitted for the degree of Doctor of Philosophy at The University of Queensland in February 2009

School of Geography, Planning and Environment Management
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This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

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Lí, T., Pullar, D., Corcoran, J., & Stimson, R., (2007). A comparison of spatial disaggregation techniques as applied to population estimation for South East Queensland (SEQ). Applied GIS, 3 (9): 1–16. – Tiebei Li was responsible for 80% conception and design, 85% of analysis and interpretation of data, and 85% of drafting and writing; David Pullar was responsible for 10% of conception and design and 10% of drafting and editing; Dr. Jonathan Corcoran was responsible for 5% of conception and design and 5% of editing; Robert Stimson was responsible for 5% of conception and design.

Lí, T., Corcoran, J., Pullar, D., Stimson, R., Robson, A. A Geographically Weighted Regression method to spatially disaggregate regional employment forecasts for South East Queensland. Applied Spatial Analysis and Policy. – Tiebei Li was responsible for 85% conception and design, 90% of analysis and interpretation of data, and 85% of drafting and writing; Jonathan Corcoran was responsible for 5% of conception and design and 5% of editing; David Pullar was responsible for 5% of conception and design and 10% of editing; Alistair Robson was responsible for 10% reviewing and updating the literature review; Robert Stimson was responsible for 5% of conception and design.

Statement of Contributions by Others to the Thesis as a Whole

There are substantial inputs made by Dr. David Pullar, Dr. Jonathan Corcoran to the research and writing represented in the thesis. These include significant contributions to the conception and design the project; technical support; provision of research data; editing and revising the draft and contributing to the research interpretation.
Published Works by the Author Incorporated into the Thesis

The following publications and presentations have been prepared whilst under PhD scholarship at the University of Queensland.

Journal Publications


Conference papers


Presentations


“Large Scale Urban Models” project report to the Office of Economic and Statistical Research (OESR) in Queensland Treasury. Brisbane, April, 2007.

“Methods for spatial allocation of population data from administrative units to the smaller areas.” Annual ARCRNSISS workshop for theory, analysis and methodology, July, 2006, Newcastle, Australia.

Additional Published Works by the Author Relevant to the Thesis but not Forming Part of it

None.
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Abstract

The spatial distribution of future population and employment has become a focus of recent academic enquiry and planning policy concerns. This is largely driven by the rapid urban expansion in major Australian cities and the need to plan ahead for new housing growth and demand for urban infrastructure and services. At a national level forecasts for population and employment are produced by the government and research institutions; however there is a further need to break these forecasts down to a disaggregate geographic scale for growth management within regions. Appropriate planning for the urban growth needs forecasts for fine-grained spatial units. This thesis has developed methodologies to predict the future settlement of the population, employment and urban form by applying a spatial disaggregation approach. The methodology uses the existing regional forecasts reported at regional geographic units and applies a novel spatially-based technique to step-down the regional forecasts to smaller geographical units. South East Queensland (SEQ) is the experimental context for the methodologies developed in the thesis, being one of the fastest-growing metropolitan regions in Australia. The research examines whether spatial disaggregation methodologies that can be used to enhance the forecasts for urban planning purposes and to derive a deeper understanding of the urban spatial structure under growth conditions.

The first part of this thesis develops a method by which the SEQ population forecasts can be spatially disaggregated. This is related to a classical problem in geographical analysis called the modifiable area unit problem, where spatial data disaggregation may give inaccurate results due to spatial heterogeneity in the explanatory variables. Several statistical regression and dasymetric techniques are evaluated to spatially disaggregate population forecasts over the study area and to assess their relative accuracies. An important contribution arising from this research is that: i) it extends the dasymetric method beyond its current simple form to techniques that incorporate more complex density assumptions to disaggregate the data and, ii) it selects a method based on balancing the costs and errors of the disaggregation for a study area. The outputs of the method are spatially
disaggregated population forecasts across the smaller areas that can be directly used for urban form analysis and are also directly available for subsequent employment disaggregation.

The second part in this thesis develops a method to spatially disaggregate the employment forecasts and examine their impact on the urban form. A new method for spatially disaggregating the employment data is evaluated; it analyses the trend and spatial pattern of historic regional employment patterns based on employment determinants (for example, the local population and the proximity of an area to a shopping centre). The method we apply, namely geographically weighted regression (GWR), accounts for spatial effects of data autocorrelation and heterogeneity. Autocorrelation is where certain variables for employment determinants are related in space, and hence violate traditional statistical independence assumptions, and heterogeneity is where the associations between variables change across space. The method uses a locally-fitted relationship to estimate employment in the smaller geography whilst being constrained by the regional forecast. Results show that, by accounting for spatial heterogeneity in the local dependency of employment, the GWR method generates superior estimates over a global regression model.

The spatially disaggregate projections developed in this thesis can be used to better understand questions on urban form. From a planning perspective, the results of spatial disaggregation indicate that the future growth of the population for SEQ is likely to maintain a spatially-dispersed growth pattern, whilst the employment is likely to follow a more polycentric distribution focused around the new activity centres. Overall, the thesis demonstrates that the spatial disaggregation method can be applied to supplement the regional forecasts to seek a deeper understanding of the future urban growth patterns. The development, application and validation of the spatial disaggregation methods will enhance the planner’s toolbox whilst responding to the data issues to inform urban planning and future development in a region.
Keywords
regional forecasts, urban spatial structure, modifiable areal unit problem, spatial
disaggregation, dasymetric mapping, geographically weighted regression.

Australian and New Zealand Standard Research Classifications (ANZSRC)
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Chapter 1 – Introduction

This chapter provides a brief introduction to the thesis. It outlines the research background, problem and context, together with the aim and supporting objectives. The research approach, and data used throughout the thesis are also introduced.

1.1 Background

This thesis applies a spatial disaggregation approach for predicting the future settlement of the population and employment activities within an urban context. For some time, the major Australian cities have experienced an increased dispersion of the population and the economic activities. This is accompanied and shaped by the economic growth and restructuring, together with demographic and housing changes (Foster, 2006). The fast-growing population and economic growth has a large impact on the urban metropolitan planning that involves managing the spatial distribution of the housing and the location of employment (Anas et al., 1998; Foster, 2006). The reason for this is that the spatial structure of the residential and economic activities directly determine the urban economic efficiency, the expenditure on new infrastructure, the transport costs and the consequent urban pressures on the environment (Gordon and Richardson, 1997; Newman, 2000). One core task in urban planning is managing the distribution of the growing population and economic activities and reducing the potential impact of the urban expansion. Therefore, predicting future population and employment distributions and their changes over time makes it essential for the planners to investigate the appropriate plans and policies to manage and shape the urban settlement activities, thus leading to a better future for the region.

Predicting a future urban spatial structure requires detailed spatial forecasts for the population and employment (Kaiser et al., 1995). The main thrust of this requirement is to determine the land use demand based on the population forecasts, the patterns of development and the economic forecasts. Predicting the distribution of the population and the location of the employment is an active area of research (Isserman, 1984; Myers and Kitsuse, 2000; Klosterman, 2002). Over the last decades, the techniques range from simply applying rent-bid analysis and trend extrapolation to using micro-simulations, discrete choice models, input-output analysis and models that fully integrate land use, and transport
demand analysis to provide a consistent forecast for the population and economic activities (Barra, 1989; Landis, 1994; Hunt et al., 2005).

In regional science, the population-related activities can be viewed as a spatial phenomenon, in that they can be analysed and predicted across a range of spatial scales. At the regional scale, regional economists tend to forecast the demographic and economic growth for a region as a whole. Most economic and demographic growth models are either completely aspatial or are regionalised into relatively large spatial units (for instance, a nation or a region). This is because the forecasts for structural demographic and economic changes are typically accurate for large geographical regions. Regionalised forecasts are usually applied to regional planning, which deals with the placement of activities, highways, electricity and business centres across a significantly larger area. At the metropolitan scale, urban analysts are often interested in the urban growth for smaller areas to determine the detailed geographic information for planning. For example, local governments are responsible for decision-making and the planning for the resource allocations and service deliveries to the local population and economy, including schools, road, police and emergency services. Models of urban planning, such as transportation and land use models, are typically spatially disaggregate, often focusing on relatively small spatial units (for example, traffic analysis zones).

Regional scientists working at the regional level make forecasts and predictions to produce output information (for example, employment growth) on a regional scale. In many cases, urban analysts and planners working at a local level also try to use the existing forecast information to make certain outputs for applications at lower spatial scales, for example, using a small area population and employment forecasts; planners can make plans and policies for local transport or urban form design. However, there is a difficulty in doing that, because the information gathered in a collective way for regional systems is often not meaningful when measuring for local information. For example, the regional demographic model would not be able to provide information on the total number of the population occupying a single block in space. Regional forecasts typically represent a generalised or aggregate geographic forecast of socio-economic variables. Socio-economic data represented by a smaller spatial unit (metropolitan regions, counties and neighbourhood-sized geographic units) can provide more detail for the spatial distribution.
Therefore, within regional science, there is a common need when working with socio-economic data is to transferring spatial data (forecasts) from one spatial scale to another. This arises from the data being reported for a set of large spatial units, but the applications need the data for a set of smaller spatial units. For instance, a census statistic zone has a population forecast for the urban regions, but it is desirable to know the breakdown of this variable for the smaller traffic analysis zones. Thus, the planners can use the output information for the locations of the population and employment to estimate the level of transportation and services they generate. Appropriate planning for the urban growth needs forecasts for the fine-grained spatial units. The methodology for spatially disaggregate the regional forecasts becomes a significant area of research in urban forecasting and planning; and this is the main focus of this thesis.

Transferring the known socio-economic data from large spatial units to smaller spatial units does not mean simply subdividing the spatial data, because the data are naturally heterogeneous within the aggregate spatial unit. This is related to a classical problem in geographical analysis called modifiable areal unit problem (MAUP) (Openshaw and Taylor, 1981), where spatial data disaggregation may give inaccurate results due to spatial heterogeneity in the spatial variables. The distribution of the population and employment is not evenly spread, but is often concentrated or dispersed at certain locations within an aggregate spatial unit. For example, the location of the residential population within an administrative zone may be near the junctions of important motorways; firms tend to settle at concentrated locations (as in a major activity centre) close to other firms. There are much other evidences of heterogeneity in socio-economic distribution that show consistent regularities and spatial structures (Ingram, 1998; Capello, 2007). The spatial disaggregation of the socio-economic data is considered complex owing to the inherent spatial properties and relationships of the spatial data, namely, spatial dependence and spatial heterogeneity (Ansellin, 1988; Haining, 1990). Spatial dependence is where the variables for population (or employment) are related in space, and hence display some degree of local similarity; and spatial heterogeneity is where the relationships between variables change across space. In addition, the relationships of spatial data are very scale dependent; they are inherently inconsistent at the different scales.

Spatial dependence, spatial heterogeneity and the effect of scale are common interrelated issues in complex urban systems and spatial analysis (Páez and Scott, 2004). They have
received increased attention in the study of spatially-disaggregated socio-economic activities in an urban context (Miller, 1999; Marlon et al., 2006). The influence of these spatial issues has motivated the research into spatial analysis and techniques. Over the decades, researchers have demonstrated the increased role of spatial analysis and spatial statistics for analysing spatial data in the study of the spatial structure of metropolitan areas (Páez and Scott, 2004; Páez, 2007). This covers a wide range of methodological areas, for example, spatial regression and the local statistics of the local association (Anselin, 1988; Getis and Ord, 1993), global and local statistics (Fotheringham et al., 2002), exploratory and explanatory data analysis (Maoh and Kanaroglou, 2007) and discrete choice models (Wadell and Ulfarsson, 2003). These spatial analytical techniques have become more persuasive in accounting for the relevance of the spatial effects (that is, spatial dependence and spatial heterogeneity) in understanding urban spatial structure. They provide a good theoretical and methodological grounding for the methodology development in this thesis when stepping down regional forecasts from large regions to smaller areas.

South East Queensland (SEQ) is the situational context for the methodologies developed in the thesis, being one of the fastest-growing metropolitan regions in Australia. Historically, the region has experienced a dispersed, low-density urban development coupled with spatially-unevenly-distributed industries and population settlements. With fast population and economic growth, a significant problem for planning is to anticipate the pattern of the growth in SEQ. In 2005, the Queensland State Government passed legislation to implement a new regional growth management plan for the SEQ region. An underlying issue is how to spatially allocate the growing population and economic activities across the region and to avoid excessive urban sprawl (OUM, 2006).

Appropriate planning for the SEQ region needs accurate forecasts for the future population and economic growth. The Queensland Government and The University of Queensland have produced forecasts for the employment and population for the SEQ region over a 20-year horizon. The spatial units of population and employment forecasts use large geographic regions but, for local area planning, they are too coarse.

Essentially, SEQ planning involves managing the spatial distribution of the population and economic activities. It requires socio-economic data in sufficient detail to capture the
significant spatial variations and relationships (for example, between the employment in the manufacturing industry in area 1 and the employment in the retail industry in area 2) to evaluate a number of planning issues, such as growth capacity, zoning and transport design. However, the major obstacle facing the urban planners and the metropolitan decision makers is that the highly aggregated regional forecasts do not provide details in the spatial distribution. The forecasts cannot be used to inform geo-targeted planning strategies, such as allocating employment opportunities to suburban centres, designing transport corridors and mixed-use urban developments. Thus, the fundamental dataset is crucial and particularly challenging in SEQ planning.

To cope with this data deficiency for the urban analysis, an important task in this research is to take the outputs of population and employment forecasts from the large regions down to the smaller planning areas and present them in greater detail in geography. Thus, the planners can use the output information to evaluate the future distribution of the regional growth and its potential impact on the urban spatial structure in SEQ.

The complexity of the spatial data has challenged the method of stepping down regional forecasts from large regions to smaller areas across the SEQ region. Based on the spatial structure of SEQ, there are a number of spatial issues seeming to pose crucial analytical problems for the spatial data disaggregation.

Firstly, SEQ is a large geographic region that combines with significant urban/rural and land use variations. The population and economic activities are highly heterogeneous and are distributed diversely.

Secondly, the study region covers a set of geographically proximate and interconnected economies. This determines that the economic development of a sub-area is highly dependent on the economic development of other sub-areas with the degree of dependency varying across the region.

Thirdly, the spatial processes and relationships (urban density) operating at the regional scale tend to be very different at the local scales.

Spatial autocorrelation, spatial heterogeneity and the effect of scale are challenging issues for spatial data disaggregation. Previous research on spatial data disaggregation has
primarily focused on the population data; this has resulted in a number of methods being proposed (see Lam, 1983; Flowerdew and Green, 1991; Martin, 1991; Mennis, 2003; Wu et al., 2005; Langford, 2006;). Overall, the existing methods for spatial disaggregation have tended to account for the spatial structures by using relatively simple assumptions (the homogeneity of the aggregate areas) (Goodchild et al., 1993). They are possible to determine a certain level of heterogeneity of disaggregated spatial data within the aggregate regions. However, many current methods do not adequately account for the important spatial effects that lying behind spatial structure (for instance, spatial dependence and spatial heterogeneity) at a satisfactory level especially for a large and complex geographical area.

Spatial effects of data dependence and heterogeneity can significantly influence the accuracy of the spatial data disaggregation from large spatial units to smaller spatial units. For example, local area $A$ may receive a higher population value than local area $B$ at a certain distance away, because the attractiveness of area $A$ is more influenced by the high population value at the surrounding areas. Similarly, local area $C$ at an urban centre might receive a higher employment value than local area $D$ at another urban centre, because of the inherently different settlement densities between the urban centres at the different locations. Thus, the relative spatial effects (spatial dependence and spatial heterogeneity) are very likely to determine the rate of spatial processes that occur in the smaller spatial units. The neglect of such spatial effects will inevitably introduce underestimations or overestimations for the data in the disaggregated areas and consequently misleading results for planning. This research shows the spatial effects are a crucial issue for spatial disaggregation when applied to the SEQ region — which involves a broad range of socio-economic variables (for instance, related to population and employment).

Nevertheless, spatial data disaggregation is an uncertain process whatever technique is applied; the results given by spatial disaggregation will contain errors. The accuracy of the spatial disaggregation is an important issue for urban studies where these values are used. Together with developing novel spatial disaggregation methods, there is a need to validate those methods by their accuracy. Although spatial data analysis and disaggregation have been researched for decades, only recently has there been a specific attempt to quantify the errors. The assessment of the effectiveness of a spatial disaggregation method for predicting socio-economic distributions is, particularly, an unresolved issue. Therefore,
both method development and validation are significant research problems for spatial data disaggregation.

1.2 Problem statement

Population and economics play important roles in regional development when the growing population and economy lead to increased occurrences of urban expansion, placing pressure on the natural environment, the infrastructure supply and transportation. The spatial distribution of the future population and the economic activities and their changes over time are important information for planning the pattern of growth in a region. The ability to make accurate forecasts for the population and economy at a spatially-detailed level provides valuable information for guiding urban planning, policy-making and development programs for the local areas. Nevertheless, the commonly-available forecasts for the population and economic growth are, typically, reported for the large geographical region levels.

The high degree of heterogeneity in the spatial distribution of the population and employment activities means that the regional forecasts will, in general, mask the spatial structure. Thus, while it may be possible to determine the spatial variations within a forecast region using spatial analysis to spatially-disaggregate the spatial data from the large spatial units down to the smaller spatial units. To account for the spatial differentials, there are patterns of population and employment for SEQ, forced by a degree of spatial dependence, spatial heterogeneity and the effects of scale. Owing to the limitation of the existing spatial disaggregation methods and coupled with their restrictive assumptions and consequent inaccuracy, the spatial disaggregation regional data for SEQ requires the application of advanced spatial analysis and spatial disaggregation techniques. The lack of comprehensive development, testing and application of a spatial disaggregation method within a context of regional forecasts represents a significant gap in the knowledge of socio-economic disaggregation.

Thus the research problem this thesis resolves is:

*How large regional population and employment forecasts can be spatially disaggregated to the small geographical areas for planning within South East Queensland (SEQ), Australia.*
Essentially, the thesis argues that both the SEQ population and the employment distribution are highly heterogeneous and that each presents different spatial patterns. The spatial dependence, spatial heterogeneity and the effect of scale formed major technical issues that largely impact on the accuracy of the regional forecast disaggregation. A methodological experiment is primarily undertaken to investigate ways to appropriately model the underlying spatial effects of the SEQ population and employment in the spatial disaggregation procedure. The proposed spatial disaggregation methods are validated through the diagnostic analysis of the methods using independent datasets. In addition, the effectiveness of the spatial disaggregation methods in terms of their implications for urban form is also thoroughly assessed.

The research into spatial disaggregation for urban analysis can be justified from several perspectives. On a theoretical ground, it investigates the patterns of regional growth by inspecting the geography of the socio-economic systems. The methodologies demonstrated here are not used merely for the sake of novelty in spatial data disaggregation, but have a broader implication in the use of spatial analysis in regional science and geographical research. On practical grounds, urban planning and management requires a large amount of data for the population distribution and the locations of employment. The findings on the outputs of spatial disaggregation (as small area data) can directly inform the SEQ urban planning, modelling and policy evaluation.

1.3 Aim and objectives

1.3.1 Research aim

The aim of this dissertation is to assess the effectiveness of spatial disaggregation techniques in spatially disaggregating the regional forecasts from large regions to smaller planning areas for SEQ. To achieve this aim, the thesis will consist of two main chapters (Chapters 4 and 5) written specifically as submissions to internationally refereed journals (Applied GIS and Applied Spatial Analysis and Policy). Each chapter presents a technique used to spatially disaggregate regional population and economic forecasts respectively. They extend the previous research by showing the way to enhance the spatial disaggregation method and the method’s validation in a new context of urban forecasts. We justify that a valuable contribution can be made to improve the understanding of urban
growth and planning through undertaking a methodological research that focuses on socio-economic spatial disaggregation.

1.3.2 Research objectives

Subsequent chapters discuss the following objectives that stem from the research problem.

Objective 1. To enhance and validate a method to spatially disaggregate the regional population forecasts, Chapter 4 (Li et al., 2007).

Research question

How can population forecasts be spatially disaggregated to fit in with spatial heterogeneity conditions in the population distribution?

The methods used to achieve this objective are:

- define the population spatial disaggregation problem and justify the study area
- review the available spatial disaggregation techniques for population data
- test a way to enhance the spatial disaggregation method to better account for the spatial heterogeneity problem for population disaggregation
- pre-test the spatial disaggregation techniques to determine the best solution for the study area
- apply the best-fitting spatial disaggregation methods for SEQ to spatially disaggregate the population forecasts over time
- generate and assess the population spatial disaggregation results.

Objective 2: To enhance and validate a method for the spatial disaggregation of regional employment forecasts, Chapter 5 (Li et al., 2008).

Research question

How can employment forecasts be spatially disaggregated to fit in with the conditions of spatial heterogeneity and spatial dependence in the employment distribution?
The methods used to achieve this objective are:

- define the problems for the economic spatial disaggregation and the desired results for SEQ
- review the current theoretical approaches and examine their suitability for the problem and limitations
- investigate the key explanatory variables of employment based on the location theory and the study area
- develop an advanced spatial method to disaggregate regional employment forecasts whilst accounting for the spatial effects
- validate the spatial disaggregation method for the study area and justify the problem
- generate and assess the employment spatial disaggregation results.

1.4 Research approach

The research approach provides an overview of the data sets and the strategy of spatial forecast disaggregation adopted through the thesis. Because this thesis has been structured to provide two manuscript submissions to referred journals (Chapters 4 and 5), further details in the data and the methods specific to these individual chapters are covered in their relevant sections.

1.4.1 Data sets for the project

There are a number of available data resources for this research. Some data are held by The University of Queensland and the access to the Queensland Government agency data is organised by the Office of Economic and Statistical Research (OESR). The selection of data is subject to their relevance to the research.

- The regional projections for the future population (2006–2026) indicating the growth are drawn from the aggregate forecasts published routinely by the Office of Economic and Statistical Research (OESR) in the Queensland Treasury.
- The output of the economic model is the jobs growth estimated every five years from 2006 to 2026 for four the sub-regions in SEQ. It is contained in an external
economic activity/employment growth generation model developed by Robinson and Mangan at the University of Queensland (Robinson and Mangan, 2006)

- Base years dwelling and population statistics are drawn from the 1996, 2001 Census of Population and Housing conducted by the Australian Bureau of Statistics (ABS)
- The database of the potential dwelling growth capacity and urban growth boundaries maintained by the Queensland Government, also through the Department of Local Government and Planning
- The spatial frameworks for projection consist of remote sensing image, land cover data and database contains spatial data in different geographic scales (SEQ, sub-regions, statistical local areas, urban centre/localities, census collection district and square grid)
- SEQ land use and land cover databases, a digital road database
- SEQ travel survey database (with respondent residential location encoded) public transport networks and stop locations, commercial and entertainment establishments locations.

1.4.2 Approach

To effectively predict the patterns of regional growth in SEQ, I take the regional population and economic growth as the major driving force and model their forecasts for the spatially-disaggregated areas. Thus, the research constitutes two problem domains in which the regional population forecasts and employment forecasts are spatial disaggregated. The thesis has been structured to provide two methods specific to these individual problem domains.

The development of methodology was justified based upon the purpose of the research. Technically, the question of spatial data disaggregation was approached from two angles. The first was to use the available data for the population and GIS modelling and statistical techniques to spatially disaggregate the regional population forecasts, as covered in Chapter 4 (Li et al., 2007). The second was to utilize various explanatory variables and advanced spatial analysis to define their theoretical relationships for the employment to
spatially disaggregate the employment forecasts; this is detailed in Chapter 5 (Li et al., 2008). To predict the interactions between growing population and employment at urban areas, the two problem domains were interlinked in this thesis; the outputs of the population disaggregation were used as a major input to drive the employment spatial disaggregation. In each proceeding chapter, the accuracy and cost-effectiveness of the spatial disaggregation techniques were assessed and compared with other existing techniques. The final stage was then to examine the results of the spatial disaggregation methods in their implication for the urban form over time. Greater detail pertaining to each procedure documented here is contained in the relevant Chapters 4 and 5. An outline of the research is presented in Figure 1.1.

The first problem considers the comparative investigation of the spatial disaggregation techniques applied to the regional population forecasts. The justification for the chosen methodologies is based on a review of the exiting spatial disaggregation techniques and the spatial structure of the study area. Technically, the techniques employ the available ancillary data of the population to determine the heterogeneity of the population across the region. It is found that the population density for different features of land for SEQ was much more diverse than the previous study regions that had been applied. Thus, a major methodological enhancement to the existing techniques was made by allowing a greater heterogeneity in the density assumptions made for the study area. A group of spatial disaggregation techniques based on a wide range of heterogeneity assumptions were tested and compared. The main purpose was to find a solution to deal with the spatial heterogeneity in the population disaggregation with a good balance of accuracy and implementation cost. We chose an appropriate technique that best fitted the spatial structure of the SEQ region to spatially disaggregate the population forecasts over time. The result was a set of disaggregated population forecasts representing the local areas across the SEQ region.
Figure 1.1: The framework of the research
As an important step towards understanding the growth pattern in SEQ, the second problem developed a method to spatially disaggregate the employment forecasts from the large regions to the smaller areas. As argued in the proceeding chapters, the spatial structure of the employment and available information is different to the population. The proposed technique differs from population disaggregation in that it uses the knowledge of economic geography and a theoretical approach to disaggregate employment forecasts rather than collecting and processing the ancillary data.

A service-based industry (the retail jobs) was selected from the employment forecasts to demonstrate the methodology. Technically, a range of explanatory variables were identified to predict the spatial structure of employment based on their correlative relationships in distribution. These include the population, existing retail centres, service sector land use, access to employees and the agglomeration effect to other service sectors, etc. To better determine the population-employment interactions, the outputs of the disaggregated population forecasts (from problem one) were used as a major input variable to predict the employment in the local areas. A novel spatial statistical model was employed to model spatial heterogeneity and local dependence of the variables for employment determinants across the study region. This has not been thoroughly specified in previous studies of spatial data disaggregation. The local relationships were then adjusted to ensure the disaggregated employment met the regional demand (forecast) for each source region. The use of a regional constrained relationship was an important procedure in this research that has seldom been carried out in previous studies in predicting the employment locations. The results gave spatially disaggregated employment forecasts and distributions across the local areas for planning (same as population disaggregation).

An essential task in this methodological research for urban spatial disaggregation is that the method needs to be justified in terms of accuracy and its effectiveness in urban analysis and planning. We validated the proposed spatial disaggregation approach within each methodology chapter. First, we undertook error analysis of the techniques using true datasets of socio-economic information which were readily available for the year 2001. For comparative purposes, several other spatial disaggregation methods were also computed. Each method and their resultant maps were compared to demonstrate that the new method generated a superior spatial disaggregation result by overcoming the problems specified in the research. Second, because the techniques are applied to the regional
forecast of the future years, the validity of the technique for spatial planning was also justified in conjunction with a judgemental approach. We justified that the spatially disaggregated forecasts are closely associated with the growing trend of the socio-economic distribution in the region. This was achieved by testing the patterns of the spatially disaggregated results using exploratory spatial data analysis and examining their implications for the patterns of growth over time. Finally, recommendations were made for improving further data collections so that the dynamic aspect of the forecasts disaggregation could be better determined.

1.5 The structure of the thesis
Chapter 1 has provided a brief introduction for the thesis. It outlines the research background and problem, together with the aim and the supporting objectives. This chapter also provides an overview of the research approach flowing through the thesis. The remaining chapters of the thesis are briefly outlined below.

Chapter 2 provides the theoretical background that has led to the research reported in the thesis. It describes the scale issues in the regional study and the basic data requirements for regional and urban analysis. Chapter 2 discusses the importance of spatial analysis for planning and the key analytical issues in the spatial data that challenge spatial data disaggregation. Finally, this chapter describes the context of the research, including the regional growth and the spatial structure of the study area, which raises the basic requirement of the spatial data disaggregation for SEQ.

Chapter 3 covers the major methodology issues in spatial data disaggregation. It revisits current spatial disaggregation techniques for the socio-economic data. A review of the spatial disaggregation techniques reveals a gap in the current state of knowledge in methodology development and validation in dealing with socio-economic disaggregation. This provides the grounds for a methodological enhancement and the validation produced in this research.

Chapter 4 investigates the spatial disaggregation methods to spatially disaggregate the population forecasts for the SEQ. To deal with the high degree of spatial heterogeneity in the population distribution, a multiple-class dasymmetric technique is presented, based on the result of a comparative investigation of a range of spatial disaggregation techniques to determine their relative accuracy. The technique is then applied to the regional population
forecasts over time. The outputs are spatially disaggregated population forecasts that can be used for urban form analysis and modelling the disaggregated employment in Chapter 5.

Chapter 5 concentrates on the methodology to spatially disaggregate regional employment forecasts for SEQ using the disaggregation results obtained in Chapter 4. A novel spatial statistical technique is proposed to overcome a number of shortcomings identified from previous theoretical approaches in dealing with spatial heterogeneity and spatial dependence in employment. The exploratory spatial data analysis is used in Chapter 5 to test the validity of the employment disaggregation results and their implications for the urban growth pattern for SEQ.

The concluding Chapter 6 specifically details the contribution of this thesis. It revisits the main findings and techniques used throughout each preceding chapter, describing how the approach and results are significant, new and innovative. The practical implications of the spatially-disaggregated regional forecasts are discussed and, finally, future research on improvements and the validation of the spatial disaggregation methods are precisely suggested.
Chapter 2 – A review of the literature and context for research

This chapter comprises a literature review of the issues that are pertinent for understanding the relevance and the context of spatial disaggregation. Focus is on the population and employment data for planning. It emphasises the aspect of spatial issues in spatial data disaggregation and relates this to the study area for SEQ.

2.1 Concept of regional science and spatial scale

Studies on the spatial phenomenon of population and employment lie within the broad scope of urban and regional science. Regional science was conceptualised as a major field of study in the 1950s. It is concerned with the study of social issues with regional or spatial dimensions. In his book, Isard (1975) defined regional science as:

- studies of systems of places, locations, cities, urban regions, patterns of human settlement, industry and economic activity, jobs income generation and receipts and resource use
- the study of diverse organisational and institutional structures of society as they govern the behaviour and spatial distribution of population and economic activities
- the systematic study of the time-space patterns of systems and the ways in which social problems associated with these patterns can be effectively attacked and resolved
- the study of joint interactions of social, political and economic behavioural units and the physical environment with meaningful regions (Isard, 1975).

Regional science extends the traditional social science. It achieves this by using a geographical or spatial perspective to examine human behaviour and activities (for example, population and employment). Human activities play out over geographic space, place social, behavioural and economic information into a geographic context, therefore,
space is an important property and context to study the patterns and processes involved in understanding human activities in regional science.

2.1.1 Defining space in geography

The idea of space has been of interest to philosophers and scientists for much of human history (Harvey, 1969). From a scientific perspective, space can be defined as an absolute term that exists for locating objects, but is independent of any matter. In the context of regional science, space is defined from a relative framework that exists only with reference to the spatial entities and processes under consideration (Meentemeyer, 1989). The relative view of space focuses on objects as the subject matter with space being measured as relationships between objects. It is a conceptual framework in which the objects are spatially referenced; and it can be used to compare and quantify the distance between objects, their sizes and shapes (Marceau 1999). Most work in human geography involves a relative view of space, because much of this work involves spatial processes, such as, migration and commuting patterns, or the dispersion of population and economic activities. (Harvey 1969; Abler et al., 1971).

2.1.2 Spatial scale in regional science

Scale is a fundamental concept in geography. The use of spatial scales in geographical studies was initially concerned with measuring the large numbers of individuals over large spatial regions. Geographers usually use a generalised measurement of the individual. Spatial scale provides a link between an object distributed in space and its simplified representation. Scientific inquiries can incorporate scale to obtain the generalised representation and capture the pattern of objects at a level of detail for particular investigation purposes (Gibson et al., 2000).

In a general sense, spatial scale refers to the degree of spatial detail (spatial variation) at which entities, patterns and processes in space can be observed and analysed (Goodchild, 2007). In absolute terms, scale can be defined as operational system used to partition geographical space into operational spatial units. Examples are provided in the use of census and administrative units, and any zoning system defined for a particular study. When we focus on studying geographical phenomenon, scale becomes a variable intrinsically linked to spatial entities and the processes to be investigated (Marceau, 1999; Atkinson and Tate, 2000). By imposing an appropriate scale, the specific spatial
characteristic of a geographical pattern or processes can be more effectively and precisely studied and understood.

Gibson et al. (2000) gives four fundamental areas where scale is important to the regional science:

- the identification of patterns and problems
- the explanation of observed patterns
- the generalisation of propositions made at level of a scale to another level of the scale
- the optimisation of some process or function.

The importance of selecting an appropriate spatial scale for regional analysis has been widely acknowledged (Goodchild and Quattrochi, 1997; Marceau, 1999). The conceptual development of the spatial scale in social science dates from the 1930s. Social scientists first underlined the importance of the scale problem in the regional studies (Gehlke and Biehl, 1934). This was followed by human geographers who were concerned with the patterns and relationships of the geographical phenomenon that varied substantially according to the spatial scales used (Yule and Kendall, 1950). Robinson (1950) defined the term known as 'ecological fallacy'. It means that the results obtained from data in the aggregate scales lead to false inferences in the relationships at the disaggregate scales. An ecological fallacy occurs when it is inferred that the results based on aggregate data are applied at the more micro level that collectively form the aggregated group. McCarthy et al. (1956) and other geographical researchers, such as Blalock (1964) and Clark and Avery (1976), also demonstrated that measurements to describe relationships and processes are very much scale-specific. In addition, spatial analysis results are most dependent on the spatial scale of the observation chosen. The scale issue was extensively and explicitly identified by Openshaw and Taylor (1981) who coined the phrase for the modifiable areal unit problem (MAUP). The MAUP describes the fact that the way a geographical region is partitioned into area units determines the result of the analysis. The analysis result based on those area units is modifiable as the different size and zonation of the area units are used to describe the phenomenon under investigation.
2.2 Regional analysis at different spatial scales

In regional analysis, socio-economic-related processes may be observed and analysed across a whole range of geographic scales. This may include national, regional and local studies. The choice of scale for a regional study is closely related to the phenomenon under investigation and the questions being posed about it. In this section, a hierarchical spatial structure is used to illustrate regional analysis at different scales in geography. The hierarchical structure can be broken down into regional, local and micro levels. At each geographical level, the key theories and methodologies are introduced.

2.2.1 Regional-level processes

The system-wide analysis can be applied to the regional level. At this level, regional scientists account for the general interactions of people in large regions across space for example, economic interactions and regional employment growth. Regional analysis is fundamental in many strategic planning and policy issues (Miller, 1998). The major outputs of analysis at this level include the regional economic and population forecasts, the economic structure, the processes between industries and interregional trade, and transport systems.

Since the 1950s and 1960s, various geographers and economists have developed a suite of regional research approaches. They are typically used to model structural changes in the population and economies in a regional context regardless of their detailed spatial distribution. Some of the research methods are based on the regional economic theory. Examples are regional economic-base analysis (Tiebout, 1962) and shift-share analysis (Dunn 1960). These are able to resolve a degree of regional differentials of economic growth based on the relationships between the local and regional economies and the changes in various industries. At a regional level input-output analysis (Leontief, 1986) is one of the most widely-used methods for the analysis of the regional economic activities. Input-output models explicitly model and predict the effect of changes in one industry on other industries in a nation's (or a region's) economy. Regional planning uses regional input-output analysis to forecast trends in employment and income changes by industry. The spatial division of input-output analysis typically uses economic regions to reflect regional economic performance.
2.2.2 Local-level processes

Research at the local-level scale focuses on the processes of smaller spatial units (neighbourhoods, suburbs or census districts). At this intermediate level, the processes focus on the actions of main elements of the urban systems, such as, the interactions and behaviours of the social/economic groups, the institutes or the local political/economic communities of a region. The problems under investigation at this level include urban land use, commuting and inter-urban transportation, and the social/behaviour geography associated with the aggregate zones.

Theories and research methods have been developed at this level since about the 1960s. The Regional spatial interaction theory (Lowry, 1964) has been widely used to predict the locations population and employment, and the patterns of metropolitan areas (for instance, Wilson, 1967, 1970, 1974; Putman, 1983; Fotheringham, 1991; Stillwell, 1991). The unit of analysis at this level is typically spatially aggregate to represent the collective behaviours of the small regions. For example, spatial interaction models are aggregate; thus, they specify an overall governing relationship for flow between locations. Another stream of research for interaction is location analysis based on microeconomic theory and location theory (Alonso, 1964). There are also other areas of research to study urban systems by exploring spatial associations across spatial units and spatial structures (Paez and Scot, 2004). These theories and the analytical approaches are not recommended for analysing the human processes at the very spatially disaggregate level. This is because the greater diversity of behaviours that exist at the lower levels of observation need a variety of social behavioural theories to explain, rather than using a simple spatial interaction formulation.

2.2.3 Micro-level processes

At the micro-level scale, research typically focuses on the fundamental units of human behaviour (an individual, a household or a job). This includes local interactions, individual social/behavioural geography, travel patterns and location decision choices. Micro-level analysis became a major area of regional science investigation because there was a greater variety of human behaviours and an increased level of spatial variability in the urban systems.

The micro-level modelling perspective represents the urban systems at the highest possible level of disaggregation. It studies the emergence of complex patterns and
relationships from behaviour and the interactions at the individual level of actors — the location choice for a household. The research methods for spatial processes at the micro-level are based on the theories and concepts of behavioural geography (Golledge and Stimson, 1997). For example, Cellular Automata (White and Engelen, 2000) describes how an individual’s actions are influenced by the locations and attributes of the neighbours. Other local research methods, such as microsimulation or agent based modelling, are used to simulate the decision choices and processes at the level of the individual actors. Such a description of an individual’s behaviour is often referred to as microeconomic theory and discrete choice theory (McFadden, 1978). The actors in microsimulation can be a household, a job (Waddell, 2002), a land parcel (Miller et al., 2004) or a synthetic unit (Wegener et al., 2002).

In comparison to spatial aggregate analysis, these local approaches have shown potential in explaining the social and economic behaviour at the individual level. Hence, they can provide a detailed pattern of urban growth at the most disaggregate spatial scale. Nevertheless, micro-level analyses are not suggested for modelling spatial variations for a large geographical area. This is because of the considerable modelling complexity and demands for micro-scale data.

2.3 Socio-economic data used for regional science

The population and economic activities of a region are the key aspects for regional studies. The ability in practice to carry out the fundamental research (the regional forecast) is critically dependent on the access to suitable sources of data (Martin, 1991). The use of economic and population information in regional studies and planning has been summarised by Kaiser et al (1995):

- to estimate the past and present of the population and employment conditions that indicate the need for revenue-sharing and local service requirements
- to make the population and economic forecast and establish policy preferences for future population and economic level on the basis of community goals
- to trace and assess the distribution of the population and economic activities and their implications in the economy and environment.
Socio-economic data that are used for regional analysis can be based on past and present data, in addition to their forecasts in the future. In the next subsections, socio-economic data for regional study in an Australia context are introduced.

2.3.1 Data from the census of population and housing

1. The Census Population and Housing data

In Australia, the major reliable source of population data used for regional-wide socio-economic research is the Census of Population and Housing. The data about population distribution are usually presented at collective scales in the form of administration units or other zones describing the area statistics of the population. Haining (1990) described the population data as area-referenced data derived from the aggregations of primary units, such as households. For a large geographic region, the spatial units used to represent the Census of Population and Housing are commonly defined by the administrative boundaries of the different levels of governments. The lowest units of population statistics refer to the basic areas of data collection. They can be aggregated up to cover the larger areas.

The Australian Bureau of Statistics (ABS) is the primary source of enumeration for population data. The Australian Census for Population and Housing is collected from individuals but compiled and reported at various levels of aggregated geographic areas. This is defined in the Australian Standard Geographical Classification (ASGC). Figure 2.1 illustrates the major ASGC hierarchical geography aggregation for the census of population.
There are different classifications defined within the ASGC. All structures are hierarchical, with different structures having a different numbers of levels. Each hierarchical level is made up of one type of geographical unit that serves a specific purpose. The spatial units at each higher level are aggregations of the spatial units at the lower level. Some spatial units used in different ASGC structures are not restricted by a hierarchical administrative system, such as the Urban Centres and Localities (UCLs). They are independently defined to represent different socio-economic characteristics or different themes of the population within that district.

Although the census data has evolved and gradually been published at a spatial detailed scale (see Gregory, 2002), the collection and reporting of the population data cannot be smaller than a certain geography of aggregation. The reasons for this are:

---

**Figure 2.1:** The ASGC structure chart, 2001 (source: ABS, 2005)
The method was designed to collect census data with the minimum of human, time and monetary costs. Basic population units often represent areas of roughly equal population size to standardise uncertainties in rate estimates.

The spatial aggregation form of population data is also required because, in many cases, the collection and the use of census data could be restricted for confidential reasons (Oliver and Philip, 1998).

The traditional uses of census data are for strategic research focusing on the large regional areas.

2. The Census of Population and Housing data of employment

For regional studies, employment is the most useful measurement of economic activity. Many governments conduct economic censuses that describe the nature and distribution of economic activities, production, commercial- and industrial-related services. In comparison to the population data, the employment information is often interpreted at larger spatial units because the distribution of the employment is more diffuse and discontinuous at the smaller level of geography.

Employment data consists of a variety of economic activities. The activities are commonly classified into different industry sectors by the Standard Industrial Classification Code (SIC). An industrial classification identifies groupings of businesses (or organisations) that carry out similar economic activities. Each such groupings define an appropriate industry category that characterises the business concerned and are referred to as activities primary to that industry (ABS, 2005). The most important use of SIC is that it represents recognisable segments of industry that are economically significant and homogeneous in terms of industrial activity. The level of details in industrial sub-categories can be flexible and range from two to six-digit code classifications. Table 2.1 provides an example of the employment data classified by industry, based on the Australian and New Zealand Standard Industrial Classification Code (ANZSIC93). Each industry has subdivisions, groups and classes to provide increasingly detailed dissections of the broad categories.
Table 2.1: Customised industries by ANZSIC93

<table>
<thead>
<tr>
<th>Industry sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, Forestry &amp; Fishing, Mining</td>
</tr>
<tr>
<td>Manufacturing</td>
</tr>
<tr>
<td>Electricity, Gas &amp; Water Supply</td>
</tr>
<tr>
<td>Construction</td>
</tr>
<tr>
<td>Wholesale Trade</td>
</tr>
<tr>
<td>Retail Trade</td>
</tr>
<tr>
<td>Accommodation, Cafes &amp; Restaurants</td>
</tr>
<tr>
<td>Transport and Storage, Communication</td>
</tr>
<tr>
<td>Finance, Insurance, Property, Business Services</td>
</tr>
<tr>
<td>Education</td>
</tr>
<tr>
<td>Health and Community Services</td>
</tr>
<tr>
<td>Cultural &amp; Recreational Services</td>
</tr>
<tr>
<td>Personal and Other Services</td>
</tr>
</tbody>
</table>

Two important pieces of information are given by the Census of Population and Housing for employment, (i) the census of population which records the employment by the employee’s place of residence, that is, the industry sectors the population is employed in and, (ii) the statistics of the labour force or journey-to-work data report employment by the location of the employer; that is, where the people actually work. The latter allows the user to infer the locations of the industry sectors. The area units of employment statistics basically conform to the administrative areas for the census of population. For the Australian census, the spatial unit of employment by the location of the employer is no smaller than the statistical local area (SLA) level.

2.3.2 Population and employment forecasts

Data from the Census of Population and Housing can be used to estimate the locations of population and employment. In addition to the census data, population and employment forecasts are an important source information for urban and regional planning. A forecast shows how much a regional area will grow or decline in the composition of the industries.
or population; from that, planning decisions can be made to allocate resources and services to the local populations and economies.

1. Population forecasts

Population forecasts are estimations of the size and composition of the population for the future years based on the assumptions (for example, migration and fertility rates and the age and ethnic composition of the population) and past growth trends. In regional science, they are primarily used to estimate the housing and transportation demand and migration planning. In comparison to the spatial unit for census data, the population is typically forecasted at large geographical areas. Regional scientists and demographers tend to forecast long-term population at the large geographical regions for several reasons:

- The use of a small area of population statistics is considered less accurate and difficult to obtain (Deichmann, 1996). The dynamics of small area data are more volatile and frequent movement in and out of the area is greater as a percentage of the population and employment (Berke et al., 2007).

- Using a small area unit is likely to exacerbate the small number problem in the less densely populated areas (rural areas) (Briggs et al., 2006). The small number problem in the observations (a lot of zero values used) might lead to biased parameter estimation and invalid statistical results.

- Many forecasting and planning tasks, requiring the historical information (for example, growth trends) associated with the census data collected periodically, follow time series. However, owing to an administrative reason or a change in land use policy, the boundaries of small areas are more likely to change between census years; thus, time series data may be non-conformable in terms of their spatial units. In contrast, the large census unit presents a higher stability in the time series.

The population forecasts are highly related to a region’s economy. The population largely determines the size and type of the labour market consumer and, also the purchasing power. Thus, population forecasts are often conducted in conjunction with economic forecasts. They are compatible indicators of urbanisation dynamics.
2. Employment forecasts

Employment forecasts are the best source of information for economic planning. Employment forecasts typically model the components of change made by many diverse economic groups that make up a region’s economy. Generally, economists tend to forecast economic change for large geographical regions. The projections for employment are more widely summarised to present trends in the economy of large geographical areas as a whole (for instance, sub-regions, regions or states) rather than to provide detailed information for the smaller spatial units. The major reasons for this are:

- large economic regions consist of a good composition of economic activities. The economic transactions between industries can be better analysed than is possible for the smaller areas.
- the economic data at the regional levels has a higher quality and reliability than that at the regional level.
- small areas tend to be economically more dependent on other regions. Using spatial disaggregated economic analysis might involve too many input-output flows between the sub-areas. This inevitably increases the complexity of the analysis and results in a low accuracy.

Both population and employment forecasts provide valuable information on structural demographic and economic changes in large regions. The information for regional forecasts does not relate to the small areas for the various economic sectors.

2.4 Location theory and urban spatial structure

The previous section examined the population and economic data and the geographical areas used to describe the different types of thematic information. At a higher tier of geographical hierarchy, the regional forecasts typically represent a generalised or aggregated geographic phenomenon of socio-economic variables. Data at this level are assumed to be homogeneously distributed within an aggregate spatial unit such as a region.

In reality, the population and employment activities are not evenly spread, but are often clustered or dispersed within the aggregate spatial unit — for example, this may be near the junctions of important motorways. Spatial distribution and activity location choices are
explained by the location theory for the urban and economic geography. It provides theoretical evidence of heterogeneity in their distribution and the underlying spatial structure in the socio-economic data.

2.4.1 Location theory

The location theory was developed from Von Thünen's (1826) bid-rent theory for economic land use. It deals with the economic mechanisms that distribute the industrial activities in space (Weber, 1929; Hoover, 1936). The location theory was then periodically extended by location theorists and economists. It became an important theoretical basis for the geographical locations of the population and economic activities (see Isard, 1956).

The location theory seeks to identify the factors that influence the location of the individual activities. It is interpreted as the regularities in the profit and cost variations in space and their consequences in terms of the location choices with respect to the requirements and conditions of the activities (Capello, 2007). The location theory consists of two distinct theories based on microeconomic behavioural concepts, the Cost minimization theory and the Profit and utility maximisation theory. These hypothesise that individuals or firms tend to choose a location that maximises their profits and utility, and/or minimises the costs of development and transportation.

Based on urban and economic geography literature, some key factors are widely recognised as forming major economic and spatial processes that organise the activities in space. The following forces will help in understanding the determinants of the population, industrial locations and urban structure.

1. Spatial demand (area of market)

The causality issues in the distribution of the population and employment is a classical topic of research in intra-urban activity locations (Alonso, 1964; Steinnes, 1982; Boanet, 1994; Daitz, 1998). The spatial distributions of the economic activities and the residential population are often spatially interacting (either in a positive or a negative manner). The population generates the demand for the goods and services, and therefore is an important determinant for the employment locations. Meanwhile, the location of the jobs also affects the people's choices for residence because they usually expect employment opportunities, low commuting cost and a good access to services.
2. **Transportation costs**

The cost minimisation theory primarily refers to the cost of transportation. The theory of localisation defines *transportation cost* as all forms of spatial friction that provide a greater attractiveness to a location that reduces the distance between the place of residence and the workplace. Transportation costs are essential in the location theory because they are involved in the concept of the agglomeration economies as the cost of interaction.

3. **Land use supply**

The supply of *land* is a direct determinant of the urban activity locations. Residential and economic location choices are always driven by the demands for additional space, in addition to service and infrastructure. The supply of land, service and infrastructure in any given urban area can be related to the urban planning policies. The regional distribution of the population and economic activities always reflects the land use planning decisions.

4. **Accessibility**

The spatial organisation of activity is also influenced by the *accessibility* or *proximity* to a market or a centre. For firms, a high accessibility means that they have easy access to markets for final goods, production factors, information, services and infrastructure. For the people, good accessibility to an activity centre and jobs means that their commuting cost is minimal, while at the same time they enjoy easy access to a wide range of recreational, health and educational services at specific locations without having to pay the cost of long-distance travel.

5. **Land value**

Another important feature in location choice is the *cost of land* or *land rent*. Land close to the CBD or other activity centres costs more than areas further away owing to the higher demand for central locations with their minimum transportation costs. Firms that locate in the more central areas need to pay higher rents for those areas. On the other hand, land price often varies between areas with different socio-economic status (for example, income or residential density).
6. Agglomeration economies

From the perspective of the regional economics, a part of the profit maximisation theory refers to the *agglomeration economy*. Agglomeration economies denote all economic advantages accruing to firms from their concentrated location close to other firms. These include, reduced production costs owing to a large plant size, the presence of advanced and specialised services, the availability of fixed social capital (for instance, infrastructures), the presence of skilled labour and of managerial expertise and, a broad and specialised intermediate goods market (Capello, 2007). All above advantages result in concentration of economic activities in space.

2.4.2 Urban spatial structure

I have introduced the location theory and major factors that influence the location of the population and economic activities. It is noted that these economic forces might push the location process of urban activities in opposite directions, that is, spatial dispersion and concentration. For example, the similarity in behaviours of the location choice might lead to the local concentration of activities at certain areas in space.

The forces of spatial clustering and dispersion resulting from location choice (for example, economic agglomeration and the cost of transportation) occur in many varieties in space. Depending on the level of spatial concentration, the pattern of the urban structure can be dispersed or clustered (Anas et al., 1998). Urban geographers have thus introduced a different concept of the urban spatial structure, which has important implications for urban planning. The two main conceptual structures are the mono-centric city and the polycentric cities.

a. Mono-centric city

Based on the location theory, the transportation access to employment is an important determinant of urban form. Alnso (1964) created a generalised *mono-centric* theory of urban form that assumes that employment is exogenous to the residential settlement pattern, and that a city grows by expanding outwards from a central area of employment and activities (the CBD). Some employment follows this outward trend, but it was often less decentralised than the population (Ingram, 1998). Starting from the 1960s, the mono-centric theory became a descriptive model for a city. This era was characterised by a fast urban expansion that was affected by the development of an improved transportation
infrastructure and the growth of individual automobile usage. Therefore, the mono-centric city often refers to a dispersed urban structure with a higher travel demand.

b. Poly-centric city

A polycentric urban region refers to intra-urban patterns of population and economic activities that are clustered at multiple urban centres in one area. Anas et al., (1998) explained that the polycentric urban form can be created by different scales of agglomeration economies. The local dependence on location choices causes urban activities to cluster in either large or small groups to facilitate interactions and save costs. Region-wide, high concentrations of economic activities can form a few small to medium-sized sub-centres interconnected by highways. The population generally follows a similar trend but presents a less centralised or more dispersed distribution (Ingram, 1998). The polycentric city has become a feature of the urban landscape for economic activity that benefits from easy access to the activities centre, close social interactions and lower costs for transportation and the environment (Kloosterman and Musterd, 2001). A more recent pattern of urban growth is termed ‘edge cities’ (Garreau, 1991). An edge city is characterised by very large concentrations of office and retail services. This is often in conjunction with other types of development, including residential, at the major transport nodes.

2.5 Basis for conducting spatial analysis

Access to the spatially disaggregated data and forecasts is now an important issue for understanding urban spatial structure and planning. The significant urbanisation and additional travel demands since the 1970s has caused large and low-density cities (Ingram, 1998) — the dispersed urban settlement where the urban sprawl had quickly placed the impacts on the urban travel patterns. Essentially, the urban activities within the sprawling areas tend to be located at a distance from each other. Consequently, the journeys for the residents of these areas become unnecessarily long and could lead to negative social and environmental consequences (for instance, congestion, air pollution and encroachments on environmental areas) (Newman, 2000; Wolman et al., 2002). The increasing pressure on the government led to significant attention on the effects of urban growth on travel demands and the environment. In recent years, a host of urban planning has gained
popularity in controlling this urban sprawl to achieve the transportation objectives (that is, reducing travel distances).

Current concerns about urban growth patterns have focused on their social and environmental impacts. In addition, there is a growing attempt to measure the urban growth pattern for planning and research into spatial analysis (Fotheringham and Rogerson, 1993; Anselin, 1988, 1999; Goodchild, 2007; Torrens, 2008). The major intentions of spatial analysis for planning are to:

- incorporate the spatial properties of urban data, such as location, density, distance, connectivity and directional relationships, to produce spatial analytical results for urban land use and transport planning
- apply exploratory spatial data analysis to detect the patterns, spatial trends and interactions between the urban activities
- provide the methodology of spatial statistics to analyse the spatial relationships and patterns of spatial data and their predictions
- provide the basis for data manipulation, integration and the conversion of data spatial scales from one scale to another.

Over the last decades, there has been a rapid increase in the literature on the measurement of the urban pattern and sprawl. Density gradients, sprawl indexes that are based on a series of measurable indicators and certain spatial analyses are some quantitative approaches used in urban studies. The characterisation of the urban spatial structure is often descriptive with some key measurable features (see Cervero and Kockelman, 1997; Galster et al, 2001; Torrens, 2008). A range of spatial attributes have been used in urban analysis:

a. Density

Density is expressed as the average number of population per area unit of developable land in an urban area. Low-density development is considered to cause more travel because urban areas might be further away from the services that are supplied by the central services nodes.
b. Diversity

Diversity refers to mixed land use, which means the degree to which different land uses commonly exist within the same area, and this is common across the urban areas. A higher level of mixed land use in a small area (for example, residential and commercial services) can significantly reduce the opportunities of long distance travel.

c. Clustering

Clustering is another important attribute that is often used to characterise urban spatial structures. It measures the degree to which the development has been tightly bunched to minimise the amount of land in a small area occupied by residential or economic sector uses, such as service sectors.

d. Concentration

Concentration is the degree to which the development is located disproportionately in the relatively few areas of the total urban area rather than spread evenly throughout.

e. Proximity

Proximity characteristics are also significant features to measure urban sprawl. It measures the degree to which the different urban activities are close to each other across the urban area. Examples include the average distance workers travel for employment, the proximity to business centres and the access to other urban resources.

Using spatial analysis, planners are able to closely analyse the locations of population and employment and the patterns of urbanisation on the population and specific industries. In certain areas, such as land use planning and transportation planning, conducting spatial analysis of these urban features (for instance, density or proximity) has to rely heavily on the spatially disaggregated socio-economic data (Harris and Batty, 1993).

However, the major obstacle facing the urban planners and analysts is that the accurate population and employment forecasts are often reported at a highly aggregated spatial unit (a region). Aggregated data for a large spatial unit typically portraying the urban areas with a uniform distribution has been widely considered as the least informative for urban analysis (measuring urban sprawl) (Fotheringham and Rogerson 1993; Dennis and Wu 1996; Rosenbaum and Koenig 1997; Moon and Farmer 2001). Essentially, urban analysts...
need forecasting information for the small spatial units which are more related to the patterns of the population and employment distribution (e.g. mono-centric or poly-centric pattern). Using this information, plans and policies can be made for the growth at the local areas, such as transport route design, and mixed land use development.

Because the spatially aggregate forecasts are too coarse for the urban analysis and planning, the choice of the proper spatial scale to use spatial data has become an essential task of spatial analysis. It is recognised that many advances in computing technology and geographical information systems (GIS) have greatly increased the opportunity for spatial analysis with more choice over the way data can be organised, with different structures best serving the different types of analysis (for example, urban structure measurement) (Tomlin 1983; Martin, 1989, 1996; Bracken 1989, 1993; Goodchild et al., 1993; Spikerman and Wegener, 2000; Wegener, 2001; Berke et al., 2006).

Goodchild (2007) summarised the usefulness of the spatial analysis for changing the scale on the spatial data as:

- the estimation of the inaccuracies that result from using data that are too coarse for modelling a given process
- the estimation of the costs and benefit associated with acquiring data at a range of scales
- the use of the data acquired at one scale to simulate the data with greater detail, such that the simulated detail matches the expectations about its general characteristics.

2.6 Spatial data disaggregation

Spatial data disaggregation is an important area of research in GIS and spatial analysis. It involves transferring and decomposing spatial data from one set of a larger spatial unit to a set of smaller spatial units within the same study area (flowerdew and Green, 1991). The concept of spatial data disaggregation is illustrated in Figure 2.3, with a spatial unit for which we have information, referred to as a source zone (four large polygons with known values in parentheses), and the spatial unit for which the information is needed is a target zone (as grid square).
The concept of spatial disaggregation raises a number of issues. What challenges spatial data disaggregation is that the greater heterogeneity of the data at the smaller scales. Using known aggregate information for large spatial units to estimate the data distribution across the smaller spatial units is difficult because of two interrelated issues in regional science, namely the ecological fallacy and the MAUP problem. The ecological fallacy (Robinson, 1950) refers to the aggregate data at the larger scale often leading to false inferences (homogeneity) of the characteristics of the individuals at the smaller scale. The MAUP problem (Openshaw and Taylor, 1981) implies that the change of the spatial unit and the scale of the data will lead to substantially different results in the variables being measured for a study area (Fotheringham and Wong, 1991). In regional science, the spatial scale is often embedded in the definition of the geographic phenomenon. In addition, a different aggregation scheme can change not only the data values but also the definition of the geographical phenomenon and the underlying properties. For example, the area of an economy may make sense at a regional level that consists of a good composition of economic activities, but at the metropolitan or neighbourhood level, the regional economy breaks down into the partitions of the economy or simply the employment areas. As a result, the economic data for the small areas tends to be more spatially dependent (driven by monetary transactions and commuting flaws between the smaller areas) and exhibits a different property. Thus, it is essential to understand the effect of scale on the spatial data and the changing spatial properties across the spatial scales (spatial dependence and spatial heterogeneity).
The above issues raise important questions of the accuracy of the spatial disaggregation. A number of studies have attempted to overcome the problem. Goodchild et al. (1993) describe a framework based upon the assumptions made in the spatial disaggregation process. One assumption was proposed by Tobler (1979) for the smoothness properties of the spatial data for continuous surface representation. He also termed the pycnophylactic property that stipulates the condition that the data value for the source zones equals the sum of the estimated values at the constituent target areas. Areal weighted proportioning, a procedure commonly found in the GIS, is one form of spatial disaggregation that assumes homogenous density for the source zones. There are applications in development that employ ancillary information to assume a greater heterogeneity within the source zone to estimate their distribution at the target zones (Goodchild et al., 1993). A discussion on the existing techniques to disaggregate spatial data is detailed in Chapter 3.

However, because spatial disaggregation is an uncertain process, no spatial disaggregation techniques can claim to give a totally accurate target zone estimate (Lam, 1983; Goodchild and Gopal, 1989). In the many methods that deal with spatial data disaggregation, there are often arbitrary assumptions made to describe the spatial properties of the data (spatial heterogeneity, spatial dependence). When geographical phenomena are very complex in nature — thus difficult to be analysed using simple assumptions — the spatial data disaggregation will inevitably lead to error propagation. To achieve the accurate spatial disaggregation result, the assumption to account for the complex spatial effects of spatial data becomes the basis of the recent method development (Vichiensan et al, 2006). In the next section, we discuss the important spatial issues that influence the spatial structure of the socio-economic data, together with how they raise major problems for spatial data disaggregation.

2.7 The spatial issues in the spatial data disaggregation

This section highlights the major spatial issues of spatial data that lie behind the spatial structure. It is an important task for spatial data disaggregation to correctly identify these concepts that work at different spatial scales, and consequently propose appropriate solutions.
a. Spatial autocorrelation

In regional science, entities distributed across a region are considered to be spatially auto-correlated rather than independent. **Spatial autocorrelation** is defined according to Tobler’s (p. 236, 1970) ‘first law of geography’ as everything is related to everything else, but the near things are more related than the distant things. Many geographical phenomenon (for instance, industry distribution) can be characterised in these terms as local similarities in some spatially varying phenomenon rather than varying randomly through space. In the urban context, spatial autocorrelation may be caused by a variety of spatial processes, including urban commuting, transportation, the diffusion of urban settlement and activity dispersion (Haining, 1990).

The effect of spatial autocorrelation can be expressed as:

\[
\text{Cov}[y_i, y_j] = E[y_i, y_j] - E[y_i] \cdot E[y_j] \neq 0, \text{ for } i \neq j
\]  

(2.1)

where \(i, j\) refer to individual observations (locations) and \(y_{i(j)}\) is the values of the random variable at that location. The covariance of \(y_i\) and \(y_j\) becomes meaningful from a spatial perspective when the particular configuration of nonzero \(i, j\) pairs has an interpretation in terms of spatial structure, spatial interaction or the spatial arrangement of the observations (Anselin, 1988).

The effect of spatial autocorrelation has various consequences for conventional data analysis. The spatial auto-correlated data invalidate the assumptions of conventional statistics that require the sampled data to be independent. Thus, this may lead to a misleading significance and an invalid spatial variability explanation. A common way of looking at this is that spatial autocorrelation introduces redundancy into the data, so that each additional item of the data provides less new information than is indicated by he sample size (Anselin, 1988; Rogerson, 2001; O'Sullivan and Unwin, 2003; Mitchell, 2005). In dealing with such a problem, spatial analysts have developed a range of solutions to measure and model spatial autocorrelation for urban analysis. Some well-known techniques are spatial autoregressive models, the local statistics of spatial autocorrelation (LISA), and Moran’s I statistics (Anselin, 1988, 1995; Moran, 1950).
b. Spatial dependence and Spatial heterogeneity

In urban systems, a spatial distribution of one type of urban entity is associated with distributions of one or more other urban entities that occur together. **Spatial dependence** means that the distribution of a variable follows the pattern of other variable(s). Its structure may result from the influence of other variable(s) exhibiting a spatial structure. This is different to physical science, which believes that rules and principles are geographically uniform; the strength of the spatial dependence for regional science might vary over space. **Spatial heterogeneity** refers to the spatial dependence or autocorrelation structure changing over a distance. Typically, the longer the distance, the stronger spatial heterogeneity in relationships that are present. Haining (1990) described the spatial heterogeneity as consequence areas responding differently to identical conditions that may be associated with different local characteristics.

To discover the spatial heterogeneous relationships, the local relationships can be estimated by:

\[
Y_i = \beta_0(u_i, v_i) + \beta(u_i, v_i)X_i + \varepsilon_i
\]  

(2.2)

where \((u_i, v_i)\) denotes the coordinates of the location \(i\) in space; \(\beta(u_i, v_i)\) is the relationship between the variable \(Y\) and the variable \(X\) at location \((u_i, v_i)\). These local relationships are heterogeneous across different locations in space.

Spatial heterogeneity and spatial dependence are important issues for spatial data disaggregation. It can raise a serious analytical problem for conventional statistical models designed for socio-economic variables that often tend to analyse relationships in a global context (Longhi and Nijkamp, 2005). If a statistical method is not able to account for such local variations in the relationships, this will inevitably lead to biased relationship estimation and inaccurate inferences at the local level. There have been some analytical solutions proposed in the geographical research to model spatial heterogeneity. These include **Multilevel models**, **switching regressions** and **geographically weighted regression** (Quandt, 1958; Duncan and Jones, 2000; Fotheringham et al., 2002; Páez and Scott, 2004).
c. Effect of scale

The spatial scale at which we examine a phenomenon can affect the spatial analysis because the spatial observations are very scale dependent. This issue has been specified in the MAUP problem. The effect of scale is a very sensitive issue in spatial data disaggregation that often involves the transfer of parameters or relationships between scales — for example, using known aggregate relationships to estimate the phenomenon at the disaggregate scale. In such circumstances, the effect of scale must be taken into account because the relationships are inherently inconsistent to explain the geographical phenomenon at the different scales.

2.8 Spatial structure and data for SEQ

The research into spatial data disaggregation in this thesis is set within the context of South East Queensland (SEQ). This is a large regional area in Australia that is experiencing rapid population and economic growth. Crucial data for the SEQ planning need accurate forecasts for the population, housing and economic activities at a spatially disaggregated scale. This research aims at overcoming certain current deficiencies in the fundamental datasets for the SEQ planning, particularly through the disaggregation of the spatial forecasts from the large regions across small planning areas, and the integration of the small area population and economic forecasting as the drivers of urban growth. These outputs at the desired geographical detail can then be used to advise urban form and the location of the transport networks and urban services.

The spatial disaggregation problem is particularly challenging in the SEQ data because of the complex and diverse geographic patterns in population and employment. In this section, the SEQ forecasts and the spatial structure of the region are examined. They provide a more detailed justification of SEQ that has been chosen as the study region for this research.

2.8.1 The spatial structure of South East Queensland

The SEQ region covers approximately 2.3 million hectares, with a population of about 2.5 million. Nowadays, SEQ is recognised as Australia’s fastest-growing region, attracting an average of 55,000 new residents each year (the main growth is migrants from other states within the nation). Because a steady amount of the new population is expected to move
into the region, SEQ is also experiencing an economic growth and is now emerging as a significant economic node in Australia.

Geographically, the SEQ region is mainly a sprawling low-density metropolis that stretches from the Noosa Shire in the north, south to the Queensland–New South Wales state border and west through Ipswich and beyond. It comprises four Regional Organisations of Councils (ROCs) that are groupings of 18 Local Government Areas (LGAs). The ROCs for SEQ are:

- Brisbane, comprising the Brisbane City Council
- The Southern Regional Organisation of Councils (SROC), comprising the Beaudesert Shire Council, Gold Coast City Council, Logan City Council and Redland Shire Council
- The Western Sub-regional Organisation of Councils (WESROC), comprising the Boonah Shire Council, Esk Shire Council, Gatton Shire Council, Ipswich City Council and Laidley Shire Council
- The Northern Sub-regional Organisation of Councils (NORSROC), comprising the Caboolture Shire Council, Caloundra City Council, Kilcoy Shire Council, Maroochy Shire Council, Noosa Shire Council, Pine Rivers Shire Council and Redcliffe City Council.

The boundaries of the SEQ region, sub-region boundaries are shown in Figure 2.3.
The urban settlement in the SEQ region dates back to 1824. Since then, Brisbane has continued as a low-density metropolis where the newer immigrants primarily settled along the coastal areas of the region. However, nowadays, the spread out settlement pattern in SEQ had been mostly impacted by mass car ownership since the 1950s. With the major highways created in the last two decades, direct links between the northern areas and southern areas of the region form an almost continuous urban development that is colloquially described as ‘the 200km city’ (Brisbane Institute, 2004). Thus, the region has experienced a significant an impact from the Australia-wide ‘sea-change’ phenomenon with the major population growth occurring along the coastline. In contrast, the western parts of the region have traditionally grown more slowly than the region as a whole. The
eastern part of the region is nowadays heavily populated and urbanised, and accounts for 90% of the region's population. The western areas account for 55% of the region's land area, but only 4.3% of the population. The major urban settlements of SEQ are Brisbane and the nearby coastal cities of the Sunshine Coast and the Gold Coast, but these drop off dramatically away from the east towards the west with the exception of the City of Ipswich. Figure 2.4 illustrates the pattern of urbanisation in SEQ. Overall, the spatial structure of the SEQ region can be characterised with a significant spatially unbalanced land-use variation. The population density varies either globally or locally with the major employment activities being highly concentrated and clustered at the regional and sub-regional centres.
2.8.2 SEQ regional plan

The current spatial structure for the SEQ region may be characterised as a very weak polycentric hierarchy of mixed-use centres and residential locations around two major city centres, namely, the city of Brisbane, and the city of Gold Coast. The spatially-dispersed urban pattern has caused serious environmental impacts. For example, before the 1950s, a large proportion of the SEQ region remained natural bushland. However, based on the statistics in 2001, only 17% of SEQ is National Park or State Forest owing to historically uncontrolled urban expansion (Brisbane Institute, 2004). Apart from the environmental
impacts, significant issues also arise with the cost of infrastructure development, transportation, energy, and services to the new demands of urban expansion.

Therefore, there has been a greater concern in the community that urban development practices in SEQ need reforms if the region is to manage future growth whilst maintaining its nature resources, lifestyle values and economic vitality. This requires a commitment to a more sustainable pattern of development, the efficient use of land and a tighter control of this dispersed form of urban development. The Queensland Government’s Smart State strategy requires that growth across the SEQ region be well managed for the sustainable outcomes. In 2005, the Queensland Government implemented a new regional growth management plan for the SEQ region, The South East Queensland Regional Plan, 2005–2026 (OUM, 2006). This incorporates an urban consolidation strategy and seeks to achieve a regionally-balanced polycentric urban structure to support the population and the economic growth. The underlying new land development for urban intensification is anticipated to occur in the western part of the region. This is planned to significantly reduce the growth pressure in the coastal areas.

Many aspects of growth and land use change are controlled by planned zoning capacities. The urban growth boundary and other land use regulations (OUM, 2006), intend to:

- consolidate the region’s urban development footprint, provide for discrete urban areas separated by inter-urban breaks to protect regional community identity and the natural environment
- increase progressively the proportion of new dwellings created by infill development and the redevelopment of existing urban areas across the region, together with well-planned green-field developments
- focus higher density and mixed-use development around the transport nodes and routes, including the potential Transit Oriented Development (TOD) sites
- locate the major employment development and trip-generating activities within the regional activity centres to improve the links between the residential areas and the employment locations and reduce the potential for travel demands
• restrict further rural residential development to the existing rural residential development and identified rural living areas.

2.8.3 Population and economic forecasts for SEQ

A range of socio-economic data is required to plan for the spatial structure of the SEQ region. The most important requirements are the population forecasts and the employment forecasts by the industry sectors.

a. Regional population forecasts

The latest SEQ population projections were released in July 2006 as part of the Queensland population projection conducted by the Office of Economic and Statistical Research (OESR) in the Queensland Treasury. The population projections were generated based on the assumptions for the future levels of fertility, mortality and migration that were developed. These assumptions were based on the historical trends and other available evidence at the SD level (Queensland Government, 2005). The population has been projected from 2006 to 2026 (using five-year intervals). Figure 2.5 illustrates that the forecasted total population of the SEQ region will continue to increase to about 3.2 million by 2015 and 3.8 million by 2026. The geographical division of the Queensland population forecasts uses statistical divisions (SD). The Brisbane and Moreton statistical divisions represent a region generally referred to as SEQ is illustrated in Figure 2.6.
Figure 2.5: Present and future population figures for Brisbane and Moreton Bay SDs between 2001 and 2026
b. Regional employment forecasts

The regional input-output economic and employment forecasts between 2006 and 2026 produced by The University of Queensland are considered to be the most up-to-date and accurate available forecast economic data relevant for the area (Robinson and Mangan, 2006). The regional economic forecasts are developed based on the consumption demand of the population and the current SEQ economic growth plan. The regional forecasts employ input-output tables that reveal the linkages and input and output monetary flows between different industry sectors. The regional government can begin to understand the important economic relationships that comprise the regional economy. This is measured
in terms of the employment growth by industry sectors for the SEQ region. The regional employment forecasts are highly aggregated and are reported at four ROCs (namely Brisbane, North ROC, South ROC, West ROC, see Figure 2.3). Figure 2.7 illustrates that each of the four sub-regions of SEQ is forecasted to experience a steady employment growth over the next 20 years. The forecasted database reports the number of jobs for 14 industry sectors by 1-digit Australian and New Zealand Standard Industry Classification (ANZSIC) in each forecast year (see Table 2.1). Thus, distinctions can be made between the numbers of job growth in the different industry sectors.

![Figure 2.7: SEQ employment forecasts](image)

Overall, both the forecasted regional population and the employment data indicate the region will keep growing continuously over the next 20 years. The economy of SEQ has been forecasted to grow; this is mainly driven by the consumption resulting from its forecasted population growth. The SEQ region is not growing homogeneously, with variations in the population and economic activity throughout the region. With this significant regional growth, information is required by the policy makers in SEQ, who are involved in planning for urban development, about the locations of the growing population and employment. Thus, they can make plans to deliver the resources and services to areas...
where the population and employment opportunities are likely to occur, in addition to
designing the preferred pattern of urban growth to achieve the transportation objectives.

The urban policies require forecast information with sufficient detail for the spatial
representation to better understand the heterogeneity and patterns of the regional growth.
In this research, the SEQ regional population and employment forecasts are used as major
inputs for spatial data disaggregation to obtain forecasts for a smaller geography that is
relevant to the SEQ planning.

2.8.4 Justification for selecting SEQ

SEQ has been a fast growing study area; the forecasted regional population and
employment indicates that the region will keep growing continuously over next 20 years.
With the large number of new people and the growing economic opportunities, the
subsequent demand for urban space both for residential and economic use will increase.
The regional plan requires that the fast population and economic growth should be well
planned to achieve a more sustainable urban spatial structure. Planning policies have been
specified that are relevant for the local areas (for example, an intensified development
within the urban land use boundaries or TOD development). The fundamental datasets for
the SEQ population and employment forecasts are both available for large geographical
regions. Given their expected spatial scales for spatial planning, SEQ provides a concrete
case study of why the spatially disaggregated data is needed and how it works with urban
planning.

Further justification of why SEQ has been selected as a suitable study area can be
attributed to the considerable complexity in the spatial structure of the region. Firstly, the
degree to which the population density varies throughout the study region is much greater
than in the previous studies undertaken (Chapter 4 will provide a further illustration).
Secondly, the employment activities are highly concentrated around the major regional
centres. They show strong local similarity (in either location concentration or dispersion)
in their geographical setting. Therefore, the nature of the population and economic data
are identified to exhibit the distinct spatial characteristics, and are based on the regional
growth policy; such settlement patterns are likely to continue in the future. This raises
different requirements for spatial disaggregating population and employment forecasts.
For population disaggregation, the major spatial issue is the high degree of spatial
heterogeneity in the residential density across the region. For the employment disaggregation, the spatial effect for the employment is more complex, involving strong local dependence and spatial heterogeneity (driven by economic agglomeration and other profit-cost factors). This requires more comprehensive solutions to account for those complex spatial issues. Therefore, SEQ is considered a suitable study area for the spatial disaggregation research in terms of its practical significance for regional planning and the technical challenges in the spatial disaggregation techniques.

2.9 Conclusion and following work

This chapter has determined the key literature and context for the research. It focuses on the geography of the socio-economic systems by reviewing the relevant theories, principles, and methodologies at the different spatial scales. Many of the theories and methodologies described are applied practically throughout this thesis. Chapter 2 emphasises the population and employment data. The location theory is introduced to explain their underlying spatial structure. The principles, theoretical knowledge and major requirements of spatial disaggregation are introduced. This leads to a discussion on the major issues posed by spatial data with regard to spatial dependence, spatial heterogeneity and the effects of scale that challenge the spatial data disaggregation. Finally, the chapter relates this to the study area for SEQ. Introducing the urban settlement and spatial structure of SEQ established the key assumptions for the SEQ population and employment distribution and consequently the different requirements for their spatial disaggregation.

Chapter 2 provides the theoretical foundation for the methodological research that is presented in this research. In dealing with spatial data disaggregation, it requires not only the theoretical knowledge about socio-economic data, but also the appropriate methodologies and tools to interpret the theoretical processes and spatial effects. The next chapter investigates the recent developments in spatial disaggregation techniques for the socio-economic data. The purpose is to evaluate the limitations and gaps in the current techniques to disaggregate the population and employment forecasts for SEQ. From this, a methodological contribution can be made for the spatial disaggregation research (this is demonstrated in the following chapters).
Chapter 3 — Spatial data disaggregation

This chapter investigates the methodology dimension of the spatial disaggregation research. This covers the principles, theoretical assumption, and implementation issues. This provides a foundation for the methodological research and contribution that will be made for spatially disaggregating the socio-economic data later in this thesis.

3.1 Introduction

In this chapter, we make a detailed review of the existing spatial disaggregation techniques. These techniques provide the different solutions to accommodate the spatial issues in the spatial data disaggregation. The effectiveness of those solutions in terms of modelling accuracy and other practical concerns (for instance, the ease of implementation) is also discussed. A review of the literature reveals a gap in both the theory and in the application of spatial disaggregation methodologies to spatially disaggregate the socio-economic data.

Many spatial disaggregation techniques are derived from the methods for areal interpolation. Areal interpolation deals with the common problem in geographical or regional research that the areal units for which the data are available are not necessarily the type of units that the analyst wants to study (Flowerdew et al., 1991). Hence, the methods of areal interpolation have been used to estimate data for one set of spatial units from another set of spatial units whose boundaries do not coincide (Lam, 1983; de Smith et al., 2007). Spatial disaggregation can be regarded as a special case of areal interpolation. It defines a method for estimating the spatial distribution of a phenomenon in a set of smaller spatial units that provide a more detailed spatial information.

Depending on the intended goal, spatial conditions and required information, the spatial disaggregation methods can be operated as either a data-driven approach or a theory-driven approach. Data-driven techniques have been well established in the spatial disaggregation literature. Typically, they derive the spatial structure of data from known data at the source zones and available ancillary data (for example, land use data). Theory-driven techniques, on the other hand, deal with spatial data disaggregation based on the theories or processes described in the regional economic and urban geography literature.
— for example, the correlative distributions between the socio-economic variables as well as other morphological factors.

This chapter consists of six sections: section two reviews the data-driven spatial disaggregation methods. These include the techniques that use the ancillary information and the techniques for which the ancillary information is not used. Section three describes the implementation issues associated with the spatial disaggregation methods. The fourth section thoroughly discusses the major findings from previous literature in the area of the accuracy of the spatial disaggregation methods. Section five introduces theory-driven approaches, which are operational for the spatial disaggregation employment data. In section six, various methods for technique validation are discussed. The final section summarises the findings from the literature and reveals the gaps to be filled by this research.

### 3.2 Data-driven spatial disaggregation approach

Data-driven approaches used to derive spatial structure from the known data towards dealing with data spatial disaggregation. In other words, one lets the 'data speak for themselves' (Gould, 1981) and attempt to derive information on the spatial pattern and structure without a pre-conceived theoretical notion.

The data-driven approach in spatial disaggregation is reflected in a wide range of different techniques. The current data-driven spatial disaggregation techniques are summarised in Table 3.1 and include their underlying assumptions, pycnophylactic property (source zone values preserved), data demand and ease of implementation. These terms are explained in the subsequent sections in this chapter, and each of these methods is reviewed. Data-driven techniques can be further separated into two categories, techniques with the ancillary data and techniques without the ancillary data.
Table 3.1: A comparison of different spatial disaggregation techniques based on the assumptions, methods and data demand

| Technique                | Use of ancillary data | Assumption                                                      | Pycnophylactic property | Complexity of implementation |
|-------------------------|-----------------------|                                                                |                         |                             |
| Pycnophylactic interpolation | None                 | Continuous density surface                                     | Yes                      | Medium                      |
| Kernel interpolation    | None                 | Polycentric and distance decay density distribution             | No                       | High                        |
| Simple area weighting   | None                 | Homogeneous source zones                                        | Yes                      | Low                         |
| Multivariate regression model | Discrete or Continuous | Source zone composed of land classes with global uniform density | No                       | Low                         |
| Regional regression model | Discrete or Continuous | Source zone composed of land classes with regional uniform density | No                       | Medium                      |
| Locally-fitted regression model | Discrete or Continuous | Homogeneity at different land class (at each source zone)      | Yes                      | Medium                      |
| EM Algorithm            | Discrete or Continuous | Source zone composed of land classes with global uniform density that conserve aggregate value | Yes                      | High                        |
| Binary division method  | Discrete (binary)    | Source zone composed of populated and unpopulated areas         | Yes                      | Low                         |
| Multiple-class dasymetric method | Discrete | Homogeneity at different land class (at each source zone)      | Yes                      | High                        |

3.2.1 Data-driven approach without ancillary data

Pycnophylactic area interpolation

Tobler's (1979) Pycnophylactic area interpolation is a widely-quoted spatial disaggregation method. The underlying assumption is that the value of a spatial variable in the neighbouring target regions tends to be similar and the underlying structure of the variable distribution is continuous over the space. The method defines a continuous density surface over the study area, which can be estimated from the source zone population figures. The volume preserving requirement is enforced to the density surface by, namely, the 'pycnophylactic property', which requires the integral of the surface over a source zone.
constrained to be equal to the known data for the zone. Subsequently, a smooth density function is employed that takes into account the effect of the adjacent zones, intending to minimise the curvature of the estimated surface. The pycnophylactic interpolation and the smoothing function iterate until there are no further changes in the pre-specified tolerance (see Figure 3.1). The final result is the data for the target areas (grid cells) which are spatially disaggregated from the source zones.

The contribution of the pycnophylactic interpolation is the method of establishing two properties essential for the accurate data spatial disaggregation, pycnophylactic property and spatial autocorrelation. The pycnophylactic property is considered an essential for accurate interpolation. It gives a greater fidelity for the approximation of the target zone values in each source zone so that the subsequent estimation of a value for each target zone is less subject to error (Lam, 1983). Many new methods inherit these two requirements when they are used to solve spatial disaggregation problems.

As reviewed by Turner and Openshaw (2001), the pycnophylactic interpolation is considered more applicable for interpolating the population with only a small reduction in
scale, when smaller target zones are applied, the underlying assumption does not seem reasonable. Nordhaus (2002) comments that the pycnophylactic method smooths the result too much and tends to miss the fine gradations in the underlying data and so might not provide an accurate disaggregation result. One modification to the pycnophylactic method can be made by combining the method with the growing available ancillary information. For example, introduce green areas, water bodies into source zones by setting their initial density to zero. Then interpolate the density over the non-zero density areas may generate more accurate disaggregation result.

Kernel interpolation

Kernel interpolation (Bracken 1993) is derived from an areal interpolation method that uses point interpolation procedures (Lam, 1983, Oliver and Webster, 1990). Similar to pycnophylactic method, the kernel interpolation techniques impose a continuous density assumption over the study area. Essentially, the method assigns the attribute value of source zone to a polygon centroid and assumes the population density drops symmetrically while staying away from the centroid based on an exponential distance decay function (within a finite extent). The exponential model of the population density was firstly proposed by Clark (1951) and given as:

\[ D_d = p_0 \exp(-B_d) \]  

(3.1)

where \( D_d \) is estimated density at a location at distance \( d \) away from the centroid; \( p_0 \) is the central density; \( B \) is a constant.

Having a polygon centroid for the source zones, a moving window filter (Silverman 1986) is applied to the study area. It focuses each centroid in turn, to estimate the population probability (weight) over a fine grid within that window. Then, each grid cell receives a share of the current centroid's population, based on their distances. Thus, the method can provide a continuous surface of the population estimate across the study area. The grid cell values may then be aggregated to the target zones. The mathematical equations of the Kernel interpolation are:
\[ \hat{P}_i = \sum_{j=1}^{c} P_j W_{ij}, \quad \sum_{i=1}^{n} W_{ij} = 1 \]  
\[ W_{ij} = \left( \frac{w_j^2 - d_{ij}^2}{w_j^2 + d_{ij}^2} \right)^a, \quad d_{ij} < w_j \]  

where \( \hat{P}_i \) is the estimated population of the cell \( i \); \( P_j \) is the empirical population at point \( j \); \( c \) is the total number of data points; \( n \) is the total number of cells in the window; and \( W_{ij} \) is the weighting of the cell \( i \) with respect to point \( j \); \( w_j \) is the initial radius of kernel window; \( d_{ij} \) is the distance from cell \( i \) to point \( j \). \( W_{ij} \) must be normalised to sum to 1 over all cells in the window and cell \( i \) will not receive the population from every point location but only from any points in whose kernel it falls.

There are number of drawbacks with kernel interpolation. An important problem in this technique is that it does not conserve the total value within each source zone. The method provides an estimate of the size of the areal unit (using the kernel window) represented by the current data point. All target zones will receive a population share from the kernel rather than from the original source zone. Martin (1996) modified the original kernel based interpolation to ensure that the data reported for the target zones are constrained to match the overall sum of the source zones. Nevertheless, the choice of a control point (centroid) to represent the zone may involve errors because, obviously, the distribution of the phenomenon is rarely symmetrical and the patterns of most socio-economic distributions are not uniform. Tobler (1999) again reviewed Martin’s 1996 approach and commented that the exponential model of the population density can only be considered a relevant approximation for the whole of an urban area. The density gradient farther out from the urban central presents more nearly as a linear fashion. The continued use of a centred exponential decay for every single source zone results in unrealistic density peaks, most obviously apparent in the large zones.

**Simple overlay method (Simple area weighting)**

Some simple cartographic processing methods are used to disaggregate the source zones, thus preserving the pycnophylactic property. The **Simple area weighting** technique perceives the spatial structure of the target areas based on their levels of overlay with
known data at the source zones. The target zone data are estimated, based on proportioning the source attribute by the area, given the geometric intersection of the source zones and the target zones. The underlying assumption is that the spatial distribution of the objects is homogeneous within each source zone. The data for each target zone can be estimated as:

\[ P_t = \sum_s \frac{A_s \times P_s}{A_{st}} \]  

(3.4)

where \( P_t \) is the estimated population count at the target zone \( t \); \( P_s \) is the observed population for the source zone \( s \); \( A_s \) is the area size of source zone \( s \); \( A_{st} \) is the area size of the intersection of the source and target zones.

The Simple Area Weighting technique is recognised as the simplest area interpolation and disaggregation technique in use in terms of the ease of implementation and the data requirements. However, the assumption used by this technique is rather restrictive for a real geographical phenomenon. The general critique is that it incorrectly assumes that the density of the population within the source zones is uniform (Fisher and Langford 1995; Langford and Fisher, 1996). Many studies have shown the overall low accuracy of the technique using a simple overlay method (see Gregory and Paul, 2005; Langford 2006; Reibel and Aditya, 2006).

Lam (1983) provides a dated review of these earlier statistical and area overlay techniques. She concluded that the limitation of the area weighting method is that it takes each source zone as independent and does not consider the smoothness (or continuity) of the changes of the values between the zones, while assuming homogeneity within the source zone. Compared with the area weighting method, the pycnophylactic method represents a conceptual improvement because the effects of the neighbouring source zones have been taken into account and the homogeneity within the zones is not required. In that circumstance, Lam (1983) suggested that the simple areal weighting yields better estimates if the data distribution is discontinuous, whereas the pycnophylactic interpolation techniques provide better results when the smoothness is a real property of the data distribution. The choice of spatial disaggregation techniques must consider the appropriateness of their underlying spatial structure.
3.2.2 Data-driven approach with ancillary data

Ancillary information

Traditional spatial disaggregation approaches empirically derive the spatial structure from the limited spatial information given by the boundaries, areas or centroids of the source zone units; no extra information is used. A typical problem with these methods is that the estimated population density assumes non-zero values everywhere, while real populations are always discretely distributed and occupy limited locations in space (Cai et al., 2006). The assumptions about the spatial structure at the source zones are considered as restrictive (for example, homogeneous density or symmetrical data distribution) because nothing is known about the data structure within the source zones.

The fast development of the GIS and remote sensing technologies makes a variety of spatial information become available. Some of this spatial information is in the form of spatially disaggregated data and closely relates to the characteristics of the socio-economic distributions. The data themes include roads, urban settlements, administrative units, rivers, elevation contours, remote sensing images, air pollution, protected areas, forest areas and wetlands. It is highly likely that the knowledge of the important variables such as the topography (land cover) or the level of urban development (land use class or road density) would affect our expectations of how the socio-economic variables might be distributed within the source zones (Flowerdew and Green, 1991). Some of this information is clearly relevant for predicting the population densities, because people are not distributed randomly across space but prefer to settle in areas with certain characteristics. It is possible to spatially overlay this data over the source zones to provide the ancillary information about the variability within the related source zones.

The ancillary data (for instance, the land cover classes) on their own say little directly about the differences in the population density. A number of techniques are devised to manipulate the different forms of ancillary information into a weighting surface coincident with the target zones to transform source zone values into target zone values. The methods using the available ancillary information to guide the spatial disaggregation are described as 'intelligent' or 'smart' spatial disaggregation techniques in many literature (see
Langford et al., 1991; Turner and Openshaw, 2001). Next, we introduce them in turn and discuss their major advantages as well as the their limitations.

**Binary division approach (binary dasymetric mapping)**

The simplest method in which the ancillary information are used is the *binary division approach* or so-called *binary dasymetric mapping* (see Langford and Unwin, 1994; Langford and Fisher, 1996). Its applicability is based on the assumption that the total population are uniformly distributed inside some part of a source zone (as urban areas) with a homogeneous density and the remaining parts of the zone necessarily have a zero value, which is possibly covered by the non-populated areas (for example, water). Thus, when this structure in the binary division overlaps the target areas, the method only considers the known values in the populated areas within the source zones allocated to the target zones.

\[
P_t = \sum_{s=1}^{S} \frac{A_{tp} \times P_s}{A_{sp}}
\]

(3.5)

where \(P_t\) is the estimated population at the target zone \(t\); \(A_{tp}\) is the area of overlap between target zone \(t\) and source zone \(s\) having land cover identified as populated; \(A_{sp}\) is the source zone area identified as populated and \(P_s\) is the total population in source zone \(s\).

Flowerdew and Green (1991) regard the binary division approach as a step toward ‘intelligence’ but a somewhat limited method, because the ancillary information used merely divides each source zone into only two categories (either it has the value of a whole zone or it has the value zero). The binary classification is suspected as dealing with the complex phenomenon with a variety of population density existing over a large geographical area. Although, the approach is based on simple binary density classification, it allows the spatial non-stationary density to be based on area weighting effect at the target zones. Therefore, it has shown robustness in the spatial heterogeneity in the population disaggregation and often performs well in comparison with other simple techniques (Fisher and Langford, 1996; Eicher and Brewer, 2001; Langford, 2006).
Multivariate regression model

The accuracy of the target zone estimation is often limited by the relatively coarse density assumption in the source zones. Some statistical techniques are developed that allow further information about a zone to be used to make the statistical estimates about the variable distribution of the socio-economic data, rather than a crude binary distinction. Since the 1950s, researchers have used a regression model for the socio-economic estimation with different types of ancillary information. In contrast to Kernel interpolation which estimate the probability of population based on the distance to the population centre, the use of multivariate regression technique was based on the relationships between the population and the various attribute variables (Lo, 1986), for example, (i) the measurement of the areas of urbanisation, (ii) the measurement of the areas of different land use, (iii) the remote sensing image pixel characteristics (Yuan et al., 1997; Harvey 2000) and, (vi) the counts of dwelling units (Green 1956; Lo 1989). The most commonly-used ancillary data for the population estimation is the land use data that describes the different levels of data concentrations.

Multivariate regression models assume that the given source zone population may be expressed in terms of a set of densities related to the areas of the ancillary classes. The density for each class is assumed to be uniform throughout the study area, but it is unknown. Using a combination of the aggregate source values and the ancillary data with the unknown densities, it is possible to develop regression equations to numerically resolve this relationship. Global regression methods obtain the estimates for density for each density class over the entire study area. Other ancillary variables may be included for these area densities, but the basic model is:

\[ P_s = \sum_{c=1}^{C} (d_c \cdot A_{sc} + e_s) \]  

(3.6)

where \( P_s \) is the total population count for each source zone \( s \); \( c \) is the density class; \( A_{sc} \) is the area size for each density class within each source zone; \( d_c \) is the coefficient of the regression model and \( e_s \) is the random error. The intercept is always set as zero, because an area with size zero should have zero population.

The regression modelling incorporating multiple density classes over the study area has been demonstrated to be accurate with spatially disaggregate socio-economic data. For
example, Langford et al. (1991), Fisher & Langford (1995) and Langford (2006) tested a series of regression models to spatially disaggregate the census data for Leicestershire. Yuan et al. (1997) applied the regression disaggregation model to four large counties in Arkansas, USA. However, the underlying assumption for the spatial uniform density for each land class is considered as the main drawback of the regression techniques. This assertion appears to be true, because many studies have shown the limited ability of regression model to account for spatial autocorrelation and spatial heterogeneity in the residuals (Fisher & Langford, 1995; Nordhaus, 2002; Langford, 2006). To overcome such issues, other solutions have to be used. For example, Liu et al. (2008) employed an area-to-point residual Kriging approach to enhance the regression-based population density estimation by interpolating spatially autocorrelated residuals. In addition, another limitation of regression approach is that the global densities it computes allow for small errors between the estimated and the actual source zone values. Therefore, the resolved densities do not maintain the volume of the aggregate data value at the source zones, that is, the pycnophylactic property is not preserved (Yuan et al., 1997).

The locally-fitted regression model

To ensure the pycnophylactic property is preserved, an additional volume preserving process was imposed in the regression models. Yuan et al (1997) and Langford (2006) demonstrated that the reliability of the estimated density can be improved by imposing the constraint that the population estimated at the target zones matches the overall sum of the source zones. The globally-estimated density for each land class could be locally adjusted by the ratio of the predicted population and the census counts at each source zone. In this way, a variation of the absolute value of the population densities is achieved, thus reflecting the differences in the local population density between the source zones. The mathematical expression for adjusting approach for the densities is:

\[ d_{cs} = \frac{P_s}{P_{es}} \times d_c \]  

(3.7)

where \( d_{cs} \) is the specific density estimates for class \( c \) in zone \( s \); \( P_s \) is the actual population of the source zones \( s \); \( P_{es} \) is the estimated population of the source zone \( s \) and \( d_c \) is the initial global density estimate of the land class \( c \).
The use of a locally-fitted regression modified the assumption of the regression model and objectively allowed spatially inconsistent density values for each land class. Preserving the population of the source unit enforce, all associated errors are inherently limited to the variation within each individual source unit. This approach is comparably simple, but is based on the relaxed homogeneity assumptions on the density and well worth being compared with more advanced techniques.

Regional regression model

The regional regression tends to relax the constant density assumption of global regression models by estimating the densities separately within each subregion of a whole study area. Each subregion can cover a number of source zones with the known data, but does not overlap any other subregions. Thus, the technique assumes population density that varies between discrete spaces (subregions of a region). Yuan et al. (1997) tested regional regression against four large counties in Arkansas, USA, and showed that the using regional density estimations improved the modelling of the spatial heterogeneity of the population over a global regression technique. The effectiveness of the regional regression was again justified by Langford (2006) when using Leicestershire, U.K., as a study area. He further tested an additional regional regression model by dividing the source zones into large (rural) regions and small (urban) regions that were not contiguous; the result showed better estimates than the arbitrary administrative division. However, the assumption used by the regional regression is still not considered satisfactory because only coarse variations between the large subregional areas are accounted. The higher level of spatial heterogeneity in the density and the spatial autocorrelation between the subregions are ignored (Fotheringham et al., 2002; Langford 2006).

EM algorithm

The EM algorithm used to estimate the global uniform density for each ancillary land class (in the same density solution class as the regression model) was introduced by Flowerdew and Green (1991) and was based on using the target zones as the control zones that meet the pycnophylactic property. The underlying assumption is that the data concerning the target zone defines the conditions relating to the intra-source zone data distribution. Thus, the source zone area can be allocated by he intersected target districts with different densities (the urban areas and rural areas). To determine the densities for each class,
Flowerdew and Green (1991) use the EM algorithm, a technique that was devised primarily to cope with missing data (Dempster et al., 1977). The method consists of two iterated steps: the E step, in which the conditional expectation of the missing data (the population the for intersection zone) is computed, given the model and observed data; and the M step, in which the model is fitted with the maximum likelihood for the entire dataset (including the data estimated in the E step) (Flowerdew and Green, 1991, 1992). The E step and the M step are given in Equations 3.8 and 3.9 respectively:

\[ \mu_{st} = \hat{\lambda}_{j(c)} A_{st} \]  

(3.8)

where \( \mu_{st} \) is the mean population of the area of intersection and \( \hat{\lambda}_{j(c)} \) is the estimated population density for the type of control zone.

\[ \hat{y}_{st} = \frac{\hat{\lambda}_{j(c)} A_{st}}{\sum_k \hat{\lambda}_{j(k)} A_{sk}} y_s \]  

(3.9)

where \( \hat{y}_{st} \) is the estimated population of the zone of intersection and \( \hat{\lambda}_{j(k)} \) and \( A_{sk} \) are the population density and the area, respectively, of each zone of intersection \( k \) that lies within the source zone \( s \).

\[ \hat{\lambda}_j = \sum_{s \in \text{area}(j)} \hat{y}_{st} / \sum_{s \in \text{area}(j)} A_{st} \]  

(3.10)

After the iteration of the E and M steps until convergence, the target zone totals can be estimated by summing the relevant sub-zone totals:

\[ \hat{y}_i = \sum_s \hat{y}_{st} \]  

(3.11)

In contrast to regression modelling, the EM algorithm incorporates an iterative best-fitting approach to derive the density for each land class that satisfies the pycnophylactic property. The technique has been used in much area interpolation literature to show how the ancillary data can be used to disaggregate the socio-economic data (see Flowerdew and Green 1991; 1992) and is considered a reliable method in terms of the accuracy in comparison with other simple techniques (Gregory 2002; Gregory and Paul, 2005). Although the estimation process of the EM algorithm is comparably complex, the method is still based on the assumption that the densities for each land class are constant across
the space. The EM algorithm is presumed to have the same level of ability to address the spatial heterogeneous density in the spatial disaggregation process as the regression model.

The dasymetric method

*The Dasymetric method* has its roots in the work of Wright (1936) in mapping the population distribution. It can be defined as any method by which the source zones are subdivided into smaller constituent regions that possess a greater internal inconsistency in the density of the variable being mapped (Langford, 2006). The nature of the multiple density representation of the dasymetric mapping has shown great potential in spatial disaggregation, especially when it works with the various land classes to estimate the proportion of the population to be distributed among these classes.

There are several ways to determine the proportions that allocate the population into the different land classes. Earlier dasymetric approaches derived the density proportions subjectively and assumed that the percentage of the population allocated to each land class was consistent across the source zones (Wright, 1936; Eicher and Brewer, 2001). For example, 70%, 20% and 10% of the population of each source zone were to be allocated to high-, medium- and low-density areas, respectively. Such a strict deterministic approach was criticised as the main disadvantage of the dasymetric mapping where the great spatial heterogeneity is missing (Bielecka, 2005). A modified version of the global proportioning approach was set forth by Gallego and Peedel (2001) who found that the results can be improved if the globally estimated proportions can be differentiated between the sub-regions within a region with distinct spatial characteristics. Rather than applying a global or regional proportion of the population for each land type, Mennis (2003) employed an area-based, locally-fitting approach to adjust the global density ratio at the source zone level and allow a greater level of spatial heterogeneity to exist.

The advantage of the dasymetric method is that it is able to present a range of residential densities (non-urban, low density residential, high density residential) within each source zone and those distinct from other source zones. Thus, the technique is developed based on a relaxed assumption that minimised the area of homogeneous density for each land class within each source zone. Different variables have been used to define the density

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variability. Langford (2006) requires the relative densities for each land class within each source zone to implement the multi-class asymmetric mapping. The equation is given as:

\[ P_t = \sum_{s=1}^{S} \sum_{c=1}^{C} \frac{A_{stc} P_s}{A_{sc}} = \sum_{s=1}^{S} \sum_{c=1}^{C} A_{stc} d_{sc} \]  

(3.12)

where \( P_t \) is the estimated population of target zone \( t \); \( A_{stc} \) is the area of intersection between target zone \( t \) and source zone \( s \), and identified as land class \( c \); \( P_s \) is the population of source zone \( s \), and \( A_{sc} \) is the area of source zone \( s \) identified as land class \( c \); \( d_{sc} \) is the relative density of land class \( c \) for source zone \( s \), which is unknown.

More recent asymmetric mapping developments have demonstrated that, in addition to the classification of the land cover, other forms of ancillary information show a strong potential to inform the socio-economic spatial disaggregation. For example, Reibel (2005) employed data on street density as a weighting variable to model the within-census tract distribution of the population in Los Angeles. Reibel and Aditya (2006) again compared the performance of street-weighted method and land classification method, and finally suggested that the land use data is preferred in terms of accuracy and reliability. Another potentially-useful source of ancillary data is the night-time light emission data. Briggs et al (2007) use the combination of light emissions and land cover data to enhance the estimates of the smaller area population densities in the European Union.

There are also other more complex solutions in the literature, which include the Bayesian areal interpolation and the Neural Networks. The Bayesian areal interpolation method (Mugglin et al., 1999) is capable of incorporating the ancillary information with a Bayesian modelling framework and using the Markov Chain Monte Carlo (MCMC) techniques for estimating the parameter of the model. Neural Networks (NNs) (Turner and Openshaw, 2001) are capable of modelling the complex geographical data under the conditions of a limited knowledge of the geographical phenomenon being examined (for example, theoretical relationships between the variables). In contrast to simple models which use simple statistical relationships between predictive variables and target variable, NN methodologies can learn to represent complex spatial data patterns based on training neural networks. A recent application of NN (Patuelli et al., 2006) developed the NN models to compute short-term forecasts of employment for 439 districts in Germany.
Although NNs are more robust against the complex spatial data, the method has been concerned with some issues. Firstly, the NN has been described as 'black box' method. The parameters used in the NN do not bear theoretical relationships to the spatial data. The lack of theoretical assumptions of the model inevitably leads to the limitations in the result interpretation. For example, the results of the NN models are often dependent on the implementation carried out by the analyst but less relevant to the driving factors. Secondly, the implementation of NN methods is very complex and computationally intensive. Therefore, considering the low transparency in model operation and high computational cost, the NN approach has not been commonly used for spatial data disaggregation.

3.2.3 Implementation issues

The ease of implementation and data demand is an important issue in the use of spatial disaggregation techniques. More advanced techniques often require a high level of computational and mathematical expertise for the users. In many cases, when there is generally little difference among the assumptions of the spatial disaggregation techniques, the choice of the method should be made on the basis of the ease of implementation and the lower data cost (Nordhaus 2002). We group the methods into three complexity categories: low complexity, medium complexity and high complexity methods.

Low complexity methods

The simple overlay method, the binary division method and the global regression methods are easy to implement. The simple overlay method requires only a source zone and a target zone data, and no ancillary data are needed. The binary division method additionally accounts for only the populated areas of the source zones to allocate values to the target zones. The use of the regression models is straightforward. The estimation is based on the spatial overlay of source zone, the target zone and the additional ancillary data. It often requires standalone statistical software, such as SPSS, to estimate the density parameters because the regression analysis is not provided by most GIS products.

Medium complexity methods

Pycnophylactic interpolation, regional regression model and locally-fitted regression models are in the medium complexity category. Some of these methods incorporate ancillary information, but do not require complex mathematic algorithms and intensive geo-processing.
High complexity methods

We consider the multiple-class dasymetric methods, kernel interpolation and the EM Algorithm as the more complex spatial disaggregation techniques. The multiple-class dasymetric methods require intensive geo-processing to estimate a range of density parameters at the local level. The kernel interpolation and EM algorithms both operate with complex mathematical algorithms. The implementation of the highly complex spatial disaggregation technique is very time-intensive. Some traditional methods have been developed as standard tools (for example, kernel interpolation), but it appears that no GIS products currently provide generic dasymetric programs that are applicable for all study areas.

3.2.4 The accuracy of techniques

Geographical phenomena are very complex in nature and are difficult to explain and analyse simply (Lam, 1983). The accuracy of the spatial disaggregation techniques is primarily determined by the appropriateness of their assumption used to state the spatial structure of the data distribution. This especially refers to the assumption about the nature of the heterogeneity of the source zone (Lam, 1983). The major density assumptions used in the different techniques are abstractly illustrated by Figure 3.2 (a)-(f), where the vertical bars represent the density for each of the land use classes and the parallel bars represent the density for the source zones. The colour (darkness) on the bar is used to distinguish the discrete density classes. They do not represent the formal measurement of densities.
The simple overlay method assumes a homogeneous density at each entire source zone (see Figure 3.2 a) and is considered most restrictive to capture the complex spatial structure of the socio-economic distribution. Other techniques without ancillary data do not impose homogeneous density assumptions at all, but the density assumptions they imply are still restricted to explain the spatial structure of the socio-economic data. For example, the assumption used by the kernel interpolation (Figure 3.2 c) is still far from reality because the population is not purely symmetrically distributed from the centroid of a source zone. Considering the appropriateness of the assumptions, volume preserving property and the ease of implementation, these approaches are not suggested for spatially disaggregating the complex socio-economic data (Lam, 1983; Tobler, 1999). The statistical approaches (regression and EM algorithm) assume multiple classified densities that are uniformly distributed across the study area (Figure 3.2 b). They have been demonstrated to present an improved spatial disaggregation accuracy over the techniques based on simple density assumptions (see Fisher and Langford, 1995; Gregory, 2002). Dasymetric mapping assumes a homogeneous density at each land class within a source zone level (Figure 3.2 d–f). Comparably, they imply more relaxed density assumptions than the global statistical approaches, as in the regression model. Many studies inferring population
disaggregation have shown a consistent finding that the dasymetric methods incorporating ancillary data provide more reliable results in the data disaggregation. A clear statement has been made by Fisher and Langford (1995) and Langford (2006) that the dasymetric method allows a greater spatial heterogeneity in the density distribution which is an important property for an accurate spatial disaggregation.

Although dasymetric methods allow high level spatial heterogeneity in density, it still seems that a range of densities will be present within the source zones. Researchers have attempted to subdivide the source zone to allow a greater density variation. For example, an incremental development for the binary dasymetric method is to move to a 3-class model that could better identify some variability present within a source zone (Figure 3.2 d and e). These works were motivated by researchers who believe that a greater flexibility in the way that the model is calibrated, together with the use of better ancillary data, could lead to more accurate spatial disaggregation results.

However, to what extent can the complex spatial variability ever be better identified and modelled using discrete classes is still debatable. This is particularly an issue for estimating a quantitatively continuous variable such as population across space. Some researchers have shown that increasing the land class variables will incrementally improve the disaggregation results (see Langford et al., 1991; Fisher & Langford, 1995; Eicher and Brewer, 2001). On the other hand, some studies showed an inconsistent finding (see Yuan, 1997; Langford, 2006) and researchers have suggested that a simpler set of density classes is desired for the better target zone estimates. They are concerned with the use of the ancillary variables only when they have strong and independent relationships with the variable of interest (Flowerdew and Green, 1989). However, the hypotheses were previously tested on a limited number of density classes (2- or 3-class) because of the simplicity of the study area applied. There is no further research attempt to test the hypothesis whether finer subdivisions of the density classes can continuously lead to more accurate results.

Considering SEQ is a large and more complex study area, there is nothing stopping the testing and evaluating of a dasymetric method with an increased number of density classes to account for the greater level of spatial heterogeneity in population. This also raises the issue of to what extent the further refinement of total number of density classes can
improve the spatial disaggregation result, when there no guarantee has been identified in any previous research.

### 3.3 Theory-driven spatial disaggregation approaches

In the last section, we have reviewed the data-driven spatial disaggregation techniques, and how the methods of disaggregation in this type can be driven by the source zone data or by combining the ancillary data of the true distribution. It is highlighted that the intelligent methods incorporating high quality ancillary data tend to be more accurate in estimating the spatial variability of the data distribution within the source zones. These researches in spatial disaggregation methods have primarily focused on the population data. However, the ancillary data is not often sufficiently reliable for spatial disaggregating other socio-economic variables. For example, unlike housing unit data or land use data, which bear a close relationship to the population, the relationship between the information on the business establishment (or land use) and the number of employment varies widely. Researchers do not precisely show the location of the jobs for an industry sector (for instance, wholesale) to inform the employment spatial disaggregation. Thus, another type of disaggregation approach which derives the spatial structure of the data from the theoretical specification is required. Based on the review in Chapter 2, theories in urban and economic geography have demonstrated the socio-economic distributions in an urban area are inherently heterogeneous.

Developing theory-driven methods is not currently an active area of research in the field of spatial disaggregation. In one piece of work based in the USA, Greenberg (1972) developed share models based on the shift-share theory to ‘step-down’ large area (multi-county) employment projections to the local level (county). In another piece of work based in the USA, Shukla and Waddell (1991) developed a discrete choice model based on the discrete choice theory to allocate the total employment from a metropolitan area to the zip code zones. For applications at smaller scales, a recent study was undertaken by White and Engelen (2000) who employed the regionally-constrained cellular automata (CA) to systematically convert the socio-economic forecasts from 40 regions to 132,000 grid cells in the Netherlands.

Some other theoretical approaches have been developed with a focus on estimating the spatial differential of the employment. They have not been formally applied in the field of
spatial data disaggregation. These include a multi-regional input-output method based on the macroeconomic theory to forecast the employments by the industries for a limited number of large economic regions (Folmer, 1986). The econometric models (Anselin, 1988) are used to predict the locations of employment based on the location theory and the regression relationships between employment and explanatory variables (for instance, distances to markets, transport costs and land prices). Some previous researches for regional employment disaggregation are summarised in Table 3.2.

Table 3.2: Different theory driven techniques for spatial disaggregation

<table>
<thead>
<tr>
<th>Technique</th>
<th>Assumptions</th>
<th>Appropriate spatial scale</th>
<th>Data demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share model</td>
<td>Regional variability of employment is determined by the identified share of regional employment at sub-areas</td>
<td>Large-medium</td>
<td>Low</td>
</tr>
<tr>
<td>Trend model</td>
<td>Employment growth at a sub-area follows the historically growth rate.</td>
<td>Large-medium</td>
<td>Low</td>
</tr>
<tr>
<td>Multi-regional input-output approach</td>
<td>The regional variability results in economic transactions between economic sectors distributed at different sub-regions.</td>
<td>Large</td>
<td>High</td>
</tr>
<tr>
<td>Cellular Automata</td>
<td>The target areas are relatively small and the employment growth of a area is influenced by its surrounding areas.</td>
<td>Small</td>
<td>Medium</td>
</tr>
<tr>
<td>Econometric models</td>
<td>The job location is jointly determined by a range of morphological factors, and each factor show spatially uniform impact on the employment.</td>
<td>Medium-small</td>
<td>High</td>
</tr>
<tr>
<td>Discrete choice model</td>
<td>The job location is determined by their maximised utility, and people or job will make optional choice from limited number of areas.</td>
<td>Medium-small</td>
<td>High</td>
</tr>
</tbody>
</table>

Typically, the appropriateness of the theory for spatial disaggregation is largely determined by the soundness of the theory specified, including assumptions, for urban behaviour or processes at certain spatial scales. A detailed discussion and method selection will be given in Chapter 5, based on the context and requirement for SEQ employment disaggregation. An important issue is that the technique starts from a theoretical specification that is subsequently confronted with the data. The theoretical model estimation or calibration is often carried out by means of spatial data. The existing techniques for spatial disaggregating employment data have tended to account for the spatial structures using relatively simple assumptions. The main conceptual problem associated with these approaches is how to address the spatial effects in spatial structure.
This is reflected in the three major methodological problems specified in Chapter 2, spatial autocorrelation, spatial heterogeneity and effect of scale. For the theory driven techniques to be operational, the application and validation of specialised spatial disaggregation techniques to better account for the spatial issues is an unsolved area. Chapter 5 in this research attempts to thoroughly re-investigate this issue by developing a technique for spatial disaggregating employment forecasts for SEQ.

3.4 Analysis of error
In the previous sections, we reviewed the different methodologies driven by the data or theoretical process to spatially disaggregate the socio-economic data. As the spatial disaggregation is an uncertain process, whatever the technique, the results given by spatial disaggregation will contain errors. The accuracy of the spatial disaggregation will be a significant issue for the urban studies in which these values are used. Together with the development of new methods, there has arisen a need to validate those methods by the evaluation of their accuracy. However, although the spatial disaggregation has been researched for a couple of decades, only recently has there been a specific attempt to quantify these errors. In this section, we review the methods used in the previous literature to validate the spatial disaggregation techniques.

3.4.1 Statistical measure of errors and visualisation
Most studies evaluate the error of the spatial disaggregation techniques using actual values that were known from independent data sources for the target zones (Flowerdew, 1988; Flowerdew and Green, 1991, 1992; Goodchild et al, 1993; Reibel, 2005; Reibel and Aditya, 2006). Different descriptive statistics were used in those studies to quantitatively measure the degree and the pattern of the disaggregation error, which include, mean error, maximum error, percentile and standard deviation. Some error measurements can be visualised in the form of the choropleth maps that are used to indicate the spatial characteristics of the error distribution. For example, Langford et al. (1991) investigated the accuracy of three regression-based methods through a comparison of the error distribution between the different techniques. Another good example is Eicher and Brewer (2001) who mapped the percentage error and the count error to compare the accuracy of the different asymmetric methods. Reibel (2005) used visualisation techniques to show the distribution of the significant errors in the results using standard deviation.
The overall error statistics are widely used to describe the accuracy of a technique. These include the mean of absolute error (MAE) (Langford, 2006), the mean of percentage error (MPE) (Goodchild et al., 1993), and the root mean square error (RMSE) (Fisher and Langford, 1995; Eicher and Brewer, 2001; Nordhaus, 2002; Gregory, 2002; Gregory and Paul, 2005; Langford, 2006). The RMSE is the most frequently-used measure of the differences between the values predicted by a model and the values actually observed from the data being estimated. These individual differences are also called residuals. The RMSE serves to aggregate them into a single measure of estimation error. Basically, it is calculated using the formula:

\[ E^{\text{RMS}} = \left[ \frac{1}{m} \left( \sum_{t} (Y_t - \hat{Y}_t)^2 \right) \right]^{1/2} \]  

(3.13)

where \( E^{\text{RMS}} \) is the RMSE and \( m \) is the number of target zones; \( Y_t \) is the actual value at the target area \( t \); \( \hat{Y}_t \) is the estimated value at the target area \( t \).

As suggested by Gregory (2002) that if the value (for instance, employment) of the target zones varies widely across the study area, some almost-insignificant errors at the target areas that have a larger population base would have serious consequences for the other areas. In this case, the RMSE can be formulated differently by calculating the proportional error, using:

\[ E^{\text{RMS}} = \left[ \frac{1}{m} \sum_{t} \left( \frac{Y_t - \hat{Y}_t}{Y_t} \right)^2 \right]^{1/2} \]  

(3.14)

Fisher and Langford’s (1995) concern is that the RMSE is highly dependent upon the mean population in the target zones itself as a reflection of the number of target zones. In dealing with this, a standardised coefficient of variation (CV) is introduced (see Fisher and Langford, 1995; Langford, 2006). A standardised CV is obtained by dividing the RMSE by the mean target zone population. The analysis of the CV is very useful in comparative studies. For example, Eicher and Brewer (2001) have employed statistical measures of CV (95% of the confidence interval and overall mean) to evaluate the comparative accuracy of the different dasymetric methods. Other statistical measures of accuracy of the spatial disaggregation include, the simple regression, t-test statistics and outlier distribution (see
Cockings et al., 1997). Overall, the use of these methods is subject to the requirement of the study.

3.4.2 Monte Carlo simulation

From a methodological perspective, it has been questioned in some literature that the results obtained by a single examination any particular methods have limited statements with the reliability and global applicability of the methods (Fisher and Langford 1995; Sadahiro 1999). This is because the distribution of spatial data is very complex and model their pattern are often dependent to the sampled data. Therefore, there is reasonably high probability that the detected variation that occurred by chance, and the technique examined solely fit the observed data will result in poor generalizability. In this regards, Fisher and Langford (1995) employed a Monte Carlo simulation to evaluate the accuracy of the different spatial disaggregation methods considering the diverse combinations of the source and target zone systems. Using Monte Carlo simulation allows the testing of the spatial disaggregation methods in a variety of geographical circumstances so that the results have a wider applicability. Cockings et al. (1997) further produced predictive models of the errors in the spatial disaggregation using a Monte Carlo simulation. The models revealed the relationships between the parameters of the target zones (perimeter, shape and population density) and the mean error produced by the simulations. In addition, the mean errors and the standard deviations of errors between the different techniques are visualised at each target zone level, which allows the detailed comparisons to be made.

Nevertheless, the Monte Carlo simulation has not been widely used as a standard validation method for spatial disaggregation techniques. This is because the Monte Carlo simulation is rather complex and computationally intensive. The method requires the observed value of a statistical test to be compared with large number of simulated ones. This involves many complex procedures such as random data generation and computational tools to iteratively test the techniques against the simulated data. Therefore, in many previous studies, when the available data are good enough to justify the significance of the result and the theoretical assumption of the technique, most researchers would choose simpler validation approaches rather than conducting a rigorous validation using Monte Carlo simulation.

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3.4.3 Theoretical examination

In addition to the numerical error evaluation, some researchers have used a theoretical examination to validate the accuracy among the spatial disaggregation methods. For example, Sadahiro’s approach (1999) is based on a stochastic model that represents diverse geographical situations. In contrast to the Monte Carlo simulation, the model discovers the relationship between the estimation accuracy and the spatial distribution of estimation error literature from a theoretical point of view, without a high computational cost. Sadahiro’s finding can be very suggestive for the choice of the spatial disaggregation methods. Nevertheless, the theoretical examination has limitations and some important spatial issues are not involved, such as the influence of shape, size and the composition of the source zones and the target zones (Sadahiro, 1999).

3.5 Conclusion

This chapter provides an extensive review of the current spatial disaggregation techniques that are primarily applied to the socio-economic data. The review covers their principles, theoretical assumptions, implementation issues and validation methods. It thoroughly discusses the major findings from the previous literature in the area of the accuracy of the spatial disaggregation methods.

The review of the current methodologies uncovers the major limitations associated with the existing methods. Of all the data-driven methods, the dasymetric mapping is well established in the spatial disaggregation literature. The method implies a more relaxed density assumption than the other techniques and presents a higher ability to resolve the spatial heterogeneity in the population disaggregation. However, previous dasymetric methods were developed, based on a coarse density classification and tested against relatively simple geographical areas. One area that has received little attention is to what extent the accuracy of the dasymetric method can be further improved for a refined density classification. This is particularly a problem for the SEQ population disaggregation, because the high degree of spatial heterogeneity in the dataset might not be easily resolved in simply two or three classes. Therefore, a further methodological investigation needs to be carried out to test the performance of the dasymetric methods that incorporate the extended number of density classes. The purpose is to identify a best
density solution for a dasymetric method that is robust to the highly heterogeneous SEQ population (this is demonstrated in Chapter 4).

This chapter also introduced the major theory-driven techniques for spatial disaggregating the employment data. Given the availability of the data this research attempts to apply a theory-driven technique to disaggregate the employment data. This chapter specified that the use of theoretical approaches for spatial disaggregation primarily depending on their theoretical soundness, including assumptions, for the patterns of employment at certain spatial scales. I emphasise the importance of the spatial dependence and the spatial heterogeneity in the employment data at the geography of metropolitan level, which necessitates a novel method over existing techniques to appropriately disaggregate the SEQ employment data whilst accounting for these spatial effects (this is demonstrated in Chapter 5).
Chapter 4 – Spatially disaggregate population forecasts for SEQ

The accuracy of the spatial disaggregation techniques largely depends on their density assumptions and the underlying spatial structure of the study area. In this chapter, a technique is presented to spatially disaggregate the regional population forecasts based on the result of a comparative investigation of multiple class dasymetric methods to determine their relative accuracy.

4.1 Introduction

Data about the future population distribution is important information for urban planning and economic activities. Using the spatially disaggregated data of the population enables planners to effectively analyse the patterns of regional growth and the planning issues. In this chapter, we present a method to spatially disaggregate the SEQ population forecasts from the large regions down to the local government areas. The intention of the analysis is to provide a better understanding of the regional variations in the population growth over the next 20 years.*

Based on the spatial structure of SEQ, the challenge for the population disaggregation is the high degree of spatial heterogeneity in the population density. The complex, heterogeneous population growth requires a spatial disaggregation method that has the ability to accommodate such spatial issues in the population distribution. Moreover, when dealing with forecasts, spatial disaggregation is an estimate of the potential spatial structure of the data that has not happened. An inherent problem is method validation, because it is often not possible to obtain the known future spatial phenomena against which to test them. To sufficiently resolve those issues, this Chapter is divided into three sections:

- to pre-test the spatial disaggregation techniques based on a range of density solutions against the historical data for SEQ. The purpose is to identify the most appropriate method to solve the spatial heterogeneity problem for the SEQ population disaggregation.

- apply the most appropriate method (derived quantitatively) to spatially disaggregate the population forecasts for SEQ over time
• generate and discuss the population spatial disaggregation results.

In the first section, we focus on developing the spatial disaggregation technique and the validation. Based on the methodology review in Chapter 3, we extend the previous methodological research, (i) by increasing the number of land classes carried by the asymmetric techniques to solve the spatial heterogeneity issue. This provides a wider range to pre-determine the number of density classes which best fits the spatial structure of study area and, (ii) to test the spatial disaggregation techniques (with different numbers of land class) against a comparably larger and more varied geographical area. SEQ is considered to be an ideal test-bed to rigorously test the accuracy of the spatial disaggregation methods. To determine the best density configuration for the population disaggregation, eight spatial disaggregation methods are developed. They incorporate different density compositions to partition the SEQ region into areas of land classes. The correlation between the population and the area of each class was calculated to determine the population density for each land class. The spatial heterogeneity effect was captured, based on the areal weighting between the land classes in the target zones. The errors in the techniques are then tested and compared using the 2001 SEQ census data. The purpose is to identify a best technique that is robust for the spatial heterogeneity in the population distribution.

The second section of this chapter moves away from method validation and focuses on disaggregating population forecasts over time using the best-fitted method. Previous spatial disaggregation methods have not been used for the population forecasts in time series. Thus, a key feature of this section is to show how the spatial heterogeneity estimated from the base year structure can be applied to spatially disaggregate he population forecasts over time.

In the third section, the results are presented as a set of spatially disaggregated population forecasts at the local government areas. Their implications for future urban spatial structure have been fully demonstrated.

Apart from the urban structure analysis and from an urban economic perspective, the economic explanation of the changes in the population over time can be growth or the movement of the spatial demand for services and possible the labour supply for the economic activities. The population growth in the local areas might lead to structural
changes in the services employment locations and the intra-regional distribution. The spatial change in the economic activities is a key aspect of urban growth; what often makes the spatial employment forecast difficult is the access to the spatial disaggregated population data. Thus, another motivation for spatial disaggregating the population forecasts is to satisfy the data requirements for the spatial employment modelling. The spatially disaggregated population forecasts are used as synthetic data to disaggregate the employment forecasts over time (see Chapter 5).

4.2 A test of spatial disaggregation techniques for SEQ

Based on the review of the spatial disaggregation methodologies in Chapter 3, the accuracy of the spatial disaggregation techniques largely depends on the appropriateness of the assumptions applied and the geography for the areas. Spatial disaggregation techniques using more relaxed density assumptions and allowing a greater level of spatial heterogeneity are theoretically more appropriate to accommodate the complexity of a large geographical area. However, this hypothesis has not been fully justified by the previous research. The concerns for the major limitations are:

- the validity of the spatial disaggregation method was always limited by the simplicity of the spatial structure of the study area. A more conclusive result could be experimentally validated by broadening the study area to include a greater spatial heterogeneous density.

- previous methodology researches basically test the limited land classes (for example, 3-classes dasymetric mapping) to resolve the spatial heterogeneity problem. There is no study to test that whether a finer subdivision of the density classes could lead to a more accurate result, nor how an optimal number of classes could be identified.

Therefore, the primary task in this section is to fully test and evaluate the accuracy of the spatial disaggregation methods to spatially disaggregate the population data for a larger and more complex geographical area (namely, SEQ). Particularly, we extend previous research in the dasymetric methods by incrementally increasing the total number of density classes from the traditional two and three classes to 4, 5, 6, 7 and 8 classes to determine the optimal density classification for spatial disaggregation. The multiple land classifications are simulated using data densities at the basic spatial unit.
for comparative validation is to determine a most appropriate method that will be used to spatially disaggregate population forecasts the future years.

4.2.1 The study area and data

The SEQ region covers a relatively large geographical area (2,279,903 hectares) and houses a population of 2,479,295. Figure 4.1 depicts the settlement pattern of SEQ that varies greatly from the city for Brisbane and the growing populations in the nearby coastal settlements of the Sunshine and Gold Coasts. The population drops off dramatically away from the coast with the exception of the two cities of Ipswich and Toowoomba. Although, the eastern part of the region is heavily populated and urbanised, it is still mixed with other land covers in many small areas. This has characterised the region with significant spatially-unbalanced land use variations and the population density varies either globally or locally.
In this study, the degree to which the population density varies throughout the study region is much greater than in the previous studies undertaken by Langford and Fisher (1996) and Langford (2006) who used the county of Leicestershire, UK. Table 4.1 describes the degree of spatial heterogeneous density for the two study areas. Leicestershire has a relatively uniformly-dispersed population of 459,772 across high, medium and low-density residential areas and covers an area of 81,700 hectares. In contrast, SEQ exhibits a greater degree of heterogeneity over the region. Specifically, there are much greater extremes of residential density, highlighted in the final column (density ratio) of Table 4.1. The density variation for SEQ is the notably due to the population concentrations that are distributed unevenly across the region. Therefore, the SEQ is
considered a more suitable study area to more rigorously evaluate the relative performances of the spatial disaggregation techniques.

**Table 4.1:** Population density variations for SEQ compared with Leicestershire, U.K.

<table>
<thead>
<tr>
<th>Study Area</th>
<th>Total Population ('000)</th>
<th>Total Size ('000 Hectare)</th>
<th>Average Density</th>
<th>Average high density</th>
<th>Average medium density</th>
<th>Average low density</th>
<th>Density Ratio (high/low)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leicestershire</td>
<td>460</td>
<td>812</td>
<td>5.6</td>
<td>37.8</td>
<td>21.1</td>
<td>4.7</td>
<td>8.0</td>
</tr>
<tr>
<td>SEQ</td>
<td>2,479</td>
<td>2,280</td>
<td>1.1</td>
<td>6.9</td>
<td>3.0</td>
<td>0.03</td>
<td>180.8</td>
</tr>
</tbody>
</table>

Data

The Australian Bureau of Statistics (ABS) provides census data for statistical local areas and urban areas. We test a single case of error for each spatial disaggregation technique using the 2001 census data of SEQ. We obtained population counts for 298 Statistical Local Areas (SLAs) that are used as source zones in this test (Figure 4.2). The census data at the Urban Centre/Localities (UCLs) were used as both control zones and target zones. In this case, the target zones are spatially non-contiguous with the source zones and congruent with the control zones (Figure 4.3). For the purpose of an accuracy evaluation, we only spatially-disaggregate the population data for the urban areas in the SEQ region; thus, overall, there are less target zones than source zones. Most target zones are smaller than the source zones except in the central urban areas where the reverse is the case; however, this only represents a small part of the data and this limitation was deemed acceptable for testing the spatial disaggregation techniques.
Figure 4.2: SLA Source zones
4.2.2 Techniques for population spatial disaggregation

There are many techniques for disaggregating different types of spatial variables, but the main focus in this chapter is on the count measurements, that is, disaggregating the population counts. In this section, we compare the accuracy of a locally-fitted regression model (using 3 classes) and seven dasymetric techniques (with different numbers of classes) for spatial disaggregating the population data. It is recognised that more spatial disaggregation techniques exist; however, this chapter includes the most representative classes of the techniques based on the relaxed density assumptions, as detailed in Chapter 3.
Density classification

We use UCLs as control zones that contain a range of densities. The UCL is an important spatial unit used to define the actual occupied areas of the population. As defined by ASGC (ABS, 2005), the UCLs are commonly made up of one or a cluster of selected census collective districts (CCD) according to their population size. A CCD is the smallest spatial unit for census collection. Thus, the multiple land classes within the UCLs can be clearly defined by using the known densities at the CCD level.

Density has been recognised as a reliable indicator for the patterns of the population distribution in urban areas (Galster et al., 2001). For a three-class dasymetric approach, the ASGC has already defined high density urban areas (urban centres) and low density urban area (urban localities) with distinguishable population densities (ABS, 2005). The areas that are not covered by the UCLs are classified as non-urban areas. In dealing with area divisions that are more than three classes, we subdivide the urban areas into multiple classes by spatially classifying the CCDs based on their dwelling density from the base year (2001) census data. For example, the CCDs with a dwelling density lower than a value for a class can be grouped into a single class. Then, the grouped CCDs in aggregate cover part of the UCLs that refer to that class.

Determining an appropriate classification method is essential for mapping the population density that is quantitatively continuous (Brewer and Pickle, 2002). There are several different classification methods for spatially organising the data. These include the Equal Interval, Quantile, Natural Breaks and Standard Interval. We use a Natural Breaks classification method to define the areas for a different number of classes. This method is desirable, because the SEQ population data are unevenly distributed, with many CCDs have similar densities and gaps between the groups of densities. With the natural breaks classification method, data values that cluster are easily placed into a single class — class breaks occur where there is a gap between clusters. Thus, the classified areas are continuous with distinguishable densities organised for the urban areas. Other classifications methods (for instance, Quantile or Equal Interval) are not used. This is because these classification methods are the most suitable for an evenly-distributed data. For example, the Quantile classification requires each land class to have roughly the same number of features; and this might introduce an estimation fallacy in our dataset (that is, an overestimation of the high density areas and an underestimation of the low density
areas). In contrast, the Equal Interval classification requires an equal range of values for the classes, which might lead to an extremely reverse effect (an underestimation of the high density areas and an overestimation of the low density areas). Consequently, these classification results often give invalid density estimation from the regression model (Section 3.2.2). For example, area divisions defined by the Quantile classification frequently returned negative values of density for some classes, which is inconsistent with our knowledge of the population density. The negative density estimate can be caused by the inaccurate density areas in the regression model that give rise to large squared residuals. Since OLS minimizes the summed squared residuals, the regression estimation (the slope of fitted line) can be adjusted by the inaccurate density areas included. When the influence of the inaccurate data (over-estimated high density area) is significant to the model fit (e.g. fitted line with negative intercept), the negative coefficients (negative density) can be determined to the other land classes. Based on the experiment with spatial data classified by the different classification methods, the areas for land classes defined by the natural break classification appear to be more realistic without returning invalid density estimations.

Multiple-class dasymetric methods

When implementing the dasymetric method, the relative ratios of density values are initially established (Equation 4.1). Each density ratio was assigned to an associated land class to receive a certain proportion of the total population from each source zone. The use of the density ratio has been a more effective method for estimating the population proportion for each land class than a subjective proportioning (Mennis, 2003). Then, an area-based locally-fitting approach was also used to adjust the global density ratio for each source zone and to allow a degree of spatial heterogeneity to exist (see Equations 4.2 and 4.3). Using the localised density ratio, the population in each area in a source zone that intersected with a land class could be determined. The population at the intersection areas were then aggregated to the target areas (UCLs) (Equation 4.4).

\[
D_c = d_c \bigg/ \sum_{c=1}^{k} d_c \quad (4.1)
\]

\[
A_{sc} = \left( a_{sc} \bigg/ a_s \right) \quad (4.2)
\]

\[
\sum_{c=1}^{k} d_c = 1
\]

\[
\sum_{c=1}^{k} a_{sc} = a_s
\]
\[ f_{sc} = \frac{(D_c \times A_{sc})}{\sum_{c=1}^{n} (D_c \times A_{sc})} \quad (4.3) \]

\[ P_i = \sum_{s=1}^{S} \left( f_{sc} \times P_i \times a_{isc} \right) / a_{isc} \quad (4.4) \]

where \( D_i \) is the global density ratio; \( n \) is the total number of land classes used in the approach; \( A_{s} \) is the area ratio; \( a_{sc} \) is the area size for each land class \( c \) within each source zone \( s \) and \( a_s \) is the size of each source zone; \( f_{sc} \) is the adjusted density ratio at the source zone level. It is a local parameter used by the target zone when taking population counts.

A modification of the dasymetric method

Mennis (2003) applied a selective sampling approach to assess the relative density fractions for each land class; this assumes the original spatial units of the population are small enough to be contained entirely within each ancillary land class. However, in this study, the size of the source zone (SLAs) varies greatly across SEQ. Many SLAs are fairly large, especially in the non-urban areas and make the sampling approach unfeasible. Instead, we estimated the initial density fractions by applying a regression model (see Equation 4.5). The regression model was used to estimate the global density ratio for each land class using the areas for each source zone intersecting with the land classes. Thus, the spatial disaggregation approach integrated the elements of the regression model and the dasymetric method to overcome the uneven size of the source zones.

\[ P_s = \sum_{c=1}^{n} (d_c \cdot a_{sc}) \quad (4.5) \]

Dasymetric methods were then repetitively implemented using land class \( c \) from two to eight classes. The land classifications that are more than eight classes are not tested in this study, bearing in mind the cost of the implementation. It is possible to test the further performance of the dasymetric techniques with more than eight density classes (for example, 10 classes, 20 classes). However, this requires the development of generic and computerized tool which is applicable to calculating complex spatial disaggregation procedure base on the different number of land class. In this research, the spatial disaggregation techniques (with density classes between 2 and 8) are considered providing a good range of density classifications for the spatial structure of the study area. The development of tools and the further testing of the spatial disaggregation techniques with
increased number of land classes will be carried out in the future research. Figure 4.4 illustrates the working process of the multiple-class dasymetric method. The procedure is consistent with all dasymetric methods with a different total number of land classes applied.

4.2.3 Results and discussion

This section tested the dasymetric techniques using a single study. The source spatial units with known population data are the SLAs and the target spatial unit where the data are received are the UCLs. The errors for the spatial disaggregation were evaluated using the actual values from the independent data sources at the target zones (UCLs). They contained the true population data for a smaller spatial unit than the SLAs and can be used to check the performance of the different disaggregation methods. Because the population count for the UCLs are reported for two types of urban areas — urban centres and urban localities — the errors in each of the spatial disaggregation techniques are only identified for the urban area and the error assessment on the non-urban area is not included.

In Figure 4.5 (a—h), the absolute errors of the disaggregated value for each technique are visualised at the target zones. The examination of the visualised error has been an efficient method for analysing the results of the spatial disaggregation techniques (Eicher and Brewer, 2001; Reibel, 2005). A visual presentation of the results provides a comparison against our knowledge of the existing development or patterns of settlement change (Langford et al, 1991). The absolute errors for the eight spatial disaggregation techniques show similar distribution patterns. In each case, the majority of the errors are concentrated in the large urban areas, the smaller urban areas generally having lower errors because of the smaller number of populations within these zones. I expect to
distinguish the degree of errors between each technique for the same target locations. By comparing the error maps, the binary dasymetric mapping produced the highest error especially in the large urban centre for Brisbane. The 3-class dasymetric method and the locally-fitted regression (3 classes) approach gave a similar distribution of error. The dasymetric methods incorporating the multiple land classes present a lower overall degree of error across the region. This suggests that multiple-class dasymetric methods are more accurate than the simple approaches to solve the spatial heterogeneity issue in the population disaggregation for SEQ. However, owing to the small number of target zones used, the comparative accuracy between the dasymetric methods is not distinguishable by using a simple error visualisation.
Figure 4.5 (a)–(d): The visualised absolute errors of eight techniques that disaggregate population from SLAs to urban footprint polygons.
Figure 4.5 (e)–(h): The visualised absolute errors of eight techniques that disaggregate population from SLAs to urban footprint polygons.
Figure 4.5: The visualised absolute errors of eight techniques that disaggregate population from SLAs to urban footprint polygons.

Table 4.2 summaries the outputs and errors for each technique for two types of urban areas, the urban centre and the urban locality. The italicised figures in the table show the value of the overestimation and the value of the underestimation.

The overall errors of the results are measured by root mean square errors (RMSE):

\[
E_{\text{RMS}} = \left[ \frac{1}{t} \sum_{t} (Y_t - \hat{Y}_t)^2 \right]^{1/2}
\]

(4.6)

where \(E_{\text{RMS}}\) is the RMSE and \(t\) is the number of target zones (UCLs); \(Y_t\) is the actual value at target area \(t\); \(\hat{Y}_t\) is the estimated value at target area \(t\). RMSE is a rigorous measure of overall error which is more sensitive to the outliers in the error distribution (Gregory, 2002).
**Table 4.2: Absolute error of spatial disaggregation techniques at Urban Centres and Urban Localities**

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Urban localities</th>
<th>Urban centres</th>
<th>Non-urban</th>
<th>Sum of UCL population</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression model</td>
<td>50,166</td>
<td>2,266,579</td>
<td>55,359</td>
<td>2,316,745</td>
<td>5,699.39</td>
</tr>
<tr>
<td></td>
<td>+ 27,505</td>
<td>+ 128,937</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-class dasymetric</td>
<td>84,954</td>
<td>2,283,856</td>
<td>3,294</td>
<td>2,368,810</td>
<td>6,544.82</td>
</tr>
<tr>
<td></td>
<td>+ 62,293</td>
<td>+146,214</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-class dasymetric</td>
<td>50,225</td>
<td>2,260,049</td>
<td>61,830</td>
<td>2,310,274</td>
<td>5,079.29</td>
</tr>
<tr>
<td></td>
<td>+ 27,564</td>
<td>+122,407</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-class dasymetric</td>
<td>35,199</td>
<td>2,210,889</td>
<td>126,016</td>
<td>2,246,088</td>
<td>3,800.89</td>
</tr>
<tr>
<td></td>
<td>+12,853</td>
<td>+73,247</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-class dasymetric</td>
<td>42,650</td>
<td>2,207,909</td>
<td>121,545</td>
<td>2,250,559</td>
<td>3,758.98</td>
</tr>
<tr>
<td></td>
<td>+19,989</td>
<td>+70,247</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-class dasymetric</td>
<td>34,277</td>
<td>2,192,596</td>
<td>145,231</td>
<td>2,226,873</td>
<td>3,428.46</td>
</tr>
<tr>
<td></td>
<td>+11,616</td>
<td>+54,954</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7-class dasymetric</td>
<td>33,747</td>
<td>2,191,666</td>
<td>145,231</td>
<td>2,225,413</td>
<td>3,399.34</td>
</tr>
<tr>
<td></td>
<td>+11,086</td>
<td>+54,024</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8-class dasymetric</td>
<td>33,353</td>
<td>2,192,581</td>
<td>146,170</td>
<td>2,225,934</td>
<td>3,533.27</td>
</tr>
<tr>
<td></td>
<td>+10,692</td>
<td>+54939</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UCL (True Value)</td>
<td>22,661</td>
<td>2,137,642</td>
<td>211,801</td>
<td>21,60,303</td>
<td>30,426.80</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SLA</td>
<td></td>
<td></td>
<td></td>
<td>2,372,104</td>
<td></td>
</tr>
</tbody>
</table>

(The italicised figures represent the value of overestimation or underestimation)
From Table 4.4, we can see that all the techniques gave an overestimate of the population for the urban areas, and an underestimate of the population for the non-urban areas. The binary dasymetric mapping technique was found the least accurate for interpolating the population from the SLAs onto the urban areas. This is evidenced by the high overestimation for both the urban centres (+146,214) and the urban localities (+62,293); and there is no population left on the non-urban land. The main problem would be the limitation of the data for the test of the binary dasymetric mapping, because target zones are congruent with the control zones. Based upon the principle of binary dasymetric mapping, there was no population in the populated area that could be allocated to the non-urban area. Therefore, from this case, we can see that the application of the binary dasymetric mapping will be constrained when the binary land classifications are defined at the target zones.

Next, the locally-fitted regression model using three density classes presents a better accuracy than the binary dasymetric method in each category. This is acceptable, because the technique takes advantages of the locally-fitting approach and the more refined population density classification. In addition, calibrating the population density at each source zone level was necessary when dealing with large areas with complex population distributions.

The 3-class dasymetric mapping produced lower errors in each density category than the binary dasymetric approach and the regression model. In comparison to the 3-class dasymetric method tested by Langford (2006) using constant density fractions, this study applied a variable density fraction that is more appropriate for resolving the spatial heterogeneity for each land class over space. However, we can see the 3-class dasymetric mapping produced a greater error in the urban centres than in the urban localities. This is possibly caused by a relatively coarse land classification in comparison to a high complexity of the study area. Some errors in the coarse land classes might mistakenly inform the disaggregation process and the potential improvement can be made by a refinement of the land classification.

The 4-class dasymetric had a significant improvement over the 3-class dasymetric approach in both urban categories. It showed a subdivision of the urban areas into more than three classes better accommodates the spatial variability for the SEQ data. The result
showed that the technique based on the complex density assumption tends to be more accurate.

Unlike the great improvement made by the 4-class method, the 5-class dasymetric method did not show a significantly better result for the urban centres (+70,247), but returned a higher overestimate of the population for urban localities (+19,989). This indicates a further density classification does not always yield a significantly improved disaggregation accuracy.

When the density division moves into six classes, the dasymetric method presents a notably better estimate for both the urban categories. However, from the six classes, the seven and eight class dasymetric methods showed very limited accuracy improvements for each urban category.

To compare the overall error for each spatial disaggregation solutions, I graphed the RMSE against the total number of density classes incorporated by the method. Figure 4.6 presents a very clear non-linear correlative relationship between the RMSE and the total number of the density classes used for the dasymetric method.

![Figure 4.6: RMSE and the number of classes for the dasymetric method](image)

The binary dasymetric mapping shows the overall poorer error (6,545 by the RMSE) among all techniques. Comparably, the regression model using variable and locally-fitted
densities presents a better accuracy (5,700 by the RMSE). However, as a simple 3-class regression approach, its accuracy did not seem to be competitive with the 3-class dasymetric mapping (5,079 smaller than 5,699 by RMSE). The 3-class dasymetric mapping produced a lower error than the simpler techniques because, (a) SEQ is more complex than the previous study areas and, (b) the dasymetric method uses a more complex local-fitting approach to account for the spatial heterogeneity in the population density. These results consolidated the previous finding in that a 3-class dasymetric technique is expected to be more accurate than the simpler methods (Fisher and Langford, 1995; Langford, 2006).

Nevertheless, the Figure 4.6 further illustrates that a 3-class dasymetric method was not satisfactory for explaining the complex heterogeneity in our dataset. The 4-class dasymetric method based on a more relaxed density assumption significantly reduced the RMSE from 5,079 to 3,801 (which is about 12% of the average population in the target zones). However, the RMSE does not continuously present an expected decrease when the density class increases from four to five classes. Following that, the dasymetric models using six and seven classes return slightly better results, but the improvement between the six and seven classes was very limited (3,428 and 3,399 by RMSE). Finally, when the density class is increased to eight classes, the RMSE stop decreasing and the method starts to show a poorer accuracy (3,533 greater than 3,399 by RMSE). Although the 8-class gives a good overall estimation for the urban centres and the localities, it does not show a good internal variation of the data in the target areas. A possible reason for this is that the regression model for the 8-class densities involves a higher standard error in the density estimation for highest density areas (class eight) that is derived from a ‘natural breaks’ classification.

In this study, we can find a relationship between the model complexity and the error of the disaggregation that has not been revealed in the previous research. Figure 4.6 indicates a trend that the error of the spatial disaggregation decreases when the density class increases. However, such a relationship tends to be unstable and insignificant as excessive numbers of land classes are imposed. The traditional 3-class dasymetric method can be further improved by a more refined density division. But, a large number of land classes is not necessary even for a large and complex geographical area. The major obstacle to enable the RMSE to reach 'zero' is that the spatial heterogeneity in the classified density is more complex than that which has been identified at the SLA level. A further improvement can
be made by modelling spatial heterogeneity, for instance, using smaller source zones. However, the capacity for improvement that can be made by the more refined density classes is very limited for going beyond the existing 4-class configuration.

Overall, the findings from this research are considered very topical and more conclusive than the previous study in the spatial disaggregation method (see Langford, 2006). Even though an independent ancillary dataset (land use data) was not employed to disaggregate the population data, the simulated land classes using the natural breaks classification of the data at the CCD level is considered as efficient to test the performance of the dasymetric method with a different total number of land classes.

The goal of these tests is to select one model from a set of competing models that best capture of spatial structure of the study area. In this study, the idea of choosing an appropriate technique uses the concept of standard model selection methods. These methods penalize goodness of fit of the models by incorporating the model complexity, for example, Akaike information criterion (AIC) (Akaike, 1973), cross-validation criterion (CV) (Browne, 2000), and the Bayes information criterion (BIC) (Albert and Chib, 1997). Doing so to ensure that the method selection is not solely based on the fit to the data but also taking into account of the model complexity. Model selection solely based on the fit to a particular set of data will result in the choice of an unnecessarily complex method that overfits the data and thus generalized poorly to other data (for example, the future data or other study areas) (Myung, 2000).

The number of classes is the only dimension of complexity that these spatial disaggregation methods consider. Thus, the method selection is carried out by trading off the accuracy (RMSE) against complexity. Based on the assessment of the results, the 4-class dasymetric method is the most effective technique to model the spatial structure of the study area with a relatively low complexity. More complex models with more than 4 density classes, having a large value in the complexity term, are not selected because their contribution to the model fit are not good enough to justify the extra complexity.

Although choosing the 4-class method appears to be subjective and a statistical model should be used to determine a reasonable number of classes from the data, the idea of method selection in this research is similar to the concept of standard model selection methods (e.g. AIC). Based on its good accuracy and generalizability, I nominate the 4-class
dasymetric method as the most effective technique to spatially disaggregate the population forecasts for SEQ.

4.3 Spatially disaggregate population forecasts for SEQ

In the last section, I have identified that the 4-class dasymetric method is more appropriate for solving the spatial heterogeneity issue in the SEQ population disaggregation. This section moves away from the method validation for SEQ and focuses on the population forecasts disaggregation using the 4-class dasymetric method. The techniques of the population spatial disaggregation have been applied to present historical data in many regional studies, but have not been used for spatially disaggregating population forecasts.

4.3.1 SEQ population forecasts

The regional population growth for SEQ has been projected from 2006 to 2026 (using a five-year interval) by the OESR in the Queensland Treasury. The population has been projected at the Statistical Divisions (SD). The SD is a large spatial unit that consists of more than one Local Statistical Area (SLA); it is considered as a most stable spatial unit for statistics or the forecast of the population within in the main structure of the ASGC (ABS, 2005). The Brisbane and Moreton Statistical Divisions represent a region generally referred to as SEQ.

The population projections for the Brisbane and Moreton SDs between 2006 and 2026 are shown in Figure 4.7. The forecasts indicate that the total population of the Brisbane SD will experience a steady increase from 1.7 million in 2006 to about 2.5 million people by 2026. Comparatively, the population in the Moreton SD is expecting a continuous growth from 0.75 million to 1.3 million, but the growth rate is slightly lower than the Brisbane SD. The geographical division of the population forecasts for SEQ at the two SD’s is illustrated in Figure 4.8.
Figure 4.7: Present and forecast population for the Brisbane and Moreton Statistical Divisions between 2001 and 2026
The SEQ regional population forecasts are spatially disaggregated to the 289 SLAs (see Figure 4.9). The reason for choosing the SLA as the target spatial unit is that it provides a good balance between a finer geography and a meaningful interpretation of the population-employment relations that is useful for local government planning.
4.3.2 Assumptions

As part of the government’s strategy for sustainable growth, a target has been set to encourage the future growth of the population within the existing urbanised areas (OUM, 2006). To achieve such a goal, the urban consolidation policies have been imposed in the regional plan (2005–2026), which include:

- incorporating an urban growth boundary to consolidate the region’s urban development footprint, providing for discrete urban areas separated by inter-urban breaks and natural environment
• encouraging new dwellings to be created by infill development and the
  redevelopment of the existing urban areas across the region

• restricting further rural residential development to the existing rural residential
development and identified rural living areas.

It is desirable to acquire the data for the future planned urban areas (for instance, derived
from planning scheme) to disaggregate population forecasts over time. However, these data
is not available by the time when this methodology is developed. Thus, the base year (2001)
land class data is used to disaggregate the population forecast for each forecast year
(2006–2026). The assumptions are, (i) based on the regional growth policy and
perspectives, there is no significant urban expansion; and major urban population growth
will not go beyond the existing urban/rural developed areas and, (ii) the population
densities are allowed to grow, but there will be no significant change in the land classes
between the areas. For example, the high-density areas will continuously exhibit an overall
high population density, and the low-density areas will still remain a low density class, and
so on for the other classes.

4.3.3 Method

The method used is shown by the following steps:

1. Apply the asymmetric procedure (Equations 4.6–4.9) to allocate the SD population
   forecast to the four land classes (namely, high density urban, medium density urban,
   low-density urban, and non-urban areas) that cover the whole SEQ (see Figure
   4.10). In this step, the global density ratios are determined based on the results of
   the regression analysis for the 2001 data (as detailed in Section 4.1.3). Then, the
   global density ratios are adjusted at the SD level based on the area occupation (area
   ratio) by each land class SDs.

2. Based on the size of classified areas, densities for each land classes are calculated for
each SD.

3. Overlay the land class polygons (having population counts) with SLA data. Thus,
each SLA contains one or more classes with known densities.

4. Once the local densities at the intersection areas are determined for each time, the
   population for the intersection areas are then calculated and aggregated to their
The same procedure is then applied to the new input of the SD population forecast for the years 2006, 2011, 2016, 2021 and 2026. The final outputs are a set of disaggregated population forecasts at the SLAs with their subtotals conforming to the population forecasts at the two SDs.

Figure 4.10: Land classification for 4-class dasymetric method

(The inset highlights the high density urban areas given by the ‘natural break’ classification. They are significant for many small SLAs around the Brisbane city).

4.4 Results of spatial disaggregation

The results of the population forecasts disaggregation for each forecast year are presented in Figure 4.11.
Figure 4.11: Results of population forecasts disaggregation 2006–2026

A regional plan for the SEQ region introduced a balanced growth strategy to promote compact growth and decentralised polycentric development (OUM, 2006). The results of the spatially disaggregated population forecasts provide a valuable dataset for analysing the pattern of the population growth. The patterns of the population distribution for each forecast year are visualised by Figure 4.11, but they do not show a significant change in the overall spatial structure.

Exploratory spatial data analysis is used to measure the spatial clustering between the populations at the SLAs. Firstly, the univariate global Moran’s $I$ (Moran, 1950) is calculated for the population at the SLAs. The univariate Moran’s $I$ statistics is defined as:
\[
I = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{N} (y_i - \bar{y})^2}
\]

(4.7)

where there are \(N\) SLAs, the population value for each SLA \(i\) is \(y_i\), and \(W_{ij}\) is the weight (or connectivity) for SLA \(i\) and \(j\). The value of Moran \(I\) range from -1 to +1. Informally, +1 indicates a strong positive spatial autocorrelation (a clustering of similar values), 0 indicates a random spatial ordering, and -1 indicates a strong negative autocorrelation pattern.

The global Moran’s \(I\) statistics for the population forecasts are given in Table 4.3. The results show that global Moran’s \(I\) of spatially disaggregated population presents a growing positive spatial autocorrelation between 2001 and 2026 (all values are significant at 1% level using permutation approach for inference with 999 permutations). This suggests that, from a global view, a more compact population growth will occur for the SEQ region. Such compact patterns can be driven by the increasing restrictions on land availability and increase in intensification through urban development of residential areas. From a planning point of view this indicates a growing pressure on the housing marketplace, high demand for services such as schools or healthcare services in the future.

<table>
<thead>
<tr>
<th>Year</th>
<th>2001</th>
<th>2006</th>
<th>2011</th>
<th>2016</th>
<th>2021</th>
<th>2026</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moran’s (I)</td>
<td>0.2995</td>
<td>0.3107</td>
<td>0.3207</td>
<td>0.3341</td>
<td>0.3457</td>
<td>0.3546</td>
</tr>
<tr>
<td>Z score</td>
<td>14.45</td>
<td>14.87</td>
<td>15.65</td>
<td>16.64</td>
<td>17.48</td>
<td>18.11</td>
</tr>
<tr>
<td>Significance level</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The population concentration always presents spatial variations. The specific location for the higher population concentrations in the future is a major subject of concern for the planners. There have been different spatial statistics for measuring the patterns of the urban structure (for example, density, proximity or clustering functions) (Galster et al., 2001). To predict a significant local concentration for the future population, a local exploratory spatial analysis method is applied. Local Indicators of Spatial Association (LISA) (Anselin, 1995) provide a measure for each unit of the region of the unit’s tendency...
to have a value that is correlated with the values in the nearby areas. LISA indicators identify ‘hot spots’ that take into account not only the high or low values in a single place (a SLA) but also the values in the nearby places. Previously, LISA has been used as an effective method for detecting patterns of local dependence for a single dataset (Luo and Wei, 2006; Riguelle et al., 2007). In this research, LISA is applied to the multiple datasets created (forecasts) to analyse the patterns of the population growth over time.

The LISA statistics can be defined as:

$$I = z_i \sum_j W_{ij} z_j$$

(4.8)

where $z_i$ and $z_j$ are standardised scores of the population values for the SLA $i$ and $j$; it is among the identified neighbours of $i$ according to the weight matrix $W_{ij}$.

Each local area and its neighbours can be L = low (below the mean) or H= high above the mean). The LISA pair LH, for example, designates an SLA that has a low-level population (below the mean) locally and high level (above the mean) in the neighbouring SLAs. I tested whether a potential spatial diffusion of the population would cause changes in the levels of these local-neighbour LISA pairs over time.

A visual interpretation by the time series in Figure 4.12 shows the minor differences in the population settlement pattern (local autocorrelation) from 2006 to 2026. Basically, the future SEQ population will keep the existing concentrations and dispersions, with slight transitions in the population clustering moving from the eastern part of the region to the west. The only notable change is in the SLA (Ipswich West) presenting an LH to HH transition between 2016 and 2021, which indicates a potential urban expansion will occur. This is possibly caused by the higher pressure on the housing market, and many people will find home in less expensive suburban areas. As proposed in the South East Queensland Regional Plan (OUM, 2006), there is good uptake of vacant land in the western suburbs as preferred for housing development to reduce the growth pressure on the existing urbanized areas. The implication of the results for planning is that with current limited provision in services, public transport and employment opportunities, the development of commerce and service activities in those areas (such as retail, schools,
healthcares, and public transport) should be well managed and planned to satisfy the new demands over the next 20 years.

Figure 4.12: local autocorrelation of spatially disaggregated of population forecasts 2006–2026

4.5 Conclusions

The spatial distribution of the population and the future urban structure for SEQ has become a focus of recent academic inquiry and planning concerns. This chapter investigates the patterns of the future population for SEQ using large regional population forecasts and the recent development in a spatial disaggregation method. The focus of this chapter has been on testing and the validation of the methods used for the spatially disaggregate population data from large forecast regions to smaller areas.
The high level of spatial heterogeneity in the SEQ population requires the spatial disaggregation technique to be very sensitive to the density variations. Existing spatial disaggregation techniques that were previously used were based on the restrictive density assumptions and tested against simple geographical areas. To better resolve the spatial heterogeneity issue, the spatial disaggregation research was extended by increasing the total number of the density classes for the dasymetric method, which provided a wider range of density configurations for the study area.

The SEQ region is used as a larger and more complex study area to rigorously test the techniques. The result demonstrates that the traditional 3-class dasymetric method can be further refined by incorporating a more detailed land class. This indicates that the technique allowing a greater heterogeneity in the assumptions tends to be more accurate than the techniques based on restrictive assumptions. The results further illustrated that an excessive density subdivision is not suggested because of its limited capacity for improvement. The appropriate land class (4 class) can be determined by the complexity of the study area and the expected cost of the implementation.

The 4-class dasymetric technique was then applied to disaggregate the regional population forecast for every forecast year. The outputs of the spatially disaggregated forecasts for the smaller planning areas provided a more precise spatial scenario of the future population distribution in SEQ. To better understand the patterns of distribution, the exploratory spatial data analysis was applied to investigate the spatial clustering of the population in the local areas over time. The results tentatively indicate that the growing population in SEQ will maintain the existing structure but with a slightly more compact pattern across the region. The population concentration in the southwest of the region will increase, but such effects remain limited. I consider this is partly limited by the available data for the dasymetric disaggregation over time. A reclassification of the land areas including the planned new urban areas is needed, especially for the longer-forecast years. This work needs to be carried out in the future should the data be available to investigate those issues.

As stressed in the previous chapter, a full understanding of urban growth pattern not only requires information on the locations of the population, but also the spatial distribution of the economic activities. The work of this chapter will be followed with an investigation of the spatially-disaggregated employment forecasts for SEQ. How the predicted population
growth will influence the future employment locations is an interest of concern for both the academics and the planners. In the next chapter, the disaggregated population data are used as a major input to drive the regional employment disaggregation. The output of the continuing work is the spatially disaggregated employment forecasts in the local areas. These forecasts provide the additional information on the underlying spatial structure of the economic activities as a result of the growing populations.
Chapter 5 – Spatial disaggregation of economic forecasts for SEQ

*Spatially disaggregated employment forecasts provide insight into future urban spatial structure and planning. This Chapter present a new method to disaggregate SEQ employment forecasts using advanced spatial analysis, demonstrating a degree of spatial dependence and spatial heterogeneity in relationships to disaggregate spatial data.*

5.1 Introduction

The disaggregation results from Chapter 4 indicate that for some time from now SEQ will experience an increasing population growth. This would have a large impact on the urban spatial structure that also involves the spatial distribution of the employment activities (Foster, 2006). It is commonly accepted in the urban planning literature that the future spatial structure of the economic activity requires detailed spatial forecasts for employment (Isserman, 1984; Kaiser et al., 1995; Myers and Kitsuse, 2000; Klosterman, 2002). The main thrust of this requirement is that future changes in the distribution of the housing and the location of the employment will tend to lead to a growing pressure on transportation and the environment (Newman, 2000). However, what is frequently the major obstacle facing the urban planners and the metropolitan decision makers is that the employment forecasts are typically reported for a highly aggregated spatial unit (Bracken, 1989; Miller, 1998). Spatially aggregate employment forecasts cannot be used directly to inform the planning strategies, for example, in the allocation of the employment opportunities to the suburban centres, designing transport corridors and mixed-use urban development. To resolve this issue of the spatial scale at which the employment forecasts are generated and the scale at which they are useful to the urban planner, spatial disaggregation techniques can be applied, which underpins the impetus of this Chapter.

Previous research on spatial data disaggregation has focused primarily on the population data, which has resulted in a number of methods being proposed (see Chapter 3). These spatial disaggregation techniques typically used homogeneity assumptions and heavily relied on the available ancillary data. However, in comparison to the population, the distribution of employment (for a single industry) is often more diffuse and discontinuous at the small level of geography. When there is a high degree of spatial variability that
cannot be directly reflected by the ancillary information (land use data) for employment, a different disaggregation solution is required.

The spatial disaggregation of the employment forecasts has been the subject of some previous research. A number of researchers have incorporated a theoretical approach, such as shift-share or regional trend analysis, in their models to account for the spatial differentials (see Greenberg, (1972); Hewings, (1976) for some early examples). Those methods for the spatial disaggregation have tended to account for the spatial structures using relatively coarse assumptions. Typically, they merely account for the important spatial effect of the spatial autocorrelation and the spatial heterogeneity for the employment data, which might lead to a less accurate disaggregation result (see the discussion in Chapter 3). This chapter redresses this by accounting for the spatial effects through the application of Geographically Weighted Regression (GWR) that controls the mechanism by which the data associated with the source zones are spatially allocated to the smaller target zones.

The regional employment forecasts consist of 14 industry sectors. This chapter takes the retail employment as a case study to exemplify the spatial disaggregation procedure. The reason is that the distribution of retail employment is more complex and which is strongly influenced by the service industry agglomeration and the population. The methodology is designed to be transparent which can be applied to other industry sectors and study areas. The GWR model for disaggregating spatial data was developed based upon the related employment determinants. These include the relationship between the population and the retail jobs. The spatially disaggregated population forecasts obtained in Chapter 4 are used to determine the employment change in the local areas over time.

The new spatial disaggregation procedure based on GWR provides a way to account for the spatial dependence and the spatial heterogeneity. Here, we apply this method to the study area, to step-down the regional employment forecasts to smaller spatial units corresponding to the local administrative units that are more appropriate for planning purposes. For comparative purposes, a standard global regression model is additionally computed. We demonstrated that the spatially disaggregated employment forecasts provided the additional valuable datasets for the urban form analysis. The findings of the analysis indicate that the extent of the suburbanisation of the retail employment remains
limited in SEQ, while the retail employment at the city centres remains more dense and intense patterns. This reflects a different growth scenario in comparison with the disaggregated population forecast for SEQ.

Chapter 5 is divided into seven sections. The next section introduces the regional employment forecasts and the planning context. In section three, we discuss the existing spatial disaggregation approaches together with their limitations and their suitability for this research. The data and the variables used for the employment spatial disaggregation will be explained in the fourth section. In section five, the GWR technique is tested using a range of exploratory data to resolve the spatial effects and section six evaluates the accuracy of the spatial disaggregation technique (for both the GWR and global regression models) with a validation exercise using the Census data. The spatially disaggregated employment forecasts and their implications for the urban form are assessed in the final section.

5.2 The regional employment forecasts

The SEQ region is a sprawling, low density, multi-centred metropolis that has a dispersed distribution of industries and population. It is comprised of 22 local government areas, but for economic modelling, the area is divided into four subregions called the Regional Organisation Councils (referred to as ROCs). They are, Brisbane, the Gold Coast (Southern ROC), the Sunshine Coast (Northern ROC), and the Western ROC (see Figure 5.1).

SEQ is a fast-growing economic region in Australia. Over the next 25 years, the SEQ region is expected to capture around 75% of Queensland's population growth and account for 70% of Queensland's Gross State Product (OUM, 2006). As part of the Queensland Government's strategy for sustainable growth, in 2005, the government implemented a new regional growth plan for SEQ. This involves the employment consolidation policies, which include, (i) new employment opportunities in the major new urban development areas; and (ii) encourage employment growth in the existing regional activity centres and the locations of economic activity (OUM, 2006).

To make an appropriate plan for the SEQ employment development, an input-output model has been developed with employment forecasts provided for the four ROCs. They are given for 14 industrial sectors (based on the ANZSIC93 industry classification system) at five-yearly interval periods over a 20-year forecast horizon. The spatial scale of the
employment forecasts using the ROCs is reasonable for the regional planning, but for the local area planning they are too course. Planners are interested in the disaggregated data at the local scale. Therefore, the objective of our research is to disaggregate the four ROC forecasts down to 289 statistical local areas (SLA) of interest to the local government. As pointed out in the introduction, there are a number of components in the variability in the employment data and these have to be accounted for in the disaggregation method. The next section will review various methods to assess which ones adequately account for the spatial dependence and the heterogeneity in their statistical approach.

Figure 5.1: The SEQ region and the ROCs
5.3 Selecting a method to estimate the regional variability of employment

5.3.1 Existing approaches

In selecting a method to estimate the regional variability of employment, we performed a critical review of the techniques developed in the economic geography. Over the years, economic geographers have developed and used a plethora of different methods for estimating the regional variability of the employment. These range in complexity from share models to multiple-regression techniques.

The two key criteria we use to select an appropriate method are theoretical soundness and practicality. This selection involved ensuring the technique we selected is widely accepted in the economic geography literature and that it could make use of the similar data we had available for the research.

Trend and share models (Greenberg, 1972; Hewings, 1976) are the simplest methods. The trend models are based on the extrapolations of the past employment growth rates (usually using regression techniques). The share models are based on the assumptions of the shift-share analysis. Greenberg (1972) developed several different models to 'step-down' multi-county employment projections to the county level in the United States of America for 1972 (based on data from 1959 through to 1967). The simplest model involved assuming the share of the local to the regional employment will be the same in a future time-period as it was in the recent past. More complex models put forward by Hewings included using regression analysis, differential growth effects (also known as competitive growth effects) based on shift-share analysis, and dynamic shift-share analysis. The benefit of these techniques is the ease of use and the good availability of data. Theoretically however, we consider the assumption that the local share of the employment remaining constant over time is unsound. Furthermore, we identified that, (i) the component of the competitive employment growth used in the simple methods is not associated with the variables related to industry location theory (an important element in our theoretical soundness criterion) and, (ii) the spatial effects (spatial dependency) of the employment between disaggregated areas are not explicitly considered. For these reasons, we did not view these techniques as appropriate for our analysis.
Regional input-output analysis (Leontief, 1986) has a long and complex history in economic geography. Generally, it involves forming sub-regional transaction tables from a larger geographical region (either national or state). One well-known example of this technique is the analysis of the economic interdependence in the four regions of the Chicago metropolitan area by Hewings et al. (2001). In this study, they used Miyazawa's extended input-output framework (Miyazawa, 1976) to demonstrate the interdependence between the four Chicago sub-regions based on production, employment and income. Regional transaction tables, such as the one just described, are generally formed by using estimation techniques. One common technique is to apply location quotients to the parent input-output table to form the regional estimates. The major limitation in this technique is that at the finer levels of geography the variables used for the disaggregation are not independent and this introduces bias and inconsistency in the estimates (Páez and Scott, 2004). Supporting our position is that no Australian input-output tables exist below the local government area level.

Discrete choice modelling (McFadden, 1974) offers a further potential technique for use in our analysis. This involves maximising the location utility and the probability functions of selected variables (such as, accessibility to labour, land-use mix, agglomeration economies etc.) (Wadell and Ulfarasson, 2003). An example of its use was the research of Wadell and Ulfarasson (2003) where they applied a multi-sectoral employment location model to cells of 150 by 150 metres in Salt Lake City in the United States of America. A recent example of using discrete choice model to disaggregating regional forecast over time was the study by Kanaroglou et al (2009). The model was applied to the Hamilton Census Metropolitan area in Canada. It utilized the small area characteristics and regional migration statistics to predict small area population at census tract level that are consistent to the large regional forecasts. Although discrete choice models can be used with spatial aggregate models to make predictions for smaller areas, there are still some issues remained. A major limitation of the technique is that the selection of the variables to use in the utility function can make a large difference in the distribution of the employment or population. A further limitation, for our purposes, was the assumption of the constant spatial relationships between geographical areas. On balance, we believed that this technique was not appropriate for our analysis.
The *cellular automata* (CA)-based method (Batty et al., 1999) has been used to link the regional demand for employment between different spatial scales. The study by White and Engelen (2000) employed the regionally-constrained CA model in the Netherlands to spatially disaggregate the socio-economic forecasts from 40 regions to 132,000 grid cells. Another approach is that of *microsimulation* that has also been used to simulate the employment data at a spatially disaggregate level. Spiekermann and Wegener (1997) propose a microsimulation approach to explicitly represent the individuals and directly model the choices of the job locations that the individual workers make based on their occupation and residential location, in addition to other constraints. Hanaoka and Clark (2007) used a microsimulation model to estimate the retail demand for the small areas (residential district level). In comparison with the analyses conducted at a spatially aggregate scale, both the CA and the microsimulation approaches can explicitly represent the dynamic and stochasticity of the employment process at a spatially disaggregated scale. However, their use for spatial disaggregating regional forecasts has been a limited application. The reason for this is that both CA and microsimulation are local approaches which focus on the fundamental unit of analysis (e.g. an individual or a parcel of land). These local approaches provide better insight into the complex dynamics of individual processes, however, without bearing direct relationships with the sub-regional processes (SLA) (Alberti and Waddle, 2000). In addition, in relation to the context of large geographic areas (SEQ), the local techniques require enormous amount of detailed spatial data and therefore very high computing power to simulate the actions of all relevant individuals. Since we are only questioning the spatial variation of employment at SLA level, the choice of complex individual-based models to predict the sub-regional wide (SLA) processes is not considered as an appropriate solution to the spatial data disaggregation.

A more flexible approach now widely used is the *Econometric modelling* (Anselin, 1988). This approach is based on multivariate regression and is used extensively in estimating the regional variability of employment. This is not surprising, given the complex nature of the employment and the multiple factors that affect the level of the employment. The most commonly-used regression method in economic geography is Ordinary Least Squares (OLS). The OLS is a linear regression method that estimates the globally constant parameters of the dependent variables by minimising the sum of the squared residuals (the difference between the predicted and observed variables). However, when the OLS is
used to model the spatial data, it is apparent that there are dependencies between the dependant variables and these relationships may vary over space (Anselin, 1988; Fotheringham et al., 1997). Spatial dependence in the dependant variables and their heterogeneity across space give rise to spatial autocorrelation patterns that affect the error terms produced by using a global estimate. This violates the assumption of the non-dependence in the error term required by the OLS estimation and requires that the researchers adjust their econometric approach. Some robust regression techniques, such as spatial econometric models (spatial regression), are available to redress the spatial autocorrelation issue (Anselin, 1988; 2002). However, the technique still depends on the assumption of the spatial invariant relationships discussed above. Using global relationships to explain the behaviour distributed over a large region might cause a serious local misspecification and a biased result (Marlon et al., 2006). For these reasons, we believe that the OLS technique and the spatial econometric models are not the optimal methods for use in our analysis.

Multilevel models (Goldstein, 1987) have been proposed in geographical research as an approach to model spatial heterogeneity. In contrast to simple regression model, multilevel models attempt to account for spatial heterogeneous process by combining a micro-level model representing disaggregate process with a (or more) macro-level model representing contextual variations in process. Thus, the multilevel models can introduce spatial varying coefficients by estimating separate variance effects specific to the level of locations (Duncan and Jones, 2000). Although multilevel models have been applied to modelling the spatial structure of spatial data, including those of Congdon (1995), Charnock (1996), Duncan and Jones (2000), there is an issue with the use of multilevel models to disaggregate spatial data. Multilevel models define spatial processes at a discrete set of spatial units at each level of the hierarchy, which implies that the spatial process is discontinuous in space. However, most spatial processes do not operate in this way because the effects of processes are continuous in space. Hence, imposing a discrete set of boundaries on spatial processes is unrealistic assumption which might lead to biased heterogeneity estimation. Consequently, the application of the multilevel models to spatially disaggregate the employment data appears limited in this research.

Geographically Weighted Regression (GWR) provides a technique to deal with the spatial heterogeneity in multivariate regression (Fotheringham et al., 1997). In contrast to the
regional regression or multilevel models which assume the parameters (e.g. population density) vary over discrete space, the GWR allows the parameters that vary across a continuous surface. Essentially, the GWR estimates the regression coefficients locally using the spatially dependent weights. The weight of the data points is determined by their distance from each of a given number of estimation locations (Waller et al., 2007). This differs from the spatially varying coefficient models that use a random effects structure to define the spatial correlations (Waller et al., 2007). Nonetheless, the GWR is becoming a more commonly-used technique in economic geography. For example, it has been applied to investigate the spatial non-stationarity in the housing market (Yu, 2004), household income (Yrigoyen et al., 2008), regional industrialisation (Huang and Leung, 2002), geographic diversity in urban and regional growth (Yu, 2006; Partridge et al., 2006) and commuting patterns (Lloyd and Shuttleworth, 2005). These studies demonstrated that the economic phenomenon can be better analysed by accounting for the spatial effects (local dependence and spatial heterogeneity) using GWR. This also motivates the application of GWR to the problem of disaggregating the regional forecasts where the relationship between the forecast variable and the explanatory variables vary across the region.

In summary and for the reasons discussed in this section, we find that the GWR is the most appropriate method, given the availability of the data and the geographical composition of the study area. The next section will provide some additional theoretical background for the technique.

### 5.3.2 Geographically Weighted Regression

GWR is a local multivariate regression function in which the data samples are weighted on their spatial proximity (Fotheringham et al., 2002). It produces a separate set of regression parameters for every observation across the study area. Therefore, it relaxes the assumption in the traditional OLS models that the relationships (regression coefficients) between the dependent and the independent variables being modelled are constant across a study area, as seen in Equation 5.1:

\[
y = \beta_0 + \beta_1 x_1 + \epsilon \quad (5.1)
\]

where: \( y \) is the dependent variable; \( x_1 \) is the independent variable; \( \beta_0 \) and \( \beta_1 \) are the parameters to be estimated and \( \epsilon \) is a random error term, assumed to be normally distributed.
In this instance, $\beta_0$ and $\beta_1$ are assumed to be constant across the region in a classical ordinary least squares regression. Where there is any geographical variation in the relationships between $y$ and both $\beta_0$ and $\beta_1$, it will be captured in the error term.

When using the Ordinary Least Squares (OLS), the parameters can be estimated by solving:

$$\beta = (X^T X)^{-1} X^T Y$$  \hspace{1cm} (5.2)

Comparatively, the specific GWR model for each observation point $g$ is specified as:

$$y(g) = \beta_0(g) + \beta_1(g)x_1 + \epsilon$$  \hspace{1cm} (5.3)

where $g$ represents the vector of co-ordinates of the location, which indicate that there is a separate set of parameters for each of the $g$ observations.

When using GWR the parameters can be estimated by solving:

$$\beta(g) = (X^T W(g) X)^{-1} X^T W(g) Y$$  \hspace{1cm} (5.4)

where $W(g)$ is the weight matrix denoting the connectivity between the observations.

The weight can be determined by several methods. Two common methods are the bi-square function and the Gaussian function. In the instance of the Gaussian function, the weight for the observation $i$ is shown in Equation 5.5:

$$w_i(g) = \exp(-d/h)^2$$  \hspace{1cm} (5.5)

where $d$ is the Euclidean distance between the location of observation $i$ and location $g$ and $h$ is a quantity known as the bandwidth of the sampled observations. The bandwidth may be defined either by a given distance or a fixed number of nearest neighbours from the analysis location. The optimal number of the nearest neighbours is determined by minimising the Cross Validation score (CV) or through selecting the model with the lowest Akaike Information Criterion (AIC) score (Hurvich et al., 1998), given as:

$$AIC_c = 2n \log_e(\hat{\sigma}) + n \log_e(2\pi) + n \left( \frac{n + tr(S)}{n - 2 - tr(S)} \right)$$  \hspace{1cm} (5.6)

where $tr(S)$ is the trace of the hat matrix.
The \( AIC \) method has the advantage of being more general in application than the CV statistics and it can be used to select between a number of competing models by taking into account the differences in the model complexity (Fotheringham et al., 2002).

5.4 Variables and Data

To demonstrate the proposed spatial disaggregation procedure, this section firstly introduces the source data of the SEQ sub-regional employment forecasts and the target spatial unit to spatially disaggregate the forecasts. Then, we explain the dependent variable and explanatory variables used to build the GWR prediction model for the retail jobs together with their data sources.

5.4.1 Target variable and spatial scales

Regional input-output economic and employment forecasts from 2006 and 2026 were available for SEQ (Robinson and Mangan, 2006). The forecast database gives the projected employment for each of the 14 industry sectors (based on the ANZSIC93 industry classification system) for the years 2001 to 2026 in five-yearly intervals. The forecasts are highly aggregated, namely for the four ROCs that collectively comprise SEQ. As an example, Table 5.1 shows the ROC forecasts for the retail trade industry. A steady economic growth in employment is expected in the ROCs over the next 25 years.

<table>
<thead>
<tr>
<th>ROC</th>
<th>2001</th>
<th>2006</th>
<th>2011</th>
<th>2016</th>
<th>2021</th>
<th>2026</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brisbane</td>
<td>67,048</td>
<td>73,612</td>
<td>78,193</td>
<td>82,054</td>
<td>85,517</td>
<td>88,510</td>
</tr>
<tr>
<td>South ROC</td>
<td>45,510</td>
<td>51,145</td>
<td>56,949</td>
<td>62,758</td>
<td>69,598</td>
<td>75,855</td>
</tr>
<tr>
<td>North ROC</td>
<td>29,368</td>
<td>34,314</td>
<td>38,791</td>
<td>43,439</td>
<td>47,596</td>
<td>51,137</td>
</tr>
<tr>
<td>West ROC</td>
<td>7,779</td>
<td>8,781</td>
<td>10,458</td>
<td>12,603</td>
<td>15,251</td>
<td>18,117</td>
</tr>
</tbody>
</table>

The objective of this chapter is to spatially disaggregate the regional forecasts from four ROCs (source zones, see Figure 5.1) to smaller spatial units for the local planning areas (target zones) to provide the detailed information on the intra-regional employment...
locations used in urban planning. We chose the statistical local areas (SLA) as the target spatial units (see Figure 5.2) because they provide a good balance between a finer geography and the meaningful interpretation of the employment relations. There are 289 SLAs in the four ROCs. This geographical level is equivalent to a ward in the U.K and to census tracks in the U.S.A.

We demonstrate a procedure to spatially disaggregate the forecasts for the retail jobs. Based on the data structure given by the regional forecasts, we take the absolute number of the retail jobs in the SLAs as the target variable for each forecast year. We use base year retail employment (1996) to estimate a GWR model for predicting the retail job forecast in the SLAs. The data used was derived from the ABS 1996 Census of Population and Housing for the SLA and the 1996 journey-to-work data (JTW). The JTW data records the total number of people commuting from a particular origin to a given destination zone across the SEQ region. The destination zones pertaining to an SLA were aggregated to form a single count for each SLA representing the total number of people who actually work in a given industry (Corcoran et al., 2008).
5.4.2 Explanatory variables and data

To forecast these target variables, we needed to find the explanatory variables having a significant known or empirical relationship. We used the theoretical criteria based on the location theory in economic geography to determine which particular explanatory variables were selected. For the retail trade, it is important to capture the relationship between the location and the profit maximisation. In short, a firm will maximise its profit by maximising the revenue (that is, being as close as possible to the market for its products) and minimising costs (such as the transportation of its products to the market) (Erickson and Wasylenko, 1980; Shulka and Waddle, 1991). When a firm chooses its location, it will usually require employment at that same location. This means that there is
a relationship between the factors affecting the location of the firm and the quantity of the employment for the location of the firm.

There are many social, economic and spatial factors that are associated with the spatial process of employment. A full set of variables can be categorised into three groups:

- the ‘social structure’ variables that incorporate the local social characteristics including population, labour market, dwelling density and amenity supply. These variables depict the social resources that attract certain industries to place their employment in that area (Steinnes, 1982; Boarnet, 1994; Deitz, 1998).

- the ‘spatial characteristics’ variables that capture the location conditions and the geographical advantages of the industries (Lee, 1989; Ozbay et al., 2003). This includes the percentage of service or industry areas within each SLA (Shukla and Waddle, 1991; Boarnet, 1994; Reilly, 1997) and a range of accessibility measures (distance to the CBD, transport, activity centre, airport, river and coast)

- the ‘economic agglomeration effect’ variables that are the spatial determinants of the employment structure (Prastacos and Brady, 1985; Waddell and Ulfarsson, 2003). The variables measure the tendency of the employment among the industry sectors to cluster in either large or smaller groups to benefit the economic agglomeration effect (facilitate interactions and save costs) (Anas and Kim, 1996; Feser and Sweeney, 2000). The measurement of the agglomeration effect describes the location probability of the jobs in a certain industry as also being strongly associated with its existing concentration (Erickson, 1980) and proximity to other industries with which it closely interacts (Waddell and Ulfarsson, 2003). Such agglomeration includes the traded or un-traded interdependencies between the industry sectors (Coe et al., 2007, p. 136).

We tested the correlation for retail employment with 15 candidate variables. These include, at the SLA level, the following:

- population
- Location Quotient (at the base year) for the incidence of jobs in retail industry in a SLA
- number of recreational sites
number of schools

percentage of service areas

distance to the main activity centre (shopping centre)

distance to airports

distance to transport nodes

distance to the nearest road

distance to the central business district (CBD)

distance to coast

local workforce (access to the labour)

average household income.

number of jobs in finance, insurance, property, and business service

number of jobs in accommodation, café and restaurants industry employment

Considering the data availability at the SLA level, the main factors affecting the level of the employment in the study area are selected based on the theoretical assumptions and their significance in the geographical processes (Huang and Leung, 2002). Although some candidate variables have strong theoretical relationships to the employment distribution, their relationships are not significant based on the observed pattern for SEQ. For example, the variable of distance to CBD frequently returned very low statistical relationship at either global or local level (low t-test value). This implies that the spatial distribution of retail jobs for the SEQ region is not dominated by the cities of Gold coast and Brisbane. Including such variables in the GWR model may lead to the poorer model fit and the inaccuracy in spatial data disaggregation.

Therefore, seven variables were selected as the most significant to drive the spatial disaggregation for the retail jobs. The variables and the data used are listed in Table 5.2. Some of those variables are highly related to the SEQ employment planning processes.

**Population (POP)** describes the market opportunities for the retail trade business and therefore the employment placements. In the urban economics, the growth and movement of the people are important determinants of the changes in the urban employment locations, especially for the retail service industries. How jobs follow the population and how that dependency varies geographically is a key issue in regional science and the
planning to model the population growth and the suburbanisation over time (Steinnes, 1982). The absolute number of population in the SLAs are obtained from the 1996 Census of the Australian Bureau of Statistics (ABS).

Local Workforce (LW) is used as a determinant variable based on the assumption that the workers in the retail trade industry live and work in the same part of the city. In addition, the retail companies like to place businesses in areas with high opportunities for employment. The location of the workers provides some guidance for the planners and developers who try to locate new employment close to where the workers live and to achieve a degree of self containment. The absolute number of the local employees (local residents who are employed in the retail industry) in the SLAs are derived from the ABS 1996 Census data.

Percentage Service Areas (PSA) is used as an attractiveness indicator for the retail jobs being located in the service areas. The expansion and movement of the retail services is often stimulated by the need for more space with better infrastructure and services. The 1999 SEQ land use data defines the recent areas of land within the region that are planned for service purposes (including the retail trade). We calculate the proportion of the land zoned for the service industries in each SLA that will be the major containment of the future retail employment.
Table 5.2: Explanatory variables for SLAs used to spatially disaggregate the retail jobs

<table>
<thead>
<tr>
<th>Name</th>
<th>Group</th>
<th>Description</th>
<th>Data sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population (POP)</td>
<td>Social structure</td>
<td>More people means there is an increased demand for goods and services, and therefore employment</td>
<td>1996, 2001 ABS census of population and housing data, and SEQ population forecasts from 2006 to 2026</td>
</tr>
<tr>
<td>Location workforce (LW)</td>
<td>Social structure</td>
<td>The higher the proportion of local residents working in the industry of the SLA means lower labour costs (directly or indirectly)</td>
<td>1996 ABS census data</td>
</tr>
<tr>
<td>Location quotient (LQ)</td>
<td>Economic agglomeration effect</td>
<td>The increase in the number of people employed as proxies for the number of firms, which, according to agglomeration theory, prefer to be surrounded with other firms in the same industry at the same location (location quotient)</td>
<td>1996 JTW data</td>
</tr>
<tr>
<td>Proportion of land zoned for ‘service’ industries (PSA)</td>
<td>Spatial characteristics</td>
<td>The higher the proportion of land zoned for ‘service’ industries allows more growth in an area than if it were lower</td>
<td>1999 SEQ land use data</td>
</tr>
<tr>
<td>Distance to the main activity centre (shopping centre) (DS)</td>
<td>Spatial characteristics</td>
<td>The closer the SLA to a main activity centre (Indooroopilly shopping centre) the higher the employment in that industry (a proxy for consumer demand in the hostelling principle)</td>
<td>1996 JTW data</td>
</tr>
<tr>
<td>Number of accommodation, café and restaurants industry employment (JARC)</td>
<td>Economic agglomeration effect</td>
<td>The higher the employment in the accommodation, café and restaurants industry generally, the higher the number of consumers who eat or drink at an establishment; who then go and purchase goods and services from retail trade establishments who need to increase employment</td>
<td>1996 JTW data</td>
</tr>
<tr>
<td>Number of jobs in finance, insurance, property, and business service in SLA employment (JFIPB)</td>
<td>Economic agglomeration effect</td>
<td>The FIPB jobs present a high level of concentration and therefore a high level of demand for goods and services within the retail service catchment, and therefore employment</td>
<td>1996 JTW data</td>
</tr>
</tbody>
</table>

Distance to Shopping Centres (DS) is an indicator for the retail job opportunities. The areas close to the activity centres have a better trade environment and a higher customer demand for goods and services (Lee, 1989; Lee and Anas, 1992). In addition, a high concentration of the retail jobs around the existing employment and activity centres (shopping centres) is also encouraged by current urban consolidation policy. The locations
of the SEQ regional activity centres are provided by the Queensland Government. As a result of some SLAs being relatively large, especially for the non-urban areas, the distances are calculated at a 1 km resolution within each SLA. The distance score for an SLA is the average of the accumulated proximities measured. It provides a more reasonable representation of the whole SLA attributes in comparison to the distance measurement from the centroid of each SLA.

The **Location Quotient (LQ)** measures the current employment concentration in the SLA compared with SEQ. It is an important indicator of the retail employment because we assume that the new jobs are more likely to be located near existing retail trade centres, given the costs of relocation and the benefit of the agglomeration economies (Isard et al., 1998; Schaffer, 1999). Using the 1996 JTW data for the 14 industry sectors, we calculate the LQ for the retail industry for each of the 289 SLAs. Based on the current SEQ strategic plan, the future employment opportunities are encouraged to remain in the existing employment centres. Therefore, we hold the LQ as a key static indicator of the spatial employment to model the effect of the employment consolidation policy.

**JARC** and **JFIPB** are the economic agglomeration variables that measure the affinities and collocation between the retail jobs and the other industry sectors. For example, retail jobs often occupy an area (or building) with other types of service jobs, such as accommodation or restaurant jobs, because they share similar customers, infrastructure and services. On the other hand, finance, business and property activities generate demand for goods and services within the retail service catchment. Thus, the distributions of the jobs of those two industries have a high probability of collocation or clustering. The efficient use of the mixed-use areas for new employment agglomeration are also expected by the SEQ regional plan to reduce unnecessary new development and transportation costs. The absolute number of the ARC jobs and the FIPB jobs at the SLAs is obtained from the 1996 JTW data.

### 5.5 Methodology

The first part of this section explains the way that the GWR model is developed and calibrated to account for spatial dependence, spatial heterogeneity and scale effects in the data space. In the second part, we demonstrate how the GWR model is used to allocate the regional employment forecasts over time.
5.5.1 Model selection

The GWR model was developed by using the base-year retail employment from 1996. We tested the correlation for retail employment with 15 candidate variables and chose the seven variables in Table 5.2 as the most significant. It is noted that some variables do not show strong global relationships but have strong relationships at the local level (evidenced by the local \( t \) statistics). We also eliminated the variables that were highly correlated to reduce the effect of multicollinearity. We also found that some predictions had negative values that are inconsistent with our knowledge of the employment changes. This is likely to be caused by a degree of heteroscedasticity in the analysis. To avoid this we applied a natural log transform to the variables for the employment and population count to improve the normality of the data's distribution. Thus, the logged variables are defined as the percentage of the residents and the employment living and working in a SLA. The use of the log transform on the socio-economic variables is also suggested in the previous literature on spatial employment modelling (Steinnes, 1982; Reilly, 1997).

In this case, the base year GWR measurement model can be formulated as:

\[
\text{LnEmp}(i) = \beta_0(i) + \beta_1(i)\text{Ln}(POP) + \beta_2(i)\text{Ln}(LW) + \beta_3(i)LQ + \beta_4(i)PSA + \beta_5(i)DS + \beta_6(i)\text{Ln}(JARC) + \beta_7(i)\text{Ln}(JFJPB) + \varepsilon(i),
\]

(5.7)

where \( Emp \) is the 1996 retail jobs in an SLA; \( i \) denotes the \( i \)th SLA location in the region; \( \beta_n \) is the coefficient for the variable \( n \); \( \beta_0(i) \) is the local intercept at location \( i \); and \( \varepsilon(i) \) is the error term remained at location \( i \).

The GWR is used to analyse the local relationships (coefficients) between the retail jobs and each of the determinant variables at the SLA level. Here, we used an adaptive kernel for the local regression to account for the irregular distance between the data observations, (defined as the number of the nearest neighbours) that is determined by minimizing the AIC score of the model. The data within the kernel are weighted by their distance from the regression point (an SLA centroid); hence, the data points closer to the regression point are weighted more heavily in the local regression, the weights decreasing with the distance from this location following a Gaussian decay function. Thus, each individual SLA (as a regression point) has a set of relationships defined in the local regression so that the resulting parameter estimates vary across the study region. The output from the GWR
using the base-year retail jobs is a set of local parameters (relationships) across the SEQ region. These are then used to estimate the retail employment in the SLAs.

5.5.2 Regional forecasts allocation

Once the spatial non-stationary employment impacts related to the determinant factors have been identified from the base-year (1996) employment, we apply the spatially regressed relationships to spatially allocate the employment forecasts for the four ROCs.

The ROC employment forecasts for each five-year period are spatially disaggregated to the SLAs. Initially, we hold the spatially varied relationships unchanged over time. The model proposes that new jobs are more likely to move into the existing employment centres rather than relocating and that the changes in the retail employment are associated with the population growth, but are also conditioned by other factors. Therefore, the population is used as the dynamic portion of the local employment model and the movements of the population over time anticipate the movements in the retail employment. The data for the population forecasts by time series (year 2006–2026) for the SLAs are obtained from the spatial disaggregation results from Chapter 4.

In addition, the regional growth effects alter the local employment processes over time. For example, the retail jobs at the Western ROC are forecast to grow faster than the other more developed ROCs owing to the economic restructuring and balanced development strategy. We consider using the invariant relationships to predict the employment because the future years might encounter underestimation over time owing to overall higher growth rates being anticipated at each of the four ROCs. The higher regional demands for the retail jobs tend to increase the impact of the explanatory variables on employment (for example, the intensity of the service land use for the retail jobs or the attractiveness of the existing shopping centres) within the ROC. For this reason, we increased the rate of the initial coefficients to capture the expected growth in demand at each of the four ROCs for each forecast year.

The employment impacts (relationships) are adjusted using the regional forecasts for each forecast year. This is where the regional economic forecasts provide an input. In this case, we assume that the employment impact of each variable will increase for every 5-year period and the increase rates are fixed within each ROC, but different between the four
ROCs. The increased rate is constrained for each forecast period by the known regional employment forecasts at the four ROCs (see Equation 5.8).

\[
\beta_n(i)' = \beta_n(i) \times \frac{E_r}{\sum_{i \in r} Emp(i)}
\]

(5.8)

where \( \beta_n(i)' \) is the adjusted coefficient for variable \( n \) in the SLA \( i \); \( \beta_n(i) \) is the raw estimated coefficient; \( E_r \) is the known regional employment forecast at the ROC \( r \); \( \sum_{i \in r} Emp(i) \) is the sum of the predicted employment for the \( i \) SLA's contained in ROC \( r \).

In this way, the number of employment forecasts for the four ROCs can be used as a parameter to be allocated to the prediction procedure of the retail jobs in the SLAs. The regionally adjusted relationships are then used to predict the employment at the SLA level to ensure that each of the sum of the predicted values for all SLAs are equal to the forecast of the ROC in which they reside. Finally, the new number of SLA jobs is calculated because their totals conform to the regional forecasts (at each of the four ROCs), so that the spatial disaggregation of the employment forecasts from the ROCs to the SLAs is complete. In the next section, we evaluate the error of the spatial disaggregation results and justify the reliability of the GWR method and its expected improvement on the global method.

5.6 Results and discussion

The first part of this section interprets the estimation results for the coefficients of the explanatory variables that imply how each determinant variable has a different effect on the retail employment across the SLAs. In the second part of this section, we present the spatial disaggregation results and evaluate the accuracy of the method with a single case of error examination using the 2001 data.

5.6.1 Interpretation of spatial variation in employment

The spatial distribution of the estimated relationships between the retail jobs and the determinant factors is illustrated in Figures 5.3(a) to 5.3(g). Each figure demonstrates that the determinant variable possesses spatially-varied effects on the retail jobs across the SEQ region. The distribution of the \( t \) values for the determinant variables are shown in Figures 5.3(h) to 5.3(n). These figures display the absolute \( t \) values greater than 1.96 and 2.58 that correspond to the 95% and 99% significant levels respectively.
(a). Distribution of parameters for logged Population

(b). Distribution of parameters for logged Local Workforce

(h). Distribution of $t$ values for logged Population

(i). Distribution of $t$ values for logged Local Workforce
(c). Distribution of parameters for Location Quotient

(d). Distribution of parameters for Percentage Service Area

(j). Distribution of t values for Location Quotient

(k). Distribution of t values for Percentage Service Area
(e). Distribution of parameters for Distance to Shops

(f). Distribution of parameters for logged JACR

(l). Distribution of $t$ values for Distance to Shops

(m). Distribution of $t$ values for logged JACR
Figure 5.3: (a)–(n): Distributions of parameters for independent variables

Figure 5.3(a) shows that there is an overall positive relationship between the population and the retail jobs except for some low negative relationships for some outliers. The population presents spatially-varied attractiveness to the retail employment across the region. A possible reason for this is that the different demographic composition across the region might cause a different demand for goods and services and employment (Western and Larnach, 1998). Some small SLAs within a high-density urban area present slightly negative relationships to the retail jobs. This possibly results from the congestion effects within the SLAs (for example, land competition with growing residential development).

Figure 5.3(b) shows spatially-uneven relationships between the retail jobs and the resident employees across the SLAs. The retail jobs are more likely to match the nature of the local workforce around the central Brisbane area, west corridor, south west and northern parts of the region. The remaining parts of the region present negative job-worker relationships. This reflects a more dispersed cross-suburban journey to work the behaviour throughout the middle and outer suburbs (Gipps et al., 1997; Corcoran et al., 2008).
Figure 5.3(c) illustrates that the spatial varied attractiveness of base year (1996) job location quotient. The highest positive effects are identified in the central Brisbane area, extending west through the western corridor, where the retail jobs present a stronger tendency to join the existing job concentration. This can reflect the current metropolitan strategies to prevent dispersed employment suburbanisation by concentrating employment in the suburban regional centres and the transport corridors (Foster 2006). The greater employment concentration in some western areas may be affected by the nearby active economic areas outside the SEQ boundary, such as the city of Toowoomba.

Figure 5.3(d) reveals the regional trend in the spatial variation of the explanatory power of the percentage service areas. It indicates that the western parts of the region have a higher capacity in the service areas for the growing retail jobs. The service areas in the eastern part of the region have been more densely filled and mixed with other services. Therefore, this shows a lower ability to attract and contain the increasing retail jobs. This result is also consistent with the literature on the regional labour markets, in that land use planning heterogeneously effects the regional distribution of the economic activity (Vermeulen and Ommeren, 2007).

The spatial variation in the impact of the distance to the shopping centres for the retail employment is illustrated by Figure 5.3(e). The map indicates that the variable does not have an expected effect on the retail jobs in the region. However, a positive relationship surrounding the Brisbane region is detected. Retail employment demonstrates a stronger tendency to locate close to the shopping centres beyond the confines of Brisbane city, showing a degree of employment decentralisation in a service industry (Ingram, 1998).

Figure 5.3(f) shows the different agglomeration effects between the retail jobs and the accommodation/café/restaurant jobs across the region. The accommodation/café/restaurant jobs in the inner northern suburbs of Brisbane are more likely to be clustered with the retail jobs. The north and west of the region show a moderate clustering effect. The southern areas show less spatial relationships between the two sectors. Figure 5.3(g) shows that the FIPB jobs also present a spatially-varied tendency to be clustered with the retail jobs. However, this is in a different pattern. The FIPB jobs in the western areas have a lower clustering effect with the retail jobs and the spatial relationships in the northern and southern part of SEQ turn out to be stronger. One explanation is that the local
economy and the regulations among the local governments form varying patterns of economic agglomeration. This determines the varying degree of the local spatial clustering between the retail and other service sector industries.

In addition to the visualised outputs discussed above, a statistical summary of the parameters estimated is given in Table 5.3, based on the 1996 retail trade employment at SLAs.

The results (p-value) of a Monte Carlo test (Leung et al., 2000) on the local estimates are reported in Table 5.3. They indicate that there is significant variation in the local parameters for the variables POP and DS. The spatial variation in the remaining variables is not significant and, in each case, there is a reasonably high probability that the variation occurred by chance.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Min (Lower quartile)</th>
<th>Median</th>
<th>Global (OLS)</th>
<th>Upper quartile</th>
<th>Max</th>
<th>p-value (Monte Carlo)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Ln)Pop</td>
<td>-1.041 (-0.042)</td>
<td>0.408</td>
<td>0.335</td>
<td>0.761</td>
<td>1.149</td>
<td>0.000</td>
</tr>
<tr>
<td>DS</td>
<td>-1.062 (-0.028)</td>
<td>-0.004</td>
<td>-0.004</td>
<td>0.067</td>
<td>0.303</td>
<td>0.000</td>
</tr>
<tr>
<td>PSA</td>
<td>-3.725 0.0626</td>
<td>0.842</td>
<td>0.082</td>
<td>1.429</td>
<td>15.727</td>
<td>0.290</td>
</tr>
<tr>
<td>(Ln)LW</td>
<td>-1.142 (-0.331)</td>
<td>0.058</td>
<td>0.046</td>
<td>0.344</td>
<td>1.950</td>
<td>0.330</td>
</tr>
<tr>
<td>LQ</td>
<td>-0.139 0.661</td>
<td>0.766</td>
<td>0.586</td>
<td>0.916</td>
<td>1.431</td>
<td>0.680</td>
</tr>
<tr>
<td>(Ln)JACR</td>
<td>-0.055 0.031</td>
<td>0.191</td>
<td>0.319</td>
<td>0.358</td>
<td>0.694</td>
<td>0.350</td>
</tr>
<tr>
<td>(Ln)JFIPB</td>
<td>-0.171 0.540</td>
<td>0.669</td>
<td>0.608</td>
<td>0.802</td>
<td>1.139</td>
<td>0.480</td>
</tr>
</tbody>
</table>

Next, to evaluate the reliability of the coefficients estimated, I plot the spatial distribution of the local r square values obtained from the GWR model in Figure 5.4. It shows the goodness-of-fit of the local models is good with the r square value varying between 0.88 and 0.99. In comparison to the global model that explains 83% of the variance, the GWR model presents an improved goodness-of-fit. The map further shows that the GWR model explains the local relationships well in a large group of the SLAs in the Brisbane city and western part of the region. The local estimates at the North ROC and the South ROC are good but it appears slightly less good in some SLAs, because they are further away from
the Brisbane city. Overall, the goodness-of-fit of the model is improved by incorporating the spatially-varied parameters.

We calculate the Moran’s $I$ statistic (Moran, 1950) for the residuals from the GWR model and the OLS model for the 1996 retail jobs. The residuals from the OLS model show a moderate degree of spatial autocorrelation ($I = 0.271$). In contrast, an $I$ value of -0.013 demonstrates that the residuals of the GWR do not exhibit strong spatial autocorrelation (see Figure 5.5). Therefore, the GWR model allowing the spatial non-stationary processes largely solved the problem of the spatially auto-correlated error terms remaining in the OLS model. As such, the spatially-varied parameters are valid to be used in the spatial disaggregation process.

![Figure 5.4: Distribution of R squares for GWR models](image)
Finally, the results of the analysis of variance (ANOVA) in which the OLS model is compared with the GWR model are given in Table 5.4. The ANOVA tests the null hypothesis that the GWR model represents no improvement over a global model (Fotheringham et al., 2002). The results are shown that both the $r^2$ square, $AIC$ statistics and the $F$ test suggest that the GWR model made a significant improvement over the OLS model for the retail jobs data for 1996.
Table 5.4: Results for AVONA for the OLS and the GWR models

<table>
<thead>
<tr>
<th>Summary of statistics</th>
<th>OLS</th>
<th>GWR</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of observations</td>
<td>289</td>
<td>289</td>
</tr>
<tr>
<td>No. of independent variables</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>No. of nearest neighbours (bandwidth)</td>
<td>n.a.</td>
<td>42</td>
</tr>
<tr>
<td>Akaike Information Criterion (AIC)</td>
<td>581.471</td>
<td>487.023</td>
</tr>
<tr>
<td>Adjusted $r^2$</td>
<td>0.833</td>
<td>0.910</td>
</tr>
<tr>
<td>$F$ statistics of GWR improvement over OLS</td>
<td>n.a.</td>
<td>5.979</td>
</tr>
<tr>
<td>Spatial autocorrelation (Moran’I)</td>
<td>0.271</td>
<td>-0.013</td>
</tr>
</tbody>
</table>

5.6.2 Evaluation of spatial disaggregation accuracy

Outputs from the employment disaggregation show a geographically-dispersed pattern of changes in the retail jobs in the SEQ region. The output maps are given for the spatially disaggregated jobs in the retail trade sector (see Figure 5.6).
To justify the accuracy of the spatial disaggregation, the percentage error of the spatial disaggregation result across the SLAs is evaluated. This is achieved by using the actual values from an independent data source for employment. The real values of the 2001 employment in the SLAs are derived from the 2001 JTW data. Then we evaluate the overall accuracy of the spatial disaggregation technique for a single time-period by measuring the root mean square error (RMSE). To demonstrate the improved estimation accuracy by accounting for the spatial non-stationary effects, we compare the errors between the GWR and an OLS approach.
Firstly, to evaluate the relative error of the spatial disaggregation, we calculate the percent error for each SLA using the following equation:

\[ E_i^p = \frac{(Y_i - \hat{Y}_i)}{Y_i} \]  

(5.9)

where \( E_i^p \) is the percent error for location \( i \); \( \hat{Y}_i \) is the estimated result; \( Y_i \) is the true value of employment count. The use of the percent error means that only the significant error at each SLA would have serious consequences.

Figures 5.7 and 5.8 show the percentage of errors in the spatial disaggregation results using the GWR and the OLS approach respectively for the 2001 retail jobs. The GWR technique clearly produced lower errors than the OLS model across SEQ. The statistical summary of percentage errors is illustrated in Table 5.5. It is noted that the GWR predictions at certain SLAs (e.g. for two SLAs in the northern area) are less accurate than that for the OLS. The possible reason for this is the outlying observations included in the GWR model. Since the data used to calibrate the GWR is in a local window (kernel), the outliers in the window can significantly distort the local parameter estimates. Comparably, the effect of outliers is less significant in a global context. To overcome this problem, an approach called 'robust GWR' (Fotheringham et al, 2002) can be employed to improve the model calibration. The approach works by imposing a weighting function (between 0 and 1) to the observations, and therefore observations having large residuals (large outliers) can be down-weighted or removed from the dataset. In this study, considering the effect of outliers is relatively a minor issue, a robust GWR is not applied to the spatial disaggregation.
Figure 5.7: Percentage of errors for the GWR method
Figure 5.8: Percentage of errors for global regression method

Table 5.5: Summary table for the percentage of error and ERMS for the GWR and OLS model (retail trade job forecast for 2001)

<table>
<thead>
<tr>
<th>Percentage of error</th>
<th>OLS</th>
<th>GWR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>10.223</td>
<td>4.590</td>
</tr>
<tr>
<td>Sum</td>
<td>175.262</td>
<td>120.731</td>
</tr>
<tr>
<td>Mean</td>
<td>0.593</td>
<td>0.459</td>
</tr>
<tr>
<td>Median</td>
<td>0.455</td>
<td>0.310</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.987</td>
<td>0.491</td>
</tr>
<tr>
<td>Count in error class 1 (0–19%)</td>
<td>69</td>
<td>94</td>
</tr>
<tr>
<td>Count in error class 2 (20%–44%)</td>
<td>96</td>
<td>102</td>
</tr>
<tr>
<td>Count in error class 3 (45%–84%)</td>
<td>78</td>
<td>63</td>
</tr>
<tr>
<td>Count in error class 4 (85%–249%)</td>
<td>37</td>
<td>27</td>
</tr>
<tr>
<td>Count in error class 5 (250%–max)</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.798</td>
<td>0.411</td>
</tr>
</tbody>
</table>
Secondly, we assess the overall error of the two techniques by measuring the root mean square errors of the disaggregated results (see Equation 5.10). RMSE is a rigorous measure of overall error that is more sensitive to the outliers in the error distribution. Based on the Equation 10, the RMSE of the GWR technique is almost two times smaller than the one produced by an OLS model (0.411 vs. 0.798).

\[ RMSE = \left[ \frac{1}{n} \sum_{i} \left( \frac{Y_i - \hat{Y}_i}{Y_i} \right)^2 \right]^{1/2} \]  

(5.10)

Overall, our results show that the GWR technique, through the incorporation of the spatial effects presents an improved accuracy for estimating the spatial variability of the employment over the technique using an OLS approach. However, it is still noted that the GWR produced some high percent errors in some SLAs. One possible reason for this is the SLAs have a relatively small number of base jobs that produce a significant percentage of error when the underestimation or the overestimation is larger than the base employment (base employment less than 10). Another possibility is that because we evaluated the result using the actual value for 2001, some larger error would be related to the unusual changes in the employment between 1996 and 2001 (very dramatic employment increases or losses) in certain areas owing to some local issues. These types of changes are not explained by the theory of the spatial effects captured in our model. Based on the current approach, some improvements can be made. First, it requires an additional forecast for the determinant variables, such as new shopping centres and industrial land use change, to model the dynamic change of the employment. Second, to uniformly adjust the employment process for each factor within each ROC is a restrictive assumption. An additional method should be applied to further derive the variability in the growth rate across the SLAs within the ROC. Third, the job density threshold needs to be defined for the SLAs, based on the planning scheme.

5.7 Results of employment disaggregation

A regional plan for the SEQ region introduced a balanced growth strategy to promote compact growth and polycentric development (OUUM, 2006). To achieve such objectives, employment consolidation policies are imposed in the regional plan. These include, (i) new employment opportunities at the major new urban development areas and, (ii) encourage
employment growth in the existing regional activity centres and the locations of the economic activity (OUM, 2006).

The spatially disaggregated population forecasts are used for analysing the pattern of the retail employment as a result of the population growth. I consider the global Moran’s I statistics for the spatial autocorrelation can be less effective in measuring the patterns of the employment growth, because the employment distribution is more centralised than the population. Instead of using global Moran’s I statistics, I focus on measuring the local spatial clustering and spatial concentration of the retail jobs to uncover their underlying patterns.

Figure 5.9 shows the spatial distributions of the spatial autocorrelation (local clustering) of the retail jobs and their significant maps of univariate local Moran’s I. The spatial autocorrelation of the retail employment for SEQ does not spread out but is highly concentrated in the major activity centres. Some coastal SLAs in the Sunshine Coast and the Gold Coast are characterised by a positive HH clustering and this effect will remain stable throughout the forecast years. The retail jobs do not show significant spatial associations beyond the existing employment centres referred to in the local Moran’s I, except for a new HH clustering that occurs at the inner western areas.

Figure 5.9 reflects a new HH growth effect that will take place in the inner west suburb (North Beaudesert) in the year 2011, with the growth effect moving into Ipswich City by the year 2016. In the following forecast years, such a locally clustered increase in the retail employment will go steady and expand to the adjacent SLA in the south. This growing HH clustering indicates that a potential urban expansion is likely to occur in the inner west and southern suburbs. Based on a distinguishable pattern from those, the development is more evenly distributed across the region; a new employment centre is emerging at the inner western suburbs. The new areas of the HH employment clustering are mainly located in the inner western suburbs and can be the result of economic restructuring, because the land uses for industry or agriculture purposes will be replaced by the growing service sectors. Moreover, new migrants tend to move into less expensive areas. This can be influential on a faster retail jobs growth in the western suburbs.
Another question that can be explained by the spatially disaggregated employment forecasts is the changing spatial structure and the location of the new employment centres. I resolve this issue by mapping the spatial concentrations of the employment over time. Spatial concentration distinguishes the urban areas in which most employment are located in the relatively few places at the relatively high densities from those in which the development is more evenly distributed across the region (Galster et al, 2001). To detect the potential employment centres where the retail jobs are highly concentrated, I define the high density value (in the SLAs) as more than twice the standard deviation of the density values for the disaggregated dataset. Thus, the predicted high degree spatial concentration of the retail employment over the forecast years is highlighted. The high densities values in the SLAs were interpolated to 500 X 500 square meters grids across the

**Figure 5.9:** Distribution of spatial clustering of retail trade jobs for each forecast year from 2006 to 2026
region (using Kernel interpolation)— see Figure 5.10. The purpose is to better visualise the location of the emerging retail employment centres.

Figure 5.10: A 3-D visualisation of density of retail trade employment greater than two times of standard deviation from 2006 to 2026

Figure 5.10 illustrates that by measuring the spatial concentration, the retail employment is highly concentrated in the Brisbane City in the base year (2006) and characterised a
mono-centric pattern. From 2011, a new employment centre is emerging through the western corridor. The increase in job concentration stretching to the west tends to be higher than the existing employment centre through the forecast years. Some commercial suburbs (Surfer’s Paradise and Southport) in the Gold Coast were the key employment areas. Their pattern was reported as more sprawl-like and evenly distributed owing to the larger size of these suburbs. After 2021, there appears to be an additional densely-developed and concentrated employment centre. Overall, Figure 5.10 indicates a changing growth pattern of the retail employment by time series, that is, a clear tendency for a transition from the mono-centric pattern to a more balanced polycentric development. This is in line with the South East Queensland Regional Plan that the urban growth is expected to shift towards a balanced and self-contained development.

In summary, these findings confirm that the extent of the suburbanisation of the retail employment remains limited in SEQ and the retail employment at the city centres remains as more dense and centralised patterns. The significant spatial clustering of employment in the western suburbs will have a crucial impact on the urban spatial structure. Thus, the SEQ employment growth reflects a different spatial scenario from the population growth that tends to be more spread out.

5.8 Conclusions

In this chapter, we presented a new method for spatially-disaggregating the regional employment forecast into smaller spatial areas. Rather than being a simple device to spatially subdivide the forecasts, our method consolidates the existing empirical and theoretical knowledge of how the spatial structure of employment is formed. One major issue that is resolved in this chapter is the spatial effects and their impact upon the disaggregation result. We argue that a high degree of spatial variability is caused by spatial heterogeneity, spatial dependence. To remedy this situation, we applied a GWR method to account for such spatial effects using a case study of the retail employment. The method uses the locally-regressed relationships to estimate employment numbers in the smaller geography whilst being constrained by the regional forecast. It utilized the characteristics of small areas to model the process of employment over time. To my knowledge, this has not been done in previous research. The results demonstrated that the application of the GWR approach provided superior results when compared to a global regression model.
The outputs of the method are spatially disaggregated regional employment forecasts across the local metropolitan areas and now at a scale that is of greater use to the urban planner. The disaggregation outputs indicate that, driven by the increased population suburbanisation, the growth pattern for the service employment will expand its centralised development that forms the region towards a more polycentric structure. New retail and service centres are emerging in the southern and western parts of the region (for instance, the Ipswich area) to accommodate the growing demand from the population in the surrounding suburbs.

A number of limitations in the current approach that have been previously noted are concerned with the dynamic changes of the employment processes over time. Further work is now required to consolidate the findings of this work and resolve the areas of current limitation. This will involve the acquisition of additional forecasts for the determinant variables (for example, the locations of the planned shopping centres) to unconditionally drive the employment disaggregation. In addition, the growth capacity in the local metropolitan areas can be imposed to control the employment allocation over time. However, the inclusion of these future research foci will depend upon the availability of the data.

Despite these limitations the spatial disaggregation process presented here marks the first stage in the development of a robust, transparent methodology that can be applied to other industry sectors and study areas.
Chapter 6 — Conclusions and future work

This is the concluding chapter that specifically details the contribution to knowledge. It revisits the main findings and techniques used throughout the preceding chapters, describing how the approach and the results are significant and innovative. The chapter concludes with a discussion on how the research might progress and provides some suggestions for future work.

6.1 Introduction

The spatial distribution of future population and locations of the economic activity has become a focus of recent academic inquiry and planning policy concerns. Spatial forecasts of the population and the employment are critical for urban growth planning and management. At a national level most population and economic forecasts produced by government and research institutes are typically reported for the large geographical regions. However, there is a further need to break these forecasts down to a disaggregated geographic scale for growth management within regions. The aggregate spatial forecast cannot provide the detailed information on the spatial distribution of the population and economic activities. In dealing with this problem, this thesis demonstrated that spatial disaggregation techniques can be used to facilitate the forecast for urban planning purposes from the large regions to the smaller spatial units. The spatially disaggregated forecasts at a finer geography can provide useful information to investigate the future distribution of the population and economic activities and their potential impact on the urban form.

The focus of this thesis has been on developing and the validation of the methods used for spatially disaggregating the regional forecasts for the SEQ region. There are two primary objectives that guide the components of the thesis, the large regional population forecast and the employment forecast are spatially disaggregated for the smaller areas. Based on the spatial structure of SEQ, both the population and economic activities are highly heterogeneous. This implies that the regional growth is not evenly spread, but is concentrated or dispersed at certain locations within a forecast region. Because of the different urban functionalities and location orientations, the population and employment exhibit diverse patterns of heterogeneity in their geographical setting, thus raising different spatial effects (for instance, spatial dependence and spatial heterogeneity). This
requires that the spatial disaggregation techniques have the high ability to accommodate the spatial structure of the data and the inherent spatial effects associated to the scale of the spatial disaggregation (discussed in Chapter 2).

The two spatial disaggregation techniques presented in Chapter 4 and Chapter 5 have used advanced GIS and spatial analysis to resolve the problem in response to the gap observed throughout the current literature in spatial disaggregation (reviewed in Chapter 3). The population disaggregation is related to MAUP problem in spatial analysis, where spatial data disaggregation may give inaccurate results due to spatial heterogeneity in the explanatory variables (population density). In Chapter 4, several statistical regression and multiple class dasymetric techniques were developed and evaluated with a focus on how to determine an appropriate land classes to better explain the spatial heterogeneity of population data. In Chapter 5, a GWR approach was proposed and tested which specifically addresses issues of spatial autocorrelation and heterogeneity of variables (employment determinant) for spatial data disaggregation. Finally, each chapter explores how useful recognised spatially disaggregated forecasts are in providing information for better understanding questions on urban form. Both methods presented and results achieved are new and innovative to the existing body of literature.

The following sections provide a discussion of the findings. The theoretical and practical implications of this research are then presented followed by discussion on future research directions.

6.2 Spatially disaggregate population forecasts

Research objective 1: Use a method to spatially disaggregate the regional population forecasts from the large regions to the smaller areas to better account for the spatial heterogeneity (Chapter 4).

What challenges the population disaggregation is the high degree of spatial heterogeneity in the population density. This has an impact on the spatial disaggregation methods that were developed, based upon the density assumptions (Goodchild et al., 1993). The existing methods for the population spatial disaggregation have tended to account for the spatial structure using the homogeneity assumptions for aggregate areas (land class with uniform density) (Goodchild, 1993). Inevitably, if a complex geographic region violates the assumptions made by a method, the method will generate error in the spatial data.
disaggregation. To spatially disaggregate the SEQ population forecast, a range of
dasymetric methods were developed for their superiority in spatially disaggregating the
spatially heterogeneous data (reviewed in section 3.4 of Chapter 3). Based on the spatial
structure of SEQ, the high degree of spatial heterogeneity in the SEQ population might not
be sufficiently represented by a simple two or three density classes that have been widely
used in previous literature. In response to this, we extend the methodology research by
incorporating a greater number of density classes in the dasymetric methods, which
provides a wider range of density configurations to resolve the spatial heterogeneity.

The multiple class dasymetric methods were tested against the census-based population
data. The findings in Section 4.2 of Chapter 4 demonstrate that a traditional 3-class
dasymetric method could be further refined by incorporating more detailed land classes.
The results indicated that the technique allowing a greater heterogeneity in the
assumption tends to be more appropriate for accommodating the spatial heterogeneity of
a large geographic area. However, the results further illustrated that an excessive density
subdivision is not suggested for data disaggregation owing to the limited capacity for
improvement and the appropriate number of land class can be reflected (derived
quantitatively) by the complexity of the study area. These findings are more conclusive
than the previous research to determine the accuracy of the spatial disaggregation
method (see Langford, 2006). The reasons for this appear to be, (i) a wider range of land
classifications for the dasymetric methods are tested and their possible accuracy are
evaluated and, (ii) a larger and more complex study area is studied where the spatial
disaggregation methods can be rigorously tested. The spatially disaggregated population
forecasts from Chapter 4 are not only rich for SEQ planning but also valuable for estimating
the patterns in the employment growth across the region.

Chapter 4 is the first study to comprehensively assess the relationship between the
increased numbers of land classes and the relative error of the spatial disaggregation. It
therefore offers a way to effectively determine the density configuration with the optimal
number of classes that best fit the spatial structure of the study area. The dasymetric
method incorporating an appropriate number of land classes has produced an accurate
disaggregation result with a relatively low operational cost. The finding achieved is most
significant and it can be extrapolated to other study areas where a spatial disaggregation is
needed.
The comparative investigation made in Chapter 4 also offers a chance to evaluate possible future advancements of the techniques that may allow an increased number of density classes and the expected accuracy associated with that increased complexity. The finding is new and significant for the current body of literature. Extending from here, it can further enable the development of a predictive equation or an optimisation method for future use to detect the spatial variability (complexity) of the dataset when a spatial disaggregation technique is determined.

6.3 Spatially disaggregate employment forecasts

Research objective 2: To enhance the methodology for spatial disaggregation of the regional economic forecasts to better account for spatial dependence and spatial heterogeneity (Chapter 5).

The method described in Chapter 5 represented an approach to spatially disaggregate the economic forecasts from the large regions to smaller administrative units using the results previously attained in Chapter 4.

An important issue solved in the employment disaggregation is that the distribution of the employment is more complex than the population that is closely associated with residential land classes (with locally uniform density). In comparison to the population data, the employment information is often interpreted at the regional level because the distribution of the employment is more diffuse and discontinuous at the smaller levels of the geography. The pattern of employment can be caused through strong spatial dependence and spatial heterogeneity. These spatial effects are manifest in situations where the regional patterns of employment and the local economic agglomerations can be clearly observable in the scale of the metropolitan level where the variable is measured (discussed in Chapter 2).

The selection of the appropriate techniques was largely controlled by the theoretical soundness and the availability of data. A GWR approach was proposed to overcome a number of shortcomings identified from previous approaches in dealing with the spatial effects (discussed in Chapters 3 and 5). Using a case study of the retail jobs, the GWR was applied to a spatial disaggregation procedure to estimate the local dependence between employment and a range of location variables (for example, the population, existing retail centres and the agglomeration economies) across the study regional. The results are a set
of spatially heterogeneous relationships (local dependence) between retail jobs and explanatory variables.

A novel predictive procedure was then applied using the locally-regressed relationships to the geo-temporal forecasting of the retail jobs for the target areas. The concept of this technique made the assumption that the retail employment would present a correlative distribution with other urban variables (population) identified within the aggregate source region. Such a correlative pattern at the different locations holds non-similar characteristics and therefore would form the basis of the reliable predictive models. To satisfy the requirement of the spatial disaggregation, the intensity of the local relationships was imposed to alter for every forecast year to meet the expected regional demands for retail job forecasts. The regionally-constrained relationships are then used to predict the new disaggregated number of employments for the target areas.

Prior to this study, the GWR was applied in the field of urban and economic geography to explore the variations in the spatial relationship, and thus allow the researcher to investigate the heterogeneities in the spatial processes and economic behaviour (see Yu, 2004; Huang and Leung, 2002). In Chapter 5, the GWR was used for the first time in the field of spatial disaggregation to predict the disaggregated employment data. The motivation for using the GWR to disaggregate the employment data is that it is designed to account for spatial autocorrelation and spatial heterogeneity. To test the hypothesis of the spatial effects that impact on the spatial disaggregation, a standard global regression model is additionally computed for comparative purposes. The result (in section 5.2. of Chapter 5) demonstrated that the GWR approach provides a reliable diagnostic to estimate the spatial effects that lead to a superior disaggregation result. The outputs of the method are spatially-disaggregated regional employment forecasts across the local metropolitan areas, now at a scale that is of greater use to the urban planner.

Both Chapters 4 and 5 validate the spatial disaggregation techniques using the available independent dataset (the Census data and JTW data), the relative error for each technique proposed was quantitatively evaluated. It further translates the meaning of the spatial disaggregation outcome in an understandable form for urban analysis. The use of exploratory spatial analysis to evaluate their implications for the urban form may also be suggested to the current literature to justify a methodology.
6.4 Contribution to knowledge

The research presented in this thesis is significant, not only through achieving the objectives of the research, but also for broadly encompassing the discipline of urban prediction, spatial analysis and spatial disaggregation. It has made the following contributions to these fields:

1. Predicting urban growth

This research demonstrates a new way to predict future growth patterns for a region by taking the regional forecasts and applying the spatial disaggregation techniques. The methodology uses the existing regional forecasts and applies a novel spatially-based technique to step-down the large regional forecasts to smaller geographical units to enhance planning. The outputs of the methods demonstrate diverse growth patterns in the SEQ population and employment, showing a strong alignment with the current urban geography literature.

2 Spatial data disaggregation

The contribution of this research to the field of spatial data disaggregation was achieved through taking the existing spatial disaggregation techniques and converting these into more appropriate techniques that produce more meaningful results for planning purposes. A significant methodological advancement has been made by extending the dasymetric method from its current simple form to techniques that incorporate more complex density classes to disaggregate the spatial data. Selecting an optimal-class dasymetric method based on balancing the cost and error of the disaggregation is also significant for the current literature. In addition, the implementation of the spatial disaggregation techniques to the regional forecasts over time and the validation in an urban growth context also shows a dedicated work for both theoretical formulation and the methodology operation.

3 Spatial analysis

This thesis provides a new opportunity and challenge in the application of spatial analysis in economic geography. The use of GWR to estimate spatially-disaggregated data and its use in the context of the regional employment forecasts is a novel application. Using a
cutting-edge spatial analysis method and the spatial data disaggregation also makes this study an innovative research.

6.5 Implications for practice

In addition to the contribution to the theory and methodology, an important outcome of this thesis is the implications for policy and practice. The spatially-disaggregated population and employment forecasts clearly map the future spatial distributions for the population and economic activities (for example, retail employment) over time. Such resulting information is very useful for SEQ planning and valuable for other organisations and the public and private sectors.

Queensland Government Agencies

Through achieving its aim, this thesis has presented not only the implications for theory, but also for the new outcomes for SEQ growth. The increasing urban expansion shaped by demographic change together with the economic growth and restructuring would have a large impact on urban metropolitan planning. The outputs from the methods tentatively indicate that the SEQ population tends to keep a dispersed development over time and the higher growth area tends to move into the southern and western part of the region. Driven by the increased population suburbanisation, the growth pattern for service employment shows an expanding centralised development that forms the region towards a more polycentric structure. New retail and service centres are emerging in the southern and western parts of the region.

Therefore, the Queensland Government can use these results to pro-actively manage the impact of regional population and employment growth on urban areas by providing geo-targeted and timely policy interventions. To better achieve the target specified in the SEQ strategic plan, geo-targeted policies can be developed that are relevant for the locations and distances between the population and the various types of economic activities. This includes producing urban services, the allocation of employment opportunities to the new suburban centres, designing transport corridors and a mixed and intensified urban development that are considered the essential aspects of future urban development.
Public sector

The geographically-detailed population and employment forecasts provide valuable information for the public sector to estimate the future locations of human activities and evaluate the spatial demand for infrastructure, public services and transportation. Thus, this could potentially enhance the deployment of finite public resources to enhance efficiency and reduce costs. For example, the transport organisations can use the forecast of the locations for the population and employment to estimate the directions and commuting flow and the level of demand for the transportation services. Emergency services can use the results of this study to assess and improve their service provision (for instance, improve the coverage of the service to the local areas). Other public sectors may include electricity, water, education, health and the police.

Private sector

The private sectors can use the results for marketing purposes. The policy making of many businesses and industries relies on the local socio-economic conditions. For example, to estimate the locations of a potential market, the cost of services and transportation, as well as the level of competition. The geographically detailed information on the population and economic activities is very useful for business decision-making.

Researchers

Both the output data and the techniques justified in this research can be used by other researchers to investigate various geographical phenomenon (such as, environmental change, pollution or health care) that are relevant to the population and economic activity distribution.

6.6 Limitations

Spatial data disaggregation is a complex problem. This research has placed emphasis on the spatial effects of the regional population and employment as a fundamental issue for spatial disaggregation. While the methods presented are applicable solutions to overcome spatial issues to a certain extent, they are still imperfect to fully interpret the mechanism of transferring spatial data from a large spatial scale to a smaller spatial scale. Individual chapters have addressed the limitations to the methods presented and the results obtained.
This section will briefly discuss two key areas that remain critical challenges for the research of the spatial data disaggregation presented in this thesis.

1. Data

Throughout this thesis, data limitations have proved to be a limiting factor for conducting the research. The major difficulty with disaggregating the 'forecast' is the variables used in the spatial disaggregation model (for example, urban land classes). Some variables are related to the attributes that change over time in an urban forecasting context (population), while some variables are indicative of the absolute values (the level of infrastructure provision). Nevertheless, it is difficult to acquire the forecasts (or plans) of some variables for future years to predict the spatially-disaggregated population and employment. The absence of the forecasts of the determinant variables has resulted in some restrictive assumptions being used in the methods for this study.

For instance, the dasymetric method assumes a fixed land classification over time. This is considered restrictive when dealing with the disaggregating population forecast, because the urban areas will expand and go beyond the existing urban areas. Ideally, a land reclassification including the new urban areas is needed, especially for the longer forecasted years. Similarly, the GWR disaggregation model should account for the dynamic of the other variables (new shopping centres or land use change) that might redistribute the employment levels in the local areas. This work needs to be carried out in the future for the data to be available to resolve those issues.

On the other hand, we consider the accuracy of the disaggregation result for this research is limited by the data for the source regions. The major problem is the source data is only available for large regions such as the SDs which restricts the detection of the fine-grained spatial heterogeneity in the spatial disaggregation. Rather than capture the spatial heterogeneity at the source zone level, we attempted to refine the high level spatial heterogeneity at the target zone level (SLAs) using historical data. However, the use of historical data for the target zones inevitably led to a proportioning effect of the data disaggregation, which is not desired for this research.
2. The scale of spatial disaggregation

I chose the SLA as the target spatial unit because it provides a good balance between a finer geography and a meaningful interpretation of the population-employment relations. Using the SLAs as the target unit is not only useful for the local government planning but also beneficial in a more reliable disaggregation result. It is considered that if data are spatially disaggregated to fairly large target units, the results tend to be more accurate (Lam, 1983). A limitation of using the SLA is that the shapes and sizes of the SLA that vary significantly across the study area. Thus, the spatial disaggregation result can be influenced by the size and shape of these SLAs. For example, some large SLAs (Ipswich and Beaudesert) presented a significant growth in the disaggregation result but the spatial heterogeneity within those big target spatial units is still missing. Therefore, the SLAs are not considered to be the best spatial resolution for representing the patterns of the socio-economic distribution. A finer spatial unit can be chosen to further represent the geographic phenomenon for the urban form analysis. A further disaggregation of the disaggregated data to 500 square meters in Chapter 5 is a good example.

6.7 Future research

A number of limitations in the current approach that have been previously noted are concerned with the dynamic changes of the employment processes over time. Further work is now needed to consolidate the findings of this work and resolve the current methodological limitations in the urban analysis. Future research is recommended in the following key areas:

- testing GWR spatial disaggregation technique with a wider range of techniques
- spatial time series analysis
- capacity constrained disaggregation
- development of generalized GIS based tools
- The Monte Carlo simulation.
6.7.1 Testing GWR spatial disaggregation technique with a wider range of techniques

Chapter 5 has examined the comparative accuracy between a new GWR method and an OLS model in the context of spatial disaggregation of employment forecasts for SEQ. The degree to which the GWR technique was found to be more accurate is attributed to the fact that the technique is superior to address the spatial autocorrelation and spatial heterogeneity in spatial data. However, the accuracy of GWR technique has not been compared with a full range of alternative techniques discussed in Section 5.3.1. Even though the limitations (e.g. the theoretical assumptions; the cost of implementation) of the alternative techniques have been discussed, it is worthwhile to fully justify their performance by including these techniques in the comparative study. For example, as reviewed in Chapter 3 and Chapter 6, both spatial autoregressive models and spatial multilevel models provide different solutions for spatial autocorrelation and spatial heterogeneity (Páez and Scott, 2004). Given the effectiveness of the GWR method, it would be interesting to test its relative accuracy against those spatial techniques using the SEQ data. The purpose is to further justify whether the proposed GWR technique is better used to disaggregate spatial data, as compared with other methods built on similar assumptions of spatial autocorrelation and spatial heterogeneity. Such enhanced comparative investigation would be a good direction of the research in the future.

6.7.2 Spatial time series analysis

The method for the employment forecasts disaggregation is based on a GWR model. It relates the retail employment to a number of independent variables to explain the change in the employment in response to the changes in the determinant variables (for instance, the population). Additionally, a time series model can be developed that attempts to predict the values of employment from the past employment values. A method that synthesises the effect of the explanatory variables and the historical trend of the retail employment can offer, potentially, an improved prediction. However, the validity of the time series model needs to be seriously analysed. If the equation that contains the lagged dependent variable as the independent variable has a serially correlated error term, then the estimates of the coefficients of the model will be biased.
The GWR model has been superior in modelling the spatially-varied employment processes. However, most time series of the employment process for the local areas always exhibit a distinct increasing or decreasing pattern for a short time period. Ignoring the local trend of the processes would inevitably lead to an increasing underestimation or overestimation of the employment in the forecast years. Thus, an alternative to modifying the employment disaggregation is to incorporate the dynamic coefficients into the GWR model to describe a growth-induced change at the target areas. Through the analysis of the historical data by time series, the local trends of the employment processes can be detected and then extrapolated to the forecast. For example, the historical data might show that the job-population ratio at a SLA is increasing (or decreasing) and this local trend is likely to continue through a forecast horizon. Thus, accounting for the local trend in the disaggregation model might possibly introduce a better heterogeneity estimate over time. However, the potential risk of using the dynamic employment processes is that it would introduce a strong job redistribution. The reliability of the result should be evaluated.

6.7.3 Capacity constrained spatial disaggregation

Disaggregation models predict the employment at the target areas through analysing the data patterns on the basis of past trends and the regional constraints. However, the current disaggregation outcome typically represents an expected growth that would occur at the target areas. Ideally, the result can be further refined by incorporating the employment growth capacities into the existing disaggregation process. The concept is that a threshold value (for example, a maximum job density) can be predetermined at each target area to control the employment allocation over time. When the number of disaggregated jobs for a target area reaches the value of the capacity, that area will stop receiving new jobs and the allocation will go into the surrounding areas using an optimisation procedure. Urban employment capacities must be obtained by compiling the planning schemes for the local government areas in the study region.

6.7.4 Development of generalised GIS-based tools

The spatial disaggregation techniques are complex to apply. Often, the operation of those methods requires intensive geo-processing and complex mathematical algorithms. The implementation of the complex spatial disaggregation technique is very time consuming and, perhaps, requires computer expertise for the geographers and the regional scientists.
Some methods have been developed as standard tools in a GIS (for instance, the kernel interpolation in the ArcGIS), but it appears that no GIS products currently provide generic and transparent asymmetric tools are available for all users. The ability to computerise the spatial disaggregation techniques would have effects on both reducing the cost implementation and increasing the efficiency. This presents an opportunity to conduct a more extensive methodological study, especially when the entire disaggregation process is required to be iteratively and routinely implemented.

To implement the multi-class asymmetric approach, I have developed a customised GIS tool using the Visual Basic for Application (VBA) embedded in the ArcGIS environment. The customised tool can conduct the entire process from the geo-processing of data input, analysis to the presentation of the results. The program is currently only accessible to the author for private use for this research. It has not been developed as a generic GIS tool that is distributable for public consumption. Converting the methods into a generic GIS tool that is accessible to a wider range of users and application will be a dedicated way forward for this research.

6.7.5 Error detection using Monte Carlo simulation

This research is based on a single case study using a large and more complex study area (namely, the SEQ region). I have made a single comparison of the spatial disaggregation results for the target units with the actual values that were known from independent data sources. To fully justify the reliability of the methods, this method needs further positivist research to generalise the findings. Ideally, a Monte Carlo simulation approach could be employed to randomly simulate the different sets of target zones to generate multiple RMSEs based on various geographical situations.

It is possible to formulate the SEQ spatial disaggregation problem as a Monte Carlo simulation for an extensive error analysis. Specifically, I can simply take the CCDs as elemental zones, and randomly aggregate the CCDs into \( m \) sets of target units. The total number of target units in each set is more than the total number of source units (289 SLAs) used to test the methods. The number of sets of simulated target units \( m \) should be large to ensure a precise statement of the error. Then each set of target units can be used for a spatial disaggregation method and return a single value of outcome (use RMSE). By changing the target zones and repeating the spatial disaggregation, it is possible to obtain
a large set of errors for each spatial disaggregation method from which the characteristics of the error can be detected. Based on the principle of the Monte Carlo stimulation, the relative performance of the spatial disaggregation method can be determined from these repeated realisations.

The Monte Carlo simulation suggested above can be effective for evaluating the sensitivity of the spatial disaggregation to the MAUP problem. However, the method is still tested against a single study area with a fixed geographical variation. This is considered to be insufficient to justify the method. The effectiveness of a spatial disaggregation method is not only reflected by its robustness in the MAUP problem, but also its sensitivity to various levels of heterogeneity in the datasets (that is, the distributions of the spatial object). This idea follows what Fisher and Langford (1995) recognised in that the Monte Carlo simulation can be limited by the simple spatial structure of the study area. Thus, a more conclusive result could be fully validated by broadening the Monte Carlo test against a wide range of study areas with different density variations. This can be very useful for testing how generic are our findings in Chapter 4 over a wider range of geographical areas with different patterns of spatial variability.

If the Monte Carlo simulation returns a consistent pattern of relationships between the disaggregation error and the number of the density classes (for example, Figure 4.6 presented in Chapter 4). We can develop a model or optimisation algorithm based on the generalised relationship. The model can be applied to a wider range of study areas to detect the spatial variability and structure for the dataset, and determine an efficient spatial disaggregation technique (for instance, using asymptotic analysis) for that study area. The consequent contribution will improve the efficiency and reduce the unnecessary cost of spatial disaggregation.

6.8 Concluding remarks

Predicting an urban growth pattern using spatial analysis will increase in importance. As spatial disaggregation techniques become more established, they will enhance the large regional forecasts that seek to derive a deeper understanding of the urban spatial structure under conditions of growth.

The development, application and validation of the spatial disaggregation techniques will supplement the planners’ toolbox. When the techniques presented in this thesis are well-
developed into deployable solutions, their added value to the urban and growth forecasts can be fully evaluated. At this point, it would then be possible to better respond to the urban form questions to inform the future development of timely and geo-targeted urban policy; that could potentially enhance the deployment of the finite public resources enhancing the efficiency and reducing the costs.
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