GIS-BASED INTERACTION OF LOCATION ALLOCATION MODELS WITH AREAL INTERPOLATION TECHNIQUES

Thesis submitted for the degree of

Doctor of Philosophy

at the University of Leicester

by

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2014

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Abstract

This research aims to explore the interactions between a selection of four location allocation models, and a selection of three interpolation techniques in the environment of Geographic Information Systems (GIS), in order to support decisions made about optimal facility locations across three case study areas in the UK and the Kingdom of Saudi Arabia. The relationship between location-allocation models and areal interpolation techniques means that in some cases, for example in the absence or unavailability of census data for smaller areas units, a researcher may be forced to use one areal interpolation technique to estimate the census data to smaller areas units or to represent the distribution of demand. The results of interactions between location allocation models and interpolation techniques were used to explore how the spatial characteristics of a problem could potentially be more or less well suited to particular areal interpolation methods (and the demand surfaces they generate) based on their assumptions and were used to examine the impacts of using those surfaces with different location-allocation models. Each location-allocation model was applied across three demand surfaces created from different areal interpolation methods. In this way, the results of this study illustrate how the inherent assumptions associated with areal interpolation techniques influence the outputs of location-allocation models and their impacts on optimal facility locations. The study demonstrated that the spatial characteristics of the case study, in terms of population densities the size of the source zones and built up areas have also played an important role in creating differences between population estimation results for each of the target areas and the three demand surfaces for each case study. The differences in demand weights for each surface, which are based on the assumptions underpinning each method, were found to be the main factors driving variations in optimal facilities selection.

Acknowledgements

My great thanks to Allah, most Gracious and most Merciful, who gave me the ability and patience to complete this study.

My great thanks also to my supervisors, Dr Alexis Comber, Dr Nicholas Tate and Prof Chris Brunsdon for the scientific guidance, advice, support and the useful comments from the time I began this work up to the completion of this thesis. I would like to express my sincere gratitude to all the government ministries and institutions in the KSA and UK who provided the data that was necessary to this work, to ensure its scientific validity.

I am very grateful to Qassim University for my scholarship and helping me to achieve my dream of studying in the UK. My great appreciation and gratitude also goes to all my family, especially to my mother, father, wife and children for their support and prayers for my success.

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Chapter One: Introduction

1.1 Introduction

This study sought to explore the interaction between different location-allocation models and different interpolation techniques in order to support the optimal facility locations. Four location-allocation models were applied to three demand surfaces for each case study and across three case studies in the UK and the Kingdom of Saudi Arabia, derived from the use of a range of standard interpolation algorithms. The need to examine the relationship between location-allocation models and areal interpolation techniques is important because in some cases, for example in the absence or unavailability of census data for smaller areas units, the researcher may be forced to use one of the areal interpolation techniques in order to estimate the census data to smaller areas units or to represent the distribution of demand needs (see for example; Cromley et al., 2012 and Tomintz et al., 2013). The spatial characteristics of the problem in terms of the degree of homogeneousness and heterogeneous distribution of the population in the census area, census area size, land uses and the different assumptions for the areal interpolation techniques can produce different weights or values for the estimations of demand needs. This raises a number of questions: what is the impact of the demand surfaces that have resulted from the use of different areal interpolation techniques on the location-allocation models and the decision of optimal facility locations? In other words, what is the impact of the objective functions and the operations embedded for the location-allocation models on the interpolation surfaces?

By considering the interaction between the models and techniques, the results of this study were used to explore how the spatial characteristics of the problem could potentially be more or less suited to generate different demand surfaces based on the assumptions of the areal interpolation methods and using those surfaces with the location-allocation models. As yet, little research has considered the interaction of some of the location-allocation models with the spatial distribution of demand based on the results of areal interpolation techniques (see Cromley et al., 2012). However, based on the objective function and the operations embedded in each location-allocation model, and the assumptions of each interpolation method, this study aimed to provide scientific support to the decisions of optimal facility locations and fill a gap in the literature regarding the suitability of a selection of interpolation surfaces to fit the characteristics of the problem and the location-allocation models. The following sections briefly introduce the methods used in this study.

1.1.1 Location-Allocation Models

Location-allocation models are mathematical formulations (Cromley and McLafferty, 2002), which aim to identify the optimal geographical location for facilities based on the demand distribution. The literature review demonstrated that the location-allocation models could provide scientific support for issues pertaining to planning and facilities locations. This research has compared the interactions results of four commonly available location-allocation models, such as the Minimise Impedance (P-median problem); the Minimise Facilities model of the Location Set Covering Problem; the Maximise Coverage model of the Maximal Covering Location Problem; and the Maximise Attendance model. All of these have their own particular statistical and mathematical bases according to their objective functions (Cromley and McLafferty, 2002 and Church and Murray, 2009). These, in turn, resulted in different solutions being suggested by each of the models when applied to the same location-allocation problem. These models are considered to be among the most important methods in Geographic Information Systems (GIS) and the most advanced methods in network analysis, they depend on the availability of three data locations (the road network, facilities and demand). The four models have been used by many researchers to support the planning of facilities locations; see for example Hakimi (1964), Teitz and Bart (1968), ReVelle and Swain (1970), Toregas et al. (1971), Holmes et al. (1972), Rahman and Smith (1991), Schilling et al. (1993), Serra and Marianov (1999), Cromley and McLafferty, (2002); Dessouky et al. (2007), Sasaki et al. (2010; 2011), Comber et al. (2011), Algharib (2011) and Tomintz et al. (2013).

The p-median model was one of the first mathematical models developed to minimise the total weighted distance, which was aggregated across all the supply and demand locations (Hakimi, 1964 and Teitz and Bart, 1968). The operations of this model depend upon the interchange or substitution of the number of locations which are required to select the chosen and candidate locations capable of minimising the weighted distance or time between the supply and demand locations (Church and Sorensen, 1994). In health geography the p-median model is frequently applied to determine the location of emergency medical services and other health facilities because it is provides the optimal distribution for the facilities locations and minimises the distance between the user and the facility (see Hodgson, 1988; Comber et al., 2011 and Tomintz et al., 2013).

The Minimise Facilities (MF) model of the Location Set Covering Problem seeks to answer the question regarding how to minimise the distances and determine the minimum number of facilities which are needed to serve the demand within a certain distance or travel time (Toregas et al., 1971 and Schilling et al., 1993). The objective function of this problem differs from others which seek to fit a set number of facilities to a demand location optimally. Thus, it identifies the number of facilities which are needed to satisfy a particular distance or travel time constraint.

The Maximise Coverage (MC) model of the Maximal Covering Location Problem (MCLP) aims to maximise the coverage for the demand weights within a certain distance or travel time (Church and ReVelle, 1974; ReVelle and Hogan, 1989b; Spaulding and Cromley, 2007 and Murawski and Church, 2009). This model is considered appropriate when there are a smaller number of suppliers and there is a need to cover the maximal demand in an area (Messina et al., 2006 and Gu et al., 2010). Thus, the MC model is considered more appropriate than the MF model when resources are limited (Church and Murray, 2009).

The Maximise Attendance (MA) model seeks to maximise the attendance of the demand within the distances used or travel time. The demand weight for each demand point is partially allocated in areas close to the majority of the demand (Holmes et al., 1972 and Algharib, 2011). The main difference between the MA model and the previous models is the allocation of a ratio of the demand weight for each demand point whereby it does not allocate the complete weight of the demand point. The distance is a critical factor for the ratio of the total demand weight for each demand point in the MA model, which subsequently decreases if the distance is increased between the facility and the demand points.

The four location-allocation models have their own particular statistical and mathematical bases associated with the objectives and inherent operations for each model. Therefore, this study chose these four models because they were applied in a number of studies and because of the capabilities of these models to support the planning and facilities location optimisation for different kinds of facilities in terms of the public or private sector. Thus, the findings of the interaction between the four location-allocation models and different interpolation techniques in this study will provide scientific support for the decisions of optimal facility locations for a wide range of users of location-allocation models.

1.1.2 Areal Interpolation Techniques

Areal interpolation techniques involve the transformation of geographic data based on certain assumptions from the source zone to the target area (Kim and Yao, 2010). The literature review has addressed several techniques which have been proposed based on their differing assumptions to provide spatially-distributed estimates of the population and for demography (Tobler, 1979; Goodchild and Lam, 1980; Lam, 1983; Langford et al., 1991; Xie 1995; Fisher and Langford, 1995 and 1996; Memmis, 2003; Brindley et al., 2005 and Cromley et al., 2009; Kim and Yao, 2010; Qiu et al., 2012 and Tomintz et al., 2013). However, this study used three interpolation techniques; Areal Weighting (AW), Pycnophylactic (Pycno) and Dasymetric (Dasy) methods in order to estimate the population of the three case studies to the target area. The three methods used in this study represent different types of areal interpolation: the AW and Pycno methods interpolate without ancillary data but with differing degrees of sophistication in the way that they allocate demand, whilst the Dasy method includes ancillary data. Ancillary data are those which can provide information about the spatial distribution of the population within the source zones such as satellite images or road networks.

The AW method is the classic interpolation method which assumes that the population is evenly distributed across the source zone (Lam, 1983; Hawley, 2005; Hawley and Moellering, 2005; Brindley et al., 2005; Cromley et al., 2009 and Qiu et al., 2012). Thus, the assumptions of the AW method aim to provide homogeneous estimations for the population based on the geometric properties or the proportion of the overlapping areas between the source zones and the target areas (Fisher and Langford 1996 and Kim and Yao, 2010). The Pycno method assumes that the population is distributed in a heterogeneous form within the source zone and uses a density function in order to provide smooth estimations for neighbouring target areas with volume-preserving properties (Tobler, 1979; Lam, 1983; and Kim and Yao, 2010).

The use of ancillary data with areal interpolation techniques has been found to improve accuracy and commonly uses remote sensing data in order to reveal the spatial distribution of the population in the target area (Langford et al., 1991; Fisher and Langford, 1995 and 1996; Eicher and Brewer, 2001 and Langford, 2007), although Comber et al. (2008) used other external data. This method assumes that the population is only distributed to the populated areas within the source zone. This study used the binary Dasy method, which is the simplest method of Dasy mapping (Fisher and Langford, 1996). Thus the operations of the binary Dasy method depends on classifying the satellite image to populated and un-populated areas and subsequently estimating the population value for the source zones to the populated areas in the target areas.

The three interpolation methods used in this study have their own particular statistical and mathematical bases associated with the objectives and inherent assumptions for each method. Therefore, the differences in the inherent assumptions for the three methods are the key factors for producing different estimations results for the population weights in the targeted areas. This is important because the population estimation results for the three interpolation methods will be the demand needs in the interaction of different location-allocation models and different interpolation techniques for each case study.

1.2 The Aim and Objectives of the Research

This research examines the interactions between four location-allocation models and different surfaces resulting from the use of the three areal interpolation techniques. In so doing it seeks to fill the gaps in the literature by providing scientific support to scientific analyses, spatial planning and optimal facility locations. The research aim and objectives are described below.

The overall aim of this research is to explore the interactions of four location-allocation models (the Minimise Impedance p-median (MI) model, the Maximise Coverage (MC) model, the Minimise Facilities (MF) model and the Maximise Attendance (MA) model) when applied to the results of three areal interpolation techniques (AW, Pycno and Dasy surfaces), using a case study of quantifying the optimal public health facility locations. In this context, this research considers the following objectives:

1) To explore the impact of inherent assumptions for the areal interpolation techniques in producing different estimations results for the target areas based on the spatial characteristics of the case studies in terms of the degree of

homogeneous and heterogeneous distribution of the population in the census area, census area size and the land use classifications.

2) To map the differences between the results of the three interpolation methods for each case study in order to explore how the different assumptions in the methods play out in terms of the differences between the surfaces in the population estimation results for each target area.
3) To explore the impact of inherent assumptions for the three areal interpolation techniques and the spatial characteristics of each case study on the results of population estimations for the surfaces; and the results of optimal facilities selection for each location-allocation model on the three demand surfaces.
4) To provide a deeper understanding and advancing knowledge regarding the objective function and the operations embedded in each of the four location-allocation models when applied to the different case study characteristics and to the results of three areal interpolation techniques.
5) To provide some important rubrics or guidelines and philosophical reflections concerning the context of the decisions of optimal facility locations and the effects of and lessons learned from the interaction of four location-allocation models with three areal interpolation techniques.

1.3 Organisation of the Thesis

The thesis proceeds into seven chapters. This section provides a brief description of these chapters as follows:

Chapter One: Introduction

An introduction to the methods which have been used in this study, is presented in Section 1.1. The research aim and objectives are presented in Section 1.2; and the organisation of the thesis is presented in Section 1.3.

Chapter Two: Background and Literature Review

The introduction is provided in Section 2.1; the background and literature review regarding areal interpolation techniques is presented in Section 2.2; and a review of the location-allocation models is presented in Section 2.3. Finally, a review summary for these techniques and models and the highlighting of the gap in the literature is subsequently drawn at the end of each section.

Chapter Three: Research Methodology

An introduction to the research methodology is presented in Section 3.1; and the case studies are discussed in Section 3.2. The data sources are outlined in Section 3.3; and the areal interpolation techniques which have been used in this study as well as the implementation of these techniques are presented in Section 3.4. Section 3.5 presents the location-allocation models that have been used in this study and the implementation of these models; and Section 3.6 presents the statistical analysis. A summary for these techniques and models is subsequently drawn in Section 3.7.

Chapter Four: Results of the Areal Interpolation Techniques

An introduction to the results of the areal interpolation techniques is provided in Section 4.1; and their results are provided in Section 4.2. Section 4.2.1 provides the results of the AW methods; Section 4.2.2 provides the results of the Pycno methods and Section 4.2.3 presents the results of the Dasy methods. An example of the calculations made using three areal interpolation techniques is presented in Section 4.2.4. The results showing the differences between the findings of all of three methods are presented in Section 4.3. Sections 4.3.1, 4.3.2 and 4.3.3 provide the results which show the differences between the three methods when applied to the three case studies. Finally, Section 4.4 provides a summary in light of the results of the three areal interpolation techniques for the three case studies.

Chapter Five: Results of Interaction between the Location-Allocation Models and Areal Interpolation Techniques

An introduction is provided in Section 5.1 and the interactions between the four location-allocation models and the three areal interpolation techniques are presented in Section 5.2. It was found that there were similar results between the MI and MC models. On this basis, Section 5.2.1 presents the results of the MI and MC models, Section 5.2.2 provides the results of the MF model and Section 5.2.3 provides the results of the MA model. A summary in light of the interaction results between the four location-allocation models and the three areal interpolation techniques is presented in

Section 5.3. Finally, some generalised points arising from the results of the interactions are presented in Section 5.4.

Chapter Six: Discussion

An introduction is provided in Section 6.1; and discussions of the results of the three areal interpolation techniques are presented in Section 6.2. Section 6.2.1 discusses the findings after employing the three areal interpolation techniques, in terms of each method and their assumptions; in addition to the effects of the spatial characteristics of the case studies, with particular consideration of the effects of census area size, populated areas and the large spatial disparities on the population densities. A number of recommendations are also provided. The results of mapping the differences between the three surfaces across the case studies are discussed in Section 6.2.2; whilst Section 6.3 discusses the results of the interaction between the location-allocation models and the areal interpolation techniques in terms of the effect of the operations for the four models and the assumptions of the population estimations for each surface. The effects of high population density in certain neighbourhoods and the large area size for some of the Lower Super Output Areas and neighbourhoods have also been provided. The effects of the limited number of Primary Health Care Centre locations and the concentration of those facilities in certain neighbourhoods with high population densities have also been discussed. Section 6.4 presents some philosophical reflections on the methods and the results; and Section 6.5 provides a summary for the discussion chapter.

Chapter Seven: Conclusion

An introduction is provided in Section 7.1. Certain rubrics and recommendations regarding the lessons which have been learned from the interactions of the models with the surfaces are presented in Section 7.2. An example of applying the MI model on the Dasy surface to select the best distribution for the facility locations across the three case studies is presented in Section 7.3 before a summary of the chapter in Section 7.4.

Chapter Two: Background and Literature Review

2.1 Introduction

Examining the relationship between location-allocation models and areal interpolation techniques is an important step for supporting the scientific aspects of spatial planning decisions and determining optimal facility locations. It is also important to fill the gap in the literature and provide scientific support regarding the interactions between location-allocation models and different demand surfaces. Many location-allocation models have been proposed in the literature in order to support spatial planning and optimal facility locations. The location-allocation models either use actual demand locations or the centroid point of census areas. However, in the absence or unavailability of census data for smaller areas in some countries, researchers may have to consider using an areal interpolation technique to estimate the population over smaller area units to represent the demand needs (see for example Langford and Higgs (2006), Cromley et al. (2012) and Tomintz et al. (2013)). This chapter focuses on studies describing areal interpolation techniques and location-allocation models and provides a critical review of those techniques and models. In so doing, it highlights gaps in the literature which support the aim and objectives of this study.

This chapter is structured in the following manner: the areal interpolation techniques are reviewed in Section 2.2, and within this section the study reviews the areal interpolation methods with no ancillary data, the areal interpolation methods with ancillary data through the use of remote sensing, the areal interpolation by using road network methods and other areal interpolation methods. A review of the techniques and a discussion of the gap in the literature is provided at the end of this section. The location-allocation models are reviewed in Section 2.3 which also presents the P-median problem (with and without the maximum distance constraint) the Coverage Models such as the Location Set Covering Problem, the Maximal Covering Location Problem and the Maximize Attendance model. Additionally, the chapter also reviews the other location-allocation models. A review summary of these models, highlighting the gap in the literature, is subsequently made at the end of this chapter.

2.2 Areal interpolation techniques

This study has classified these techniques as discussed by Hawley and Moellering (2005) into four types (see Tables 2.1 and 2.2):

2.2.1 Areal interpolation methods without ancillary data

This section reviews two areal interpolation techniques: Areal Weighting and Pycnophylactic methods (see Table 2.1). The common denominator of these methods is that the two methods without ancillary data and the volume for the source zone are preserved, which means that the population allocated to the target areas within each source zone are equal to the sum of the population for this zone (Lam, 1983). However, the Non-volume Preserving method such as the Point-based Areal Interpolation method (Lam, 1983) is excluded from this review.

2.2.1.1 The Areal Weighting (AW) method

The AW method will be described mathematically in the research methodology chapter. This method has frequently been used as a benchmark for comparison by a number of authors especially in studies that have included a variety of methods for results comparison (Qiu et al., 2012). For example, Goodchild and Lam (1980) discussed the techniques of Areal Interpolation based on the use of areas of intersection as weights to distinguish between variables, both extensive and intensive. There have been other discussions regarding Areal Interpolation methods, such as Lam (1983) who considered two main types: the Non-volume-preserving and Volume-preserving methods. The key to maintaining the total value of the variable appears to lie in the Volume-preserving methods. These include the Pycnophylactic and the AW overlay method. Martin (1989) offered an approach to the representation of demographic data from the census population in targeted areas within the United Kingdom, which relied on the use of inverse distance weighting. The AW method provides a distribution that is homogeneous and unified for all target areas, as exemplified by Brindley et al. (2005) who used different methods for Areal Interpolation, such as the Postpoint method, the Enumeration Districts Centroid method and the AW method to show the effect of alternative illustrations of population estimates on the results of air pollution exposure. Their findings revealed that homogeneous distribution in the AW method results had a significant impact upon the variables.

Other studies, for example Hawley (2005) and Hawley and Moellering (2005), compared four areal interpolation techniques including the AW method. The study found that the performance of this method in terms of the accuracy of results was less than for the other three methods. Cromley et al. (2009) used the AW method to correct boundary changes and subsequently estimate population changes which occurred in the Chinese census data between 1982 and 2000. They found that the analysis applied in this study was appropriate for those countries facing boundary changes in census units. However, where population estimates require accurate information, more advanced areal interpolation techniques may provide a more accurate representation of the population than that of the AW method. Generally, the AW method requires several modifications to overcome the presumption of homogeneity within the target area. It also requires modifications to provide additional data and a more realistic distribution of the population in the target area.

Table 2.1 The classifications and characteristics for the Areal Interpolation Techniques

The Classification of the Areal Interpolation Techniques	Method	Variable Distribution	Functions	The Literature
Areal Interpolation methods without ancillary data.	The AW method	Homogeneous	Spatial Overlay	Goodchild and Lam (1980); Lam (1983); Brindley et al. (2005); Hawley (2005); Hawley and Moellering (2005) and Cromley et al. (2009).
	The Pycno method	Heterogeneous	Neighbours Smooth Density Function	Tobler (1979); Lam (1983); Rase (2001); Hay et al. (2005); Hawley (2005); Hawley and Moellering (2005); Comber et al. (2008) and Kim and Yao (2010).
Areal Interpolation methods with ancillary data by using remote sensing.	The Dasy method	Heterogeneous	Spatial Overlay for the Land Use or the Land Cover Classification	Wright (1936); Langford et al. (1991); Fisher and Langford (1995); Fisher and Langford (1996); Eicher and Brewer (2001); Mennis (2003); Hawley (2005); Hawley and Moellering (2005); Langford and Higgs (2006); Langford (2007); Maantay et al. (2007); Comber et al. (2008); Kim and Yao (2010) and Cromley et al. (2012).

Table 2.2 The classifications and characteristics for the Areal Interpolation Techniques

The Classification of the Areal Interpolation Techniques	Method	Variable Distribution	Functions	The Literature
Areal Interpolation by using road network methods.	The Road Network method	Heterogeneous	Spatial Overlay	Xie (1995); Voss et al. (1999); Reibel and Bufalino (2005) and Merwin et al. (2009).
Other Areal Interpolation methods using ancillary data	A variety of methods such as the Intelligent Areal Interpolation Approach, Statistical Approach, Control Zones, Hierarchical Bayes Approach, Cokriging Method, Ordinary Kriging Method and Spatial Micro-Simulation model.	Heterogeneous	A variety of functions such as Poisson's process, Expectation Maximization Algorithm, Spatial statistics, The Spatial Correlation and Cross-Correlation and Spatial Micro-Simulation.	Flowerdew and Green (1989; 1991; 1992); Flowerdew et al. (1991); Goodchild et al. (1993); Muggling and Carlin (1998); Wu and Murray (2005); Cai et al. (2006) and Tomintz et al. (2013).

2.2.1.2 The pycnophylactic (Pycno) method

Tobler (1979) propounded the smooth Pycno method based on the variable distribution and the functions described in Table 2.1. Thus: "Imagine that Figure A consists of blocks of clay, each state being represented by a different colour, and that the masses of clay are proportional to the population. We now wish to sculpt this surface until it is perfectly smooth, but without allowing any clay to move from one state to another and without removing or adding any clay. This physical picture is a reasonable approximation to the mathematical method proposed" (Tobler, 1979: 520), Smooth Pycnophylactic Interpolation for Geographical Regions, Tobler, W. (1979), *Journal of the American Statistical Association*, 74, no. 367, pp 519-530, reprinted by permission of the publisher (Taylor& Francis Ltd, http://www.tandf.co.uk/journals). The Pycno method will be described mathematically in the research methodology chapter.

A number of studies have used the Pycno method because it can provide heterogeneous estimations for the target areas which can be relied upon to represent the spatial distribution of the population. For example, Rase (2001) used triangulated irregular networks in comparison to a regular grid for Tobler's method, to maintain the original boundaries of the polygons. Hay et al. (2005) presented the risk of malaria to the population through the use of census data for Kenya using AW, Pycno interpolation and accessibility potential interpolation approaches. In more recent studies of Areal Interpolation techniques, Comber et al. (2008) developed a database describing general classes of non-overlapping land-use by combining Pycno interpolation with Dasymetric mapping techniques. This work depended on the values of the target zones being equal to those of the source zones (the Pycno criterion). They found that one of the benefits of using this approach was that it provided a way to overcome differences in areal reporting units. As shown in the reviewed studies, the main advantage in using the Pycno method is the ability to create heterogeneous variables in the target areas. However, the disadvantage of this method is that it is not reliant on ancillary data for describing the source zones. In other words, the values of the populations estimated will be distributed in all areas within the target areas. Thus, the use of ancillary data can be helpful for providing more accurate information about the actual distribution of the population within the target area and for ensuring an accurate estimate for the study area (see Kim and Yao, 2010).

2.2.2 Areal Interpolation methods with ancillary data by using remote sensing

The use of ancillary data within areal interpolation techniques contributes to providing an improvement in the accuracy of the estimations results for those techniques (see Table 2.1). The Dasy method is one of the interpolation techniques which commonly uses remote sensing data in order to reveal the spatial distribution of the population in the target area (Langford et al., 1991; Fisher and Langford, 1995 and 1996; Eicher and Brewer, 2001 and Langford, 2007). The Dasy method "utilises ancillary information resources to internally redistribute variables within the limits of their tabulation zone so as to create subzones of relative homogeneity and thereby ensure that mapped discontinuities better reflect the true underlying geography" (Langford and Higgs, 2006: 297).

One of the earliest attempts to estimate population data was provided by Wright (1936) who estimated the densities and the distribution of population in Cape Cod using 'topographic' information as ancillary data. Indeed, Dasy approaches have been studied widely and the use of remote sensing data and these approaches has in recent years become widely available for geographical research (Hawley, 2005; Langford, 2006; Comber et al., 2008 and Kim and Yao, 2010). There are a number of authors who have used remote sensing as part of their areal interpolation methods. Langford et al. (1991) used a remote sensing technique by obtaining several images from a satellite, organising them into several types using different spectral signatures, and then analysing them to classify the land-use in the region. They discussed three statistical models which were used for predicting population density within the target areas: the simple model, the shotgun model, and the focused model. Additionally, Fisher and Langford (1995) used the Monte Carlo method for the testing of five methods: the Dasy method, the AW method, the shotgun model, the focused model and the simple model. They determined that the Dasy method provided the best results and was therefore superior to those of the AW method. Another study focused on the impact of the classification error for the original Landsat scene on the Dasy method (Fisher and Langford, 1996).

Some authors have addressed Dasy approaches by testing five methods from among the Dasy mapping techniques and areal interpolations. There are as follows: the grid and polygon binary methods, the polygon and grid three-class method and the traditional limiting variable method (Eicher and Brewer, 2001). The results showed that the error produced by the traditional limiting variable was less when compared to other methods. Mennis (2003) used Dasy mapping with two new techniques to create raster surface representations of the population and its density. The first technique involved the empirical sampling approach and the second AW, by integrating the relative differences in areas between different classes. Another study presented a simple method for areal interpolation in order to extract the information from the pixel in the raster map which was dependent on binary Dasy mapping (Langford, 2007).

There are other authors who have sought to improve estimates of the population in the targeted areas and provide additional information to simulate the reality of the real population. For example, Maantay et al. (2007) developed "The Cadastral-based Expert Dasymetric system", to study the incidence of asthma in New York City, employing "land-use filters and modelling by expert system routines." Their study showed that this technique could help to improve analysis, which used information on the distribution of the population in urban centres. Additionally, Kim and Yao (2010) developed a new Hybrid method which exploited the strengths of, and addressed the flaws in, the Dasy mapping and Pycno interpolation methods. One of the most important conclusions of this study was the comparison, in terms of estimation accuracy, of the results of this Hybrid method with those of other methods such as the AW, the Dasy and the Pycno method. The analysis presented in Table 2.3 shows that the performance of the Hybrid method was the best based on the two tests.

Table 2.3 Estimation accuracy results from four interpolation methods

Interpolator	**Without ancillary information**		**With ancillary information**	
	The AW method	**The simple Pycno method**	**The binary Dasymetric method**	**The hybrid method**
The root mean squared error (RMSE)	**941**	**916**	**769**	**745**
The mean absolute percentage error (MAPE) %	**37.21**	**35.14**	**27.59**	**26.58**

"Total target zones N = 1923, mean population of target zones = 6156" table source (from Kim and Yao, 2010: 5667), with permission from: http://www.tandfonline.com/doi/abs/10.1080/01431161.2010.496805.

The population estimation results for the Dasy method were also used to represent the demand needs with two-step floating catchment area, and location-allocation models. For example Langford and Higgs (2006) combined the two-step floating catchment area technique to measure the accessibility to healthcare with an estimate of population data (demand) by using areal interpolation techniques. The analysis of this study showed that there was a rise in population estimates with the Dasy technique, which led to lower accessibility to healthcare. Cromley et al. (2012) proposed the use of the Maximal Covering Location Problem with different representation of the demand surfaces that resulted from the use of intelligent areal interpolation for the Dasy, centroids or uniformly distributed methods. The study found that the use of intelligent areal interpolation, such as the Dasy method, was useful for improving the spatial distribution assumptions for the demand needs and improving the results for the Maximal Covering Location Problem.

The literature review discusses the Dasy method as a technique proposed to overcome some of the disadvantages present in the AW and Pycno methods. However, in terms of actual analysis, the Dasy technique lacks a uniform methodology, resulting in differences in terms of the selection of ancillary data (Langford and Higgs, 2006). Therefore, combining the Dasy method with other methods, such as the Pycno method with some modifications, produced a better estimation for the variables within the target areas (see Comber et al., 2008 and Kim and Yao, 2010).

2.2.3 Areal interpolation by using road network methods

The areal interpolation road network technique is “overlay of the source-zone layer and the network layer to determine the length of street segments within each source zone; then allocate the population to the street segments in each source zone by length to get the population per unit length” (Xie, 1995: 297). Generally, the majority of houses are distributed in streets and therefore this technique provides an estimate of the population along the streets of the target area.

Various authors have addressed areal interpolation by using road networks (see Table 2.2). For example, Xie (1995) presented an overlaid network algorithm using the length of street segments, the class of street segments (hierarchical weights) and the house bearing of street segments. This method works well with 'TIGER/Line files' because houses are usually located evenly on the streets and the population data can be read from each street in the network. The author found that the assignment of hierarchical weights provided the best results out of the three methods.

Voss et al. (1999) introduced two new spatial interpolation methods by using road network areal interpolation: the network of road segments (length method) and the internal node counts method. The results showed that the nodal method of counting represented a significant improvement on areal interpolation by using the road network. Additionally, Reibel and Bufalino (2005) tested two methods - the street weighting technique and the area weighting technique - and found evidence that errors in the first method were less than those in the second method. Merwin et al. (2009) proposed a neural network approach for the road network areal interpolation and the results of this approach were compared to the AW, the Dasy and ordinary least squares regression. From the findings in some studies for the road network areal interpolation, this technique may encounter problems in estimating the distributed population, for example, in industrial areas, or streets with no population, such as those in new city neighbourhoods (Reibel and Bufalino, 2005).

2.2.4 Other areal interpolation methods using ancillary data

There are some other methods in addition to the AW, the Pycno, the Dasy and the road network methods, which have been developed to improve areal interpolation techniques that focus on ancillary data (see Table 2.2). For example, Flowerdew and Green (1989; 1991) and Flowerdew et al. (1991) developed an intelligent areal interpolation approach based on Poisson equations to provide better estimates of areal interpolation according to a regression relationship between variables on the source zones. Additionally, Flowerdew and Green (1992) developed a method for normally distributed data, which depended on earlier work regarding the expectation maximisation algorithm. Goodchild et al. (1993) presented a new method dependant on control zones so that the analyst could enter additional information to aid the estimation process. Muggling and Carlin (1998), extending from Flowerdew and Green (1989), developed a hierarchical Bayes approach through Markov Chain Monte Carlo methods. One of the main advantages for this method was that it not only provided estimates of the population in the form of points but also provided an estimate for the distribution of the population in the target area through Markov Chain Monte Carlo methods.

In recent studies, some authors have used statistical methods applied in other sciences. For example, Wu and Murray (2005) presented the use of the Cokriging method to interpolate the population density in the Columbus metropolitan area of the USA. The study applied the spatial and cross correlations of population and the study found that the outcome of applying the cokriging method was better than the use of the regression approach. Cai et al. (2006) proposed the use of three areal interpolation methods – the AW, the Ordinary Kriging and a modification of the Pycno methods - to provide sex and age population estimates of small population areas in the USA. The study found that the Pycno interpolation method was better and more accurate than the Ordinary Kriging method; whilst the Ordinary Kriging method was better and more accurate than the AW method. Some other authors have used the Spatial Micro-Simulation model to estimate the birth rates for small areas, and then use these results with the Location-Allocation models in order to identify the optimal locations and re-location of antenatal classes (Tomintz et al., 2013). Based on the literature review, this study has been one of a few studies that have used the results of areal interpolation techniques with the location allocation models.

2.2.5 Review summary for the areal interpolation techniques

The literature review has shown that there are simple and complex areal interpolation techniques that can be used to estimate the population in the target areas. The AW, Pycno and Dasy methods are the most commonly used methods in the literature. However, the three methods differ in terms of the use of ancillary data, the assumptions of the variable estimation and the spatial functions used. For example; the AW method does not use ancillary data and assumes that the population is evenly distributed across the source zone (Lam, 1983; Hawley, 2005; Hawley and Moellering, 2005; Brindley et al., 2005; Cromley et al., 2009 and Qiu et al., 2012). Thus, this method produces homogeneous estimations for the target areas based on the geometric properties of the overlapping areas between the source zones and the target areas. The Pycno method does not use ancillary data and assumes that the population is distributed in a heterogeneous form within the source zone. The spatial function for this method depends on neighbours' smooth density in order to provide heterogeneous estimations for the target areas with the volume-preserving properties (Tobler, 1979; Lam, 1983; and Kim and Yao, 2010). In contrast, the Dasy method depends on incorporating ancillary data such as land use or land cover and assumes that the population is evenly distributed across the populated areas within the source zone. The operations, of this method depends on the spatial overlay functions for the source zones, the classification of land use or land cover data and target areas. Thus, this would help this technique to provide more realistic data about the actual spatial distribution of the population and provide heterogeneous variables in the target areas.

In summary, the differences between the three methods in terms of the use of ancillary data, the assumptions of the variable estimation and the spatial functions used are clear as described above. Thus, the use of the three methods on one case study will produce different population estimations results within the target areas based on the assumptions of the variable estimation and the spatial functions of the methods and the spatial characteristics of the case study. The study indicated at the beginning of this chapter the importance of the results of the areal interpolation techniques in relation to the location-allocation models. To date, there are little research has focused on the interaction of some of the locational-allocation with the areal interpolation techniques. In doing so, the study aims to explore how the different assumptions in the methods play out in terms of the differences between the surfaces in the population estimation results for each target area. It also aims to explore the impact of inherent assumptions for the three areal interpolation techniques and the spatial characteristics of each case study on the results of population estimations for the surfaces and the results of decisions of the optimal facilities selection for each location-allocation model on the three demand surfaces. By considering the interaction between the models and techniques, the results will be used to explore how the spatial characteristics of the problem in hand may be more or less suited to generate different demand surfaces based on the assumptions of the areal interpolation methods and then to use those surfaces with location-allocation models.

2.3 Location-allocation models

Many studies demonstrated that the location-allocation models could provide the scientific support for the planning and facility location issues (see Hakimi (1964), Teitz and Bart (1968), ReVelle and Swain (1970), Toregas et al. (1971), Church and ReVelle (1974), Holmes et al. (1972), Rahman and Smith (1991), Schilling et al. (1993), Serra and Marianov (1999), Cromley and McLafferty (2002), Spaulding and Cromley (2007), Church and Murray (2009) and Tomintz et al. (2013)). These models aim to solve the location problems and to identify the optimal facilities locations by minimising the total weighted distance or time which is aggregated across the supply locations and the demand weights (Teitz and Bart, 1968; Daskin and Stern, 1981; Schilling et al., 1993; Spaulding and Cromley, 2007 and Church and Murray, 2009). There are a number of location-allocation models and the differences between the models are related to the differences in their objective functions, how they search through possible solutions and how potential solutions are evaluated. Additionally, there are different statistical and mathematical bases which are associated with the different inherent operations for each model. These, in turn, result in different solutions being suggested by each of the models when applied to the same location allocation problem.

Location-allocation models have been studied in many fields since 1960, for example, geography, spatial planning, industry, engineering, and public administration (Cromley and McLafferty, 2002 and Teixeira and Antunes, 2008). Additionally, there are different classifications for the location-allocation models in the literature (see Cromley and McLafferty, 2002; Daskin, 2008 and Church and Murray, 2009). However, the study has reviewed a number of these studies which have used location-allocation models in the context of GIS, or in other contexts through the following classifications: 1) P-median problem with and without maximum distance constraints. 2) The Coverage models such as the Location Set Covering Problem, the Maximal Covering Location Problem and the Maximise Attendance Problem. 3) The other location-allocation models.

2.3.1 The P-median problem with and without maximum distance constraint

The first definition of the p-median problem was proposed by Hakimi, who states, "We would like to find the location of the police station p such that the maximum distance from p is minimum" (1964: 450). The p-median model was one of the first developed mathematical models to minimise the total weighted distance, which was aggregated over all of the supply and demand locations (Hakimi, 1964 and Teitz and Bart, 1968). Teitz and Bart (1968) also proposed a p-median problem that incorporated interchange heuristics as an alternative search approach. The operations of this model depended upon the interchange or substitution of the number of locations and were required to select those candidate locations capable of minimising the weighted distance or time between the supply and demand locations (Church and Sorensen, 1994 and Church and

Murray, 2009). The study will describe the p-median model mathematically in the research methodology chapter.

In an integer linear programming, the p-median model was first formulated by ReVelle and Swain (1970) (Church, 2003). Their objective was to minimise the total weighted distance of the demand on several points. Some authors have modified the version of the p-median problem to the distance constrained median or maximum distance between the supply and demand locations (Toregas et al., 1971). Additionally, Khumawala (1973) presented an efficient heuristic method for the p-median problem with maximum distance constraints in order to improve the solutions of the problem. Other authors have compared two heuristic p-median problems with maximum distance constraints to detect the capabilities of these methods (Hillsman and Rushton, 1975). Rosing et al. (1979) compared optimal solutions derived by the linear searches with the heuristic p-median model presented by Teitz and Bart (1968) and this model was better when the size of the problem was greater than the capacity of other methods. Rahman and Smith (1991) also compared two heuristic methods, Teitz and Bart and Ardalan's p-median problem, with and without maximum distance constraints. The study found that the performance of Teitz and Bart's heuristic was better than Ardalan's with and without maximum distance constraints. Church and Sorensen (1994) tested two heuristic approaches, the global-regional interchange approach and Teitz and Bart's (1968) p-median model. The study found that the performance of the global-regional interchange approach was as robust as that of the p-median formulated by Teitz and Bart. Chaudhry et al. (1995) presented a revision and correction for the p-median heuristic method with and without maximum distance constraints, and tested this method with the original Teitz and Bart p-median heuristic method.

A number of recent studies have presented the capabilities of GIS to support location-allocation models by examining and evaluating the spatial distribution and accessibility of services using the p-median. Some authors, for example Cromley and McLafferty (2002), presented a formulation of the p-median problem in health services by assigning a number of demand sites and the volume of demand at each site. Mitropoulos et al. (2006) presented some new proposals to try to increase demand for primary healthcare centres rather than hospitals. This method was based on the p-median problem and mixed integer programming, and aimed to evaluate and determine the distance between patients and health facilities and to clarify the equitable distribution of health services among citizens in an area of Western Greece. Algharib (2011) applied the p-median model with the centroid points for the districts in Kuwait in order to support the spatial planning for fire station locations. Other authors have also used the p-median model with estimation results from the spatial micro simulation technique to estimate the birth rates for small areas, to identify the optimal locations and re-location of antenatal classes (Tomintz et al., 2013).

The p-median problems are an essential springboard for many researchers seeking to analyse the problems of public services. Some authors have used the same models, and other authors have modified these based on different assumptions in order to improve the solutions for the problem. The p-median model and all extensions of this model are founded on the assumption that optimal accessibility to locations can be achieved by minimising the total distance between the supply and demand. However, there are cases in which the use of the p-median model may be less appropriate, because the model does not realistically suit those systems that have a hierarchical nature (Hodgson, 1988). According to Rahman and Smith (2000: 440) "it has frequently been observed that the use of service facilities may decline rapidly when the travel time exceeds some critical value". In this case the p-median model may lead to solutions that are unacceptable from the standpoint of service. However, the most important advantage of this model is that the ability of p-median to minimise the sum of the weighted distance between the supply and demand.

2.3.2 The Coverage Models

The coverage models are considered as other types of location-allocation models which aim to provide a complete coverage or maximal coverage or partially coverage for the weights of the demand points based on the distances used or travel time (Church and Murray, 2009). The differences between the coverage models relate to the differences in the objectives functions and operations in how they search through possible solutions to allocate the demand points and identify the optimal facilities sites. This study has classified these models as follows:

2.3.2.1 The Location Set Covering Problem (LSCP)

The LSCP seeks to minimise the number of facilities needed to cover or serve all demands within a certain distance or timeframe (ReVelle and Hogan, 1989a and

Schilling et al., 1993). The operation of this problem differs from others which seek to fit a set number of facilities to a demand location optimally. It identifies the number of facilities which are needed to satisfy a particular distance or travel time constraint. Since 1970, some authors have started to formulate other mathematical models in order to support the facilities locations problems. For example Toregas et al. (1971) formulated a mathematical model of the LSCP to determine the maximum time or distance between the user and the location of emergency services. Additionally, Toregas and ReVelle (1973) showed how to solve most LSCPs without linear programming optimisation with a choice of subsequent basic variables in columns and rows. Gleason (1975) applied the LSCP to determine the minimum number of (express) bus stops required over a certain distance, in order to specify a maximum distance a person needed to walk to reach the nearest bus stop. The main disadvantage when the authors used the LSCP could be seen in the example of ambulance services as at the time the model did not consider the possibility that the server could be busy (Marianov and ReVelle, 1994).

A number of authors have attempted to develop the LSCP to corresponded relatively well with the problem to be solved. For example, ReVelle and Hogan (1989a) developed the Probabilistic Location Set Covering Problem (PLSCP), to provide a local estimate of the busy fraction within the scope of geographic coverage around a node. The "probabilistic optimization models attempt to deal with congestion inside the location model rather than as an after-the-fact modification, as do the descriptive models" (Marianov and ReVelle, 1994: 168). Additionally, Marianov and ReVelle (1994) developed the Queuing Probabilistic Location Set Covering Problem (Q-PLSCP). The main difference between this model and ReVelle and Hogan's model was related to the minimum number of facilities that needed to be located, according to a certain distance or time around the node. Moreover, ReVelle et al. (1996) formulated three models. The first was the Maximal Conditional Covering Problem (MCCP1) and the second the (MCCP2). The objective of the models was to maximise the servers, with the primary coverage of servers determined from the LSCP provided for all of the demand nodes. The third was the Multi Objective Conditional Covering Problem (MOCCP). This model was different to the first as the primary coverage as not all of the nodes in this model were required.

Recently, Rajagopalan et al. (2008) formulated the Dynamic Available Coverage Location (DACL) model based on the LSCP and this model was an extension of Marianov and ReVelle's Q-PLSCP. The objective of the model was to identify the minimum number of ambulances locations for each group in the face of major changes that occurred in the pattern of demand, fulfilling the coverage requirements (Rajagopalan et al. 2008). The LSCP has also been used to determine locations where potential supply sites have not been defined a priori (Straitiff and Cromley, 2010).

As has been shown in the review above, the LSCP models are mainly used to determine the least number of possibilities for services to serve a geographical area, and are often used to determine the ambulance service, as shown previously. In fact, initial applications for some models often appear with some disadvantages, as seen when the authors have applied LSCP. One of the main disadvantages is this model does not consider the possibility that the server may be busy, and for example in the case of ambulance services receiving a call, this is a key concern (Marianov and ReVelle, 1994). Based on this limitation, some extensions such as probabilistic LSCP have been suggested for overcoming this and providing a local estimate of the busy fraction, within the scope of geographic coverage around a node (ReVelle and Hogan, 1989a). This does not preclude the possibility that this model is one of the early models, which provided an important stage in analysis to determine the minimum number of suppliers to cover the size of the demand within a certain distance or timeframe.

2.3.2.2 The Maximal Covering Location Problem (MCLP) and Maximise Attendance (MA) model

The first model is the MCLP, which seeks to maximise the coverage for the demand weights within a certain distance or travel time (Church and ReVelle, 1974; ReVelle and Hogan, 1989b; Spaulding and Cromley, 2007 and Murawski and Church, 2009). In terms of facility selections, the operations of the MCLP are different to those of the LSCP. The operations of the MCLP aim to provide solutions to cover the largest possible area of demand according to certain distance requirements or the time elapsed between supply and demand. Church and ReVelle (1974) formulated a mathematical model of the MCLP to locate the p-facilities within a set of possible supply sites. Hillsman (1984) proposed altering the distance criterion of a p-median problem to obtain a new set of coefficients, depending on the information about population and the distance from a MCLP. ReVelle (1986) developed the Maximum Capture Location Problem in order to capture the total demand for the set of new facilities. Additionally, ReVelle and Hogan (1989b) formulated the Maximum Available Location Problem (MALP) the aim of which was to serve the largest number of people that could find the service within a standard time.

Some authors, for example Marianov and ReVelle (1996: 112), have argued that the MCLP “does not consider the possibility that a server may be busy at the time the call arrives, that is, the possibility of congestion”. Marianov and ReVelle (1996) developed the Queuing Maximal Availability Location Problem (QMALP), and the main difference between this model and that proposed by ReVelle and Hogan (1989b) was the minimum number of servers or facilities that were believed to be necessary within a certain time and distance to the service from the node.

More recently, Spaulding and Cromley (2007) presented a reformulation of the Maximum Capture Location Problem to locate a set of home improvement stores for new entrants into seventy-five towns in southeast New Hampshire by using data representation and GIS capabilities. Another study modified the original formulation of the MCLP to the Maximal Service Area Problem, in order to generate service areas to be the travel time zones for the facilities and then reduce the costs and maximise the benefits in emergency situations (Mahmud and Indriasari, 2009). Alexandris and Giannikos (2010) introduced a new model for the MCLP based on the capabilities of GIS in order to better represent the demand for the location of bank branches in the municipality of Athens. The main advantage of their study was the use of polygons (instead of discrete points) in order to represent the demand needs.

Several authors have addressed location-allocation models when trying to increase access to health services within geographical areas, by transferring services or the introduction of new services in areas with poor access to healthcare. In contrast, other authors, for example Murawski and Church (2009) have suggested improvements in the transport network to improve access to healthcare through the development of links from transport networks to roads in the Suhum District of Ghana. Their method was based on the Maximal Covering Network Improvement Problem.

In the second model is the MA model, which aims to maximise the attendance of the demand within the distances used or travel time, the demand weight for each demand point is partially allocated in areas that are close to the majority of demand (Holmes et al., 1972 and Algharib, 2011). The model is another kind of coverage problem and the operations of this model are different to those of the previous models. The main difference between the MA model and the previous models is that the adoption of MA model requires the allocation of a ratio for the demand weight for each demand point and does not allocate the complete weight of the demand point. The distance is a critical factor for the ratio of the total demand weight for each demand point in the MA model, which subsequently decreases if the distance is increased between the facility and the demand points. Holmes et al. (1972) developed the MA model under the maximum travel restriction in order to provide partial coverage of demand when the services available into the facilities did not allow for the provision of complete coverage of the demand. Algharib (2011) applied the MA model and a range of other models with the centroid points for the districts in Kuwait in order to support the spatial planning for fire station locations.

As has been shown by the review above, the MCLP models have been predominantly used to determine the maximum geographical coverage ‘number of people’ within the desired facility distance and therefore the developments in this model have been primarily aimed at increasing geographical coverage and providing alternatives when the facility may have been busy. The main advantages when authors used the MCLP models were the adoption of a Maximal Covering Location Problem on mandatory closeness constraints. Accordingly, this model provides an important option in the distribution of public facilities in comparison with previous models. It also leads to superior patterns of population coverage (Church and ReVelle, 1974). However, one of the challenges in the application of maximum coverage relates to the distance (Schilling et al, 1993); although, these models provide important solutions for supporting the spatial planning of facilities. The use of the MA model in the literature review was minimal compared to other models; however, the operations of the MA model revealed that the distance between the facility and demand was the main factor in allocating the ratio from the demand weight for each facility.

2.3.3 Other location-allocation models

There are also a number of other location-allocation models in a range of studies that have demonstrated GIS capabilities for supporting location-allocation models in terms of examining and evaluating the spatial distribution and supporting the planning of facility locations. For example, Lindeskov (2002) used the Multi-Facility Location Allocation Problem, a mathematical model, to assess the geographical distribution of ambulance centres in Denmark within certain distances from demand points on the road network. Ryan and Getz (2005) presented some measurements used in location-allocation modelling to describe the spatial distribution of water resources in terms of buffer, describing distances, plotting nearest neighbours and the framework of the spatial location-allocation.

Some authors have turned to the use of other methods; for example, Mapa et al. (2007) addressed location-allocation problems by combining GIS and mathematical modelling in education facility management in the city of Sao Carlos, Brazil. This method was based on the use of mixed integer linear programming with several scenarios, according to a network of points covering the city, defined by 700 metres. Teixeira and Antunes (2008) discussed the hierarchical location models for public facility planning, and analysed the primary school network on the redeployment of Coimbra's. Their method was based on a hierarchical location model based on several levels of demand and facilities. Although most of the authors went on to analyse the location of services and their demand, in contrast, some authors tended to analyse the location of services according to the number of variables. For example, Panichelli and Gnansounou (2008) presented a new approach for analysing bio-energy locations in Northern Spain, depending on the cost of the resources through a location-allocation model. This method was based on the use of 'a least-cost approach', such as the biomass farm gate cost and transport costs.

Other studies have proposed a location optimisation model, derived from GIS, to identify an appropriate expansion for helicopter emergency medical services in British Columbia (Schuurman et al., 2009). The results showed that the location optimisation model could be used to support the health service planners and optimise the location of additional healthcare facilities. Gu et al., (2009) compared the GIS-facility location solution with the optimal solution, according to static facilities and transportation facilities in South Carolina, by the use of a customised algorithm.

There have also been a number of studies that have used other heuristic searches for location-allocation models, which are included in many optimisation solutions, particularly for evaluating supply and demand problems. Genetic algorithms and grouping genetic algorithms are part of another family of heuristic search approaches developed to solve the p-median model for very complex (highly dimensional) supply and demand problems (Hosage and Goodchild, 1986; Goldberg, 1989; Church and Sorensen, 1994; Falkenauer, 1998; Pitaksringkarn and Taylor, 2005; Sasaki et al., 2010 and Comber et al., 2011). Additionally, there are other heuristic location-allocation approaches such as the Greedy, Simulated Annealing, Tabu Search, Hybrids and Ant Colony approaches (Church and Sorensen, 1994 and Church and Murray, 2009).

2.3.4 Review summary for the location-allocation models

The literature review has shown that there are many types of location-allocation models which are primarily related to the analysis of the supply and demand problems and support the decisions of facility locations. The p-median model and the coverage models are the most commonly used methods in the public and private sectors facilities in the literature. These models differ in terms of their objective functions and their operations and how they search through possible solutions in order to minimise the total weighted distance or time which is aggregated across the supply locations and the demand weights, minimising the number of facilities, maximising the coverage or attendance and how potential solutions are evaluated. The p-median model is the oldest standing model and seeks to minimise the total weighted distance or time aggregated across the supply locations and the demand. The literature review demonstrated that the heuristic searches for this model were better than other search approaches (Teitz and Bart, 1968; Rahman and Smith, 1991 and Church and Sorensen, 1994).

The LSCP is another kind of location-allocation model which sought to answer the question of how to minimise the distances and determine the minimum number of facilities which were needed to serve the demand within a certain distance or travel time (Toregas et al., 1971 and Schilling et al., 1993). This model has been developed and extended by many authors in order to overcome some of the disadvantages in terms of the busy fraction, the number of servers and maximising the servers (ReVelle and Hogan, 1989a; Marianov and ReVelle, 1994; ReVelle et al., 1996). The MCLP is another example of the coverage problem and the objective function of this model depends on maximising the coverage for the demand weights within a certain distance or travel time (Church and ReVelle, 1974; and Church and Murray, 2009). The MCLP has been considered to be more appropriate than the LSCP when resources are limited (Church and Murray, 2009). Maximising the coverage for each facility has been an important aim for the planners, and therefore this model could provide important solutions for supporting the spatial planning of facilities. However, some other planners believe that maximising attendance should have been in accordance with the distance, and when the distance increased the attendance would decrease. In this case the MA model could provide the solutions for maximising attendance and allocating a ratio from those demand weight areas which were close to the majority of demand within a certain distance or travel time (Holmes et al., 1972 and Algharib, 2011).

The spatial distribution for the demand needs is an important factor in the location-allocation problems. The p-median and coverage models were developed to support the facility location planning using centroid or point representation for the demand surface (Cromley et al., 2012). Most of the studies reviewed on the location-allocation models have used census data to represent the spatial distribution of the demand such as the centroids of census units. However, what is the impact of using alternative methods to represent the spatial distribution of the demand such as areal interpolation techniques on the location-allocation models?

In order to answer this question, this study aims to provide scientific support to the decisions of optimal facility locations and fill the gap in the literature regarding the suitability of a range of location-allocation models to the interpolation surfaces and the characteristics of the problem. Additionally, it aims to explore the impact of inherent assumptions for the three areal interpolation techniques and the spatial characteristics of each case study on the results of population estimations for the surfaces and the results of optimal facilities selection for each location-allocation model on the three demand surfaces. Finally, it aims to provide some important rubrics or guidelines and philosophical reflections to contextualise facilities locations decisions and the effects of, and lessons learned from, the interaction of the location-allocation models with areal interpolation techniques.

Chapter Three: Research Methodology

3.1 Introduction

The overall aim of this research is to explore the interactions of different location-allocation models and different interpolation techniques, in order to provide scientific support to the decisions of optimal facility locations and to fill a gap in the literature regarding the suitability of different interpolation surfaces in terms of how they fit the characteristics of different problems and different location-allocation models. To achieve this aim the study seeks to explore the following: how can different assumptions in the interpolation methods affect the differences between the surfaces in the population estimation results for each target area? How can the spatial characteristics of a specific problem be more or less suited to generating different demand surfaces, based on the assumptions of the areal interpolation methods? What is the impact of the inherent assumptions for the areal interpolation techniques and the spatial characteristics of each case study on the results of the population estimations for the surfaces, and the results of optimal facility selections for each location-allocation model on different demand surfaces? Finally, the study seeks to provide a deeper understanding and advance knowledge of the objective function and the operations embedded in each location-allocation model when applied to case studies with different characteristics and to different surfaces derived from the use of a range of standard interpolation algorithms.

The literature review demonstrated several techniques that can be used, based on different assumptions, to provide spatially-distributed estimates of the population and demography (Tobler, 1979; Goodchild and Lam, 1980; Lam, 1983; Langford et al., 1991; Xie 1995; Fisher and Langford, 1995 and 1996; Memmis, 2003; Brindley et al., 2005 and Cromley et al., 2009; Kim and Yao, 2010; Qiu et al., 2012 and Tomintz et al., 2013). In contrast, there are many types of location-allocation models which relate primarily to the analysis of supply and demand problems and support planning and facility location issues (see Hakimi, 1964; Teitz and Bart, 1968; ReVelle and Swain, 1970; Toregas et al., 1971; Holmes et al., 1972; Church and ReVelle, 1974; Rahman and Smith, 1991; Schilling et al., 1993; Serra and Marianov, 1999; Cromley and McLafferty, 2002; Dessouky et al., 2007; Sasaki et al., 2010; 2011; Comber et al., 2011; Algharib, 2011 and Tomintz et al., 2013). In doing so, this study used three common interpolation techniques; Areal Weighting (AW), Pycnophylactic (Pycno) and Dasymetric (Dasy) methods, in order to estimate the population of the three case studies in the target areas. The assumptions, source zones and grid cell sizes for the target areas and implementations of these techniques are described in the areal interpolation techniques section below. Additionally, the study used four commonly available location-allocation models: the Minimise Impedance (MI) P-median Problem, Minimise Facilities (MF) model of the Location Set Covering Problem, Maximise Coverage (MC) model of the Maximal Covering Location Problem and Maximise Attendance (MA) model; all of which have their own particular statistical and mathematical bases which are associated with the objective functionality of each model. The operations, required parameters and implementation of these models are described in the location-allocation models section and Figure 3.1 presents a description of the research methods.

This chapter is structured as follows: the case studies are presented in Section 3.2; 3.2.1 detailing the city of Leicester and 3.2.2 describing the cities of Buraydah and Unayzah. The data sources are presented in Section 3.3. The areal interpolation techniques applied are presented in Section 3.4, while Sections 3.4.1, 3.4.2 and 3.4.3 provide an outline of the AW, Pycno and Dasy methods, along with details of the implementation of these methods. The location-allocation models used in this study are detailed in Section 3.5; Sections 3.5.1, 3.5.2, 3.5.3 and 3.5.4 explain the operations of the MI, MC, MF and MA models, the required parameters and the implementation of these models. Section 3.6 offers a statistical analysis and finally a summary of the techniques and models are presented in Section 3.7.

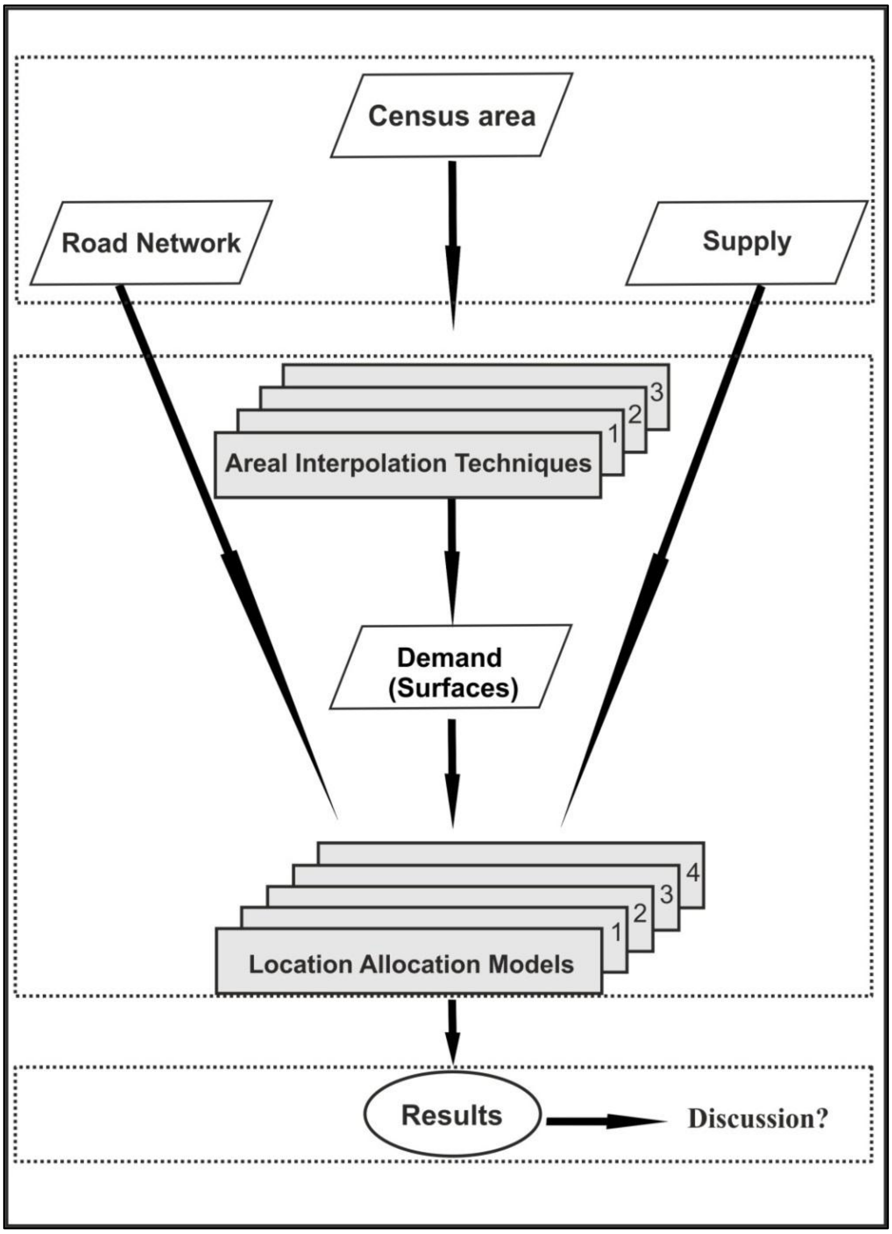


Figure 3.1: Description of the research methods

3.2 Case studies

This study has chosen three case study locations (Leicester, Buraydah and Unayzah) in order to examine the interactions between location-allocation models and interpolation techniques. Preparing three case studies makes it possible to explore the impacts of the inherent assumptions made by areal interpolation techniques on different spatial characteristics of the case studies, in terms of the size of the source zones, patterns and distribution of population densities and land uses as described in the next section.

Additionally, it allows the impact of the objective functions of the location-allocation models on different characteristics of the case studies to be explored.

3.2.1 Leicester city

Leicester is the main city in the county of Leicestershire, in England. According to the 2001 population census, the population of Leicester numbered 279,921 people, distributed across 187 Lower Super Output Areas (LSOAs) designed by Martin (2010) (see Table 3.1 and Figure 3.2). These LSOAs are polygons which represent the city's population census data. The LSOAs were chosen because the size of each zone was suited to the size of the target areas in this study. The reasons for choosing Leicester as one of the comparative case studies are the differences in its spatial characteristics in terms of the population densities, source zones and land use when compared with the other case study locations. Additionally, the city's availability of facility locations differed significantly compared to the other two case study areas. For example, the city of Leicester has a homogeneous population density within the LSOAs, small sized source zones, large built-up areas and a large number of facility locations compared to those in the other two case studies.

The areal interpolation techniques were applied in order to estimate the population of the LSOAs in Leicester. The demand points represent the census data which have been areally interpolated within the target areas using three techniques: the AW, Pycno and Dasy methods. The demand could be for any kind of public and private sector facilities, for example health facilities, schools, retail opportunities and so on. However, this study chose General Practitioner (GP) locations as the supply facilities, which supported the overall aim of the study. There are 76 GP locations in Leicester, and in some cases GP services were duplicated at the same location. Two of the locations were situated outside the borders of the LSOAs, and so the study chose 66 GP locations as the supply points (see Figure 3.2).

Table 3.1 Population of Leicester and GPs.

City	Population census (2001) Leicestershire	Population census (2001) Leicester City	GPs**
			City only
Leicester	609,578*	279,921	76
% of Leicester in Leicestershire			
%	100	45.92	40.86

*Data Source: Leicestershire County Council. Key results from the UK 2001 Census. Produced by the Research and Information Team, Chief Executive's Department, County Hall.
**Data Source: The total number of GPs in Leicester city was obtained from the Leicester City Primary Care Trust (2012). The total number of GPs in Leicestershire was approximately 186, calculated according to the total number of GPs in the UK.

3.2.2 Buraydah and Unayzah cities

Buraydah is the main city in the Al Qassim region in the centre of the Kingdom of Saudi Arabia (KSA). According to the population census data for 2004, at that time the total population of Buraydah was 377,701 people, distributed across 70 neighbourhoods (see Table 3.2 and Figure 3.2). Unayzah is the second main city in the Al Qassim region, consisting of 27 neighbourhoods, and according to the population census data of 2004, the total population of Unayzah was then 137,244 people (see Table 3.2 and Figure 3.2). The neighbourhoods are comprised of polygons which represent the smallest unit area available for the population census data from the Ministry of Economy and Planning in the KSA. Buraydah and Unayzah cities were chosen as case studies due to the differences in their population densities patterns and the differences between source zones and land use between these areas and Leicester city (see Figure 3.2), as well as the availability of a different number of Primary Health Care Centres (PHCCs) facilities compared to the first case study. Buraydah and Unayzah are spatially characterised by the large area size for the neighbourhoods and heterogeneous population density.

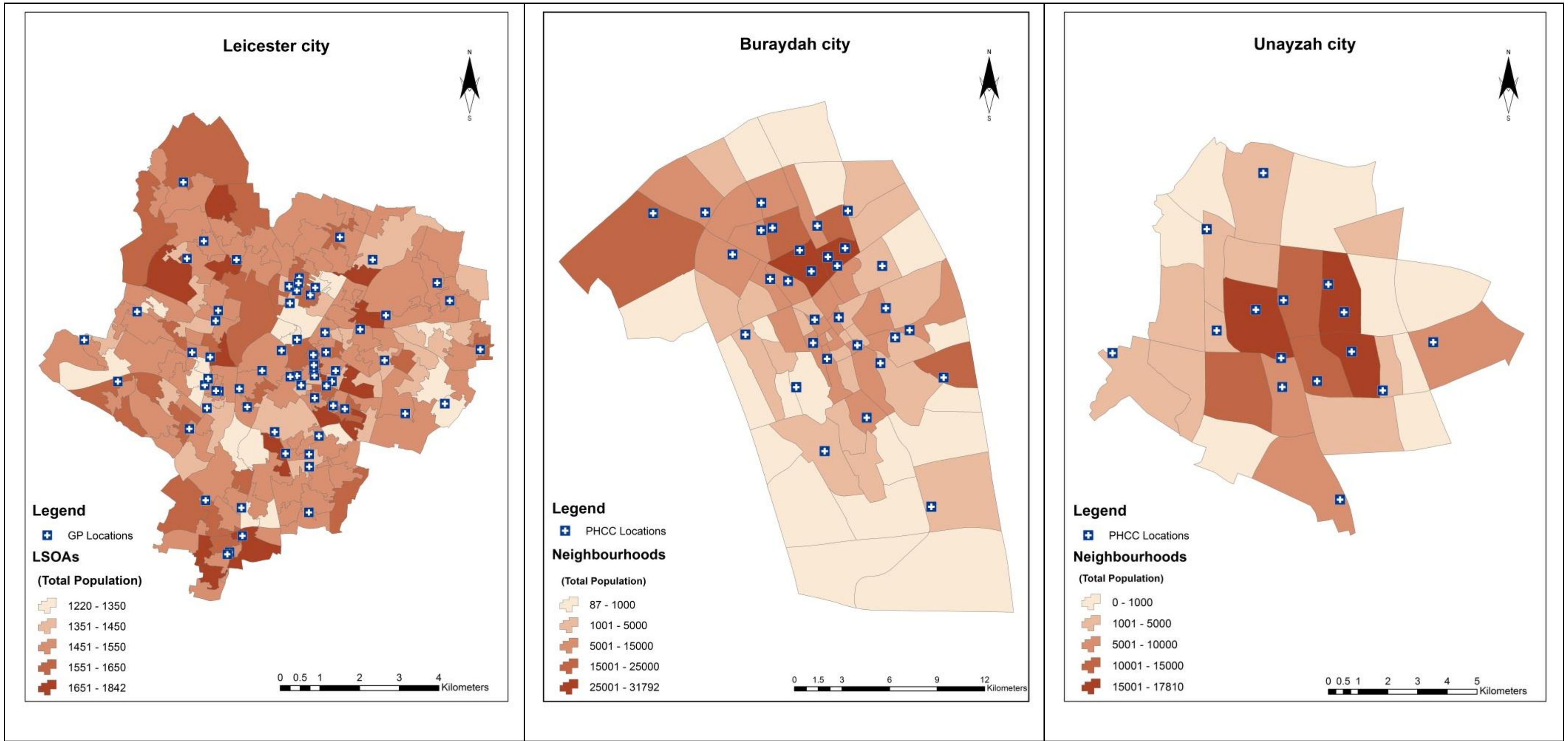
The demand points represent the census data that have been areally interpolated within the target areas using three techniques: the AW, Pycno and Dasy methods. The supply points represent the locations of the PHCCs in Buraydah and Unayzah cities. There are 31 PHCC locations in Buraydah and 15 PHCC locations in Unayzah (see Table 3.2).

Table 3.2 Population of Buraydah and Unayzah and the PHCCs

City	Population census (2004) Governorates*	Population census (2004) City only	PHCCs** City only
Buraydah	505,845	377,701	31
Unayzah	138,351	137,244	15
% of Al Qassim region			
%	63	50.68	30.06

*Governorates are geographic areas consisting of a large city and a number of small villages that are affiliated with it administratively. Data Source: Ministry of Economy & Planning, Central Department of Statistics & Information. Preliminary Results of 1425AH - 2004AD Population & Housing Census.

** The total number of PHCCs in the Al Qassim region is 153. Obtained from the Ministry of Health (2010), General Directorate of Health Affairs in the Al Qassim region.



a) Leicester	b) Buraydah	c) Unayzah

Figure 3.2: The population densities and GP or PHCC locations in: a) Leicester; b) Buraydah; and c) Unayzah. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

3.3 Data sources

In order to explore the interactions of different areal interpolation techniques with different location-allocation models, the first requirement was a set of data covering the LSOAs and neighbourhoods data, census data, a road network dataset and information about the locations of GPs in the UK case study and PHCCs in the KSA case studies. The data and sources were as follows:

3.3.1 LSOAs, neighbourhoods, census data and satellite images

The LSOAs and 2001 census data for Leicester were downloaded from the UK national academic data centre (EDINA). The satellite image data used with the Dasy method in this research was the Landsat Enhanced Thematic Mapper (ETM+) 2001 for the city of Leicester, downloaded from the Global Land Cover Facility [http://glcf.umd.edu/]. The neighbourhood data for Buraydah and Unayzah were provided by Al Qassim Municipality on behalf of the Ministry of Municipal and Rural Affairs in the KSA. The 2004 census data for the neighbourhoods in the KSA case studies was provided by the Ministry of Economy and Planning. Population census data in the KSA is not available in digital form; however, the researcher converted the data into digital format so that it could be used and combined with the data from neighbouring areas. The satellite image data that was used for Buraydah and Unayzah was the Landsat Enhanced Thematic Mapper (ETM) 2003, obtained from King Abdulaziz City for Science and Technology in the KSA.

3.3.2 Road network

The road network data for Leicester city was appropriate for use in a GIS system, containing all the categories of roads which were downloaded from EDINA. Road network data for Buraydah city, which was also appropriate for use in a GIS system, was provided by the Al Qassim Municipality on behalf of the Ministry of Municipal and Rural Affairs in the KSA. Road network data for Unayzah city was provided by the Municipality of Unayzah. The road network in the KSA is categorised into main roads and secondary roads.

3.3.3 Data about GP and PHCC locations

The GP locations were created by the researcher based on postcodes and full addresses; this information was downloaded from the Leicester City Primary Care Trust [http://www.nhs.uk/Services/Trusts/GPs/DefaultView.aspx?id=3576]. The PHCC locations in Buraydah and Unayzah were also created by the researcher, based on information obtained from the General Directorate of Health Affairs in the Al Qassim region on behalf of the Ministry of Health.

3.4 Areal interpolation techniques

This study has applied three areal interpolation techniques for wide use in population estimations. The three areal interpolation methods applied were the AW, Pycno and Dasy methods. The main objectives when using these methods was to estimate the total number of people within the LSOAs in Leicester and in the neighbourhoods in the Buraydah and Unayzah case studies.

The target areas were represented by a grid with a cell size measuring 90-metres. The cell size was specified as 90m because in the KSA case studies, neighbourhoods are often divided into large numbers of blocks and each block is then subdivided into number of houses: so the 90m was specified to represent each block. The size of the grid also provided an example of the demand points within the larger neighbourhood areas in KSA. The grids cells for the three case studies were created using the R Project for Statistical Computing. However, there were at least six demand points in the smallest LSOA area in Leicester. The output from the three techniques used in this study represented demand needs in order to explore the interaction in areal interpolation between different location-allocation models and different interpolation techniques and support optimal facility locations.

3.4.1 The AW method

The AW method is the classic interpolation method which assumes that the population is evenly distributed across the source zone (Lam, 1983; Hawley and Moellering. 2005; Brindley et al., 2005; Cromley et al., 2009 and Qiu et al., 2012). The AW method was chosen for this research because it is widely used, especially in studies comparing population estimates using different areal interpolation techniques. Therefore, based on the assumptions of homogeneity in the population distribution for the AW method, the functionality of this method depends on the geometric properties or the proportion of the overlapping areas between the source zones and the target areas (Fisher and Langford 1996 and Kim and Yao, 2010).

The AW method was applied using the following equation [from Lam (1983) and Langford (2006)]:

$$POP_t = \sum_s \left(\frac{P_s \, A_{ts}}{A_s} \right) \qquad Equation\ (1)$$

Where:

POP represents the population variable;

t represents the target area (grid cell size 90m);

s represents the source zones (LSOAs or neighbourhoods);

P_s represents the population of the source zones (LSOAs or neighbourhoods);

A_{ts} represents the intersection area between the layers of the target area and the (LSOAs or neighbourhoods); and

A_s represents the area of the source zone (LSOAs or neighbourhoods).

3.4.1.1 Implementation of AW method

This section provides a description of the implementation stages applied in the AW method. The source zone layers comprise a map (polygon) that divides each case study into a number of LSOAs or neighbourhoods. The first stage was the creation of the output of the source zones (the layer of the target areas) specified as grid cells of 90m for each case study. The second stage was the creation of the A_{ts} layer to intersect the source zones (LSOAs or neighbourhoods) with the target areas. The objective of this process was to unite the source IDs for the target areas (the LSOAs or neighbourhoods polygons) and the target zone layers (the grid cell within the LSOAs or neighbourhoods). The third stage was the use of Equation 1 for the AW method to calculate the estimated weight of the population. The final stage was calculation of the sum of the estimated weight of the population for the all intersected areas within each target area.

3.4.2 The Pycno method

Tobler (1979) proposed the Pycno method based on the Z value of each grid cell divided by the total number of cells within the source zone. The Pycno method assumes that the population is distributed heterogeneously within the source zone and this method depends on a smooth density function in order to provide heterogeneous estimations for the target areas with volume-preserving properties (Tobler, 1979; Lam, 1983; and Kim and Yao, 2010). This method was chosen in this research because of the ability of the Pycno interpolation to provide a heterogeneous estimation for target areas. Therefore, this technique provided different weights for the population estimation than those provided by the other two techniques. It is possible to provide a simplified description of the implementation of the Pycno method, as described by Hawley (2005: 20-22) and Hawley and Moellering (2005: 412):

$$\iint_{R_i} Z(x,y)dxdy = H_i \qquad Equation\ (2)$$

Where:

R_i represents region *i*;

Z represents the density; and

H_i represents the (population variable) in region *i*.

Initially it was necessary to assign an identity (from 1 to M) for each cell (within a dense grid) in order to classify the source polygon (R_i) within which the cells were enclosed. Subsequently the cell value can be set as shown below:

$$Z_{m,n} = \frac{H_i}{N_i} \qquad Equation\ (3)$$

Assuming that N_i is the count of cells inside the source zone layer i, conversion of the source polygon data to a grid (resolution 90m) will do for each case study. Conversion means transforming the initial to a grid: so each cell is then given a new population, (which is the average of the four neighbours):

$$Z_{i,j} = \frac{1}{4}\left(z_{i,j+1} + z_{i,j-1} + z_{i+1,j} + z_{i-1,j}\right) \qquad Equation\ (4)$$

For each of the cells in region *i*, the adjustments relating to each region would then be stored as the combined difference between the new, smoothed, value of the cell and the original value of the cell. This provides an average adjustment for each region which can then be combined with the new smoothed value of the region (provided that no cell has a value below zero). It is then possible to calculate the total population for each region, allowing the difference of the average population to be computed as described below:

$$\overline{d_k} = \left(\frac{H_k - H_k}{A_k}\right) \qquad Equation\ (5)$$

The sum of the average population difference and each cell in region *k* is then calculated. Repetition occurs until one of two outcomes is achieved; either all of the adjustments fall below a specified constraint or the number of iterations exceeds the maximum input iteration previously specified by the analyst. This process yields a 2½-D population surface. Upon completion of the process, the population contained by each cell is reallocated to the target area. This is achieved by first creating a grid with a resolution of 90m to represent the layer of the target area, which then contains a statistical summary of the pycnophylactic surface. Once the values attributed to each layer of the target area are added together the estimated population is apparent.

3.4.2.1 Implementation of the Pycno method

This section provides a description of the source zone layer and the target areas, as well as the implementation stages applied with the Pycno method. The source zone layers were the LSOAs in Leicester and neighbourhoods in the KSA case studies. This research used the 'Pycnophylactic Interpolation' package for the R Project for Statistical Computing, developed by Brunsdon (2011) [http://cran.r-project.org/web/packages/pycno/pycno.pdf]. This package is described as follows: "given a Spatial Polygons Data Frame and a set of populations for each polygon, compute a population density estimate based on Tobler's pycnophylactic interpolation algorithm. The result is a Spatial Grid Data Frame” (Brunsdon, 2011: 1). The layer of target areas comprised the grid (output), and the cell size was 90m; so this should cover all the LSOAs or neighbourhoods in each case study. Then the results of Pycno interpolation were exported as a (.csv) file to calculate and display the results.

3.4.3 The Dasy method

The Dasy method depends on the use of remote sensing data which was the ancillary information for the distribution of the population over the target areas (Langford et al., 1991; Fisher and Langford, 1995 and 1996; Eicher and Brewer, 2001; Langford, 2007). This method assumes that the population is only distributed in populated areas within the source zone. The reason the Dasy method was chosen for this research was that it is commonly used when there are satellite images available for the source zone. Additionally, the adoption of the Dasy method to acquire ancillary information through the use of satellite images can provide more realistic data in order to estimate the population in the targeted areas, even when combined with other methods (Hawley, 2005; Hawley and Moellering, 2005; Comber et al., 2008; Kim and Yao, 2010).

3.4.3.1 Implementation of the Dasy method

This section provides a description of the source zone layer and the target areas and the implementation stages that were applied in the Dasy method. The source zone layer was a map (polygon) dividing each case study area into a number of LSOAs or neighbourhoods. The target zone layer comprised the grid (output), with cell sizes of 90m. The first stage was to apply supervised classifications to the subset of satellite images for each case study using ERDAS Imagine software. This was done by selecting four main land use classifications for Leicester (building or artificial area, green spaces, water and ground), and then defining a large number of training classifications inside each land use class, based on the author’s knowledge of these areas.

In contrast, in Buraydah and Unayzah, the study applied a supervised classification to the subset of satellite images and then selected five land use classifications (building or artificial area, green spaces, road, water and ground). The road class was added to the KSA case studies due to the large size of the roads in the KSA; for example, the two case studies included some main roads with a width of 30-80 metres. The study also defined a large number of training classes inside each land use class, based on the author's knowledge of these areas.

The second stage involved saving the results of the supervised classification (classified image) for each case study in raster format. The third stage of the study was the reclassification of the area of interest using ArcMap software, for the buildings or artificial areas in each case study and the conversion of the raster layers to vectors. The fourth stage was the creation of intersecting layers for each case study to intersect the source zone layer with the residential areas pixels layer (building or artificial area) (see Figure 3.3), within a 90m grid cell (target area). The objective of this process was to unite the source ID between the source zone (the LSOAs or neighbourhoods polygons), the residential areas layer and the target area. The sixth stage was the use of Excel and Access software to calculate the sum intersection area for each source zone. After calculating the sum area, the tables were once again joined with the intersection layer to apply the logarithms and to calculate the estimated weight of the population using the two modified equations for the areal weighting method, as described below:

$$POP_d = (\frac{P_s}{\sum_i}) \qquad Equation\ (6)$$

$$POP_t = (POP_d \times A_i) \qquad Equation\ (7)$$

Where:

POP represents the (population variable);

d represents the population density;

s represents the source zone;

P_s represents the population of the source zone;

i represents the intersection area between the source zone layers, the residential areas and the target areas;

t represents the target areas (grid cell size of 90m); and

A represents the area.

The final stages were the calculation of the sum of the estimated weight for the population for each pixel within each target area in ArcMap and then the displaying of the results of the Dasy method.

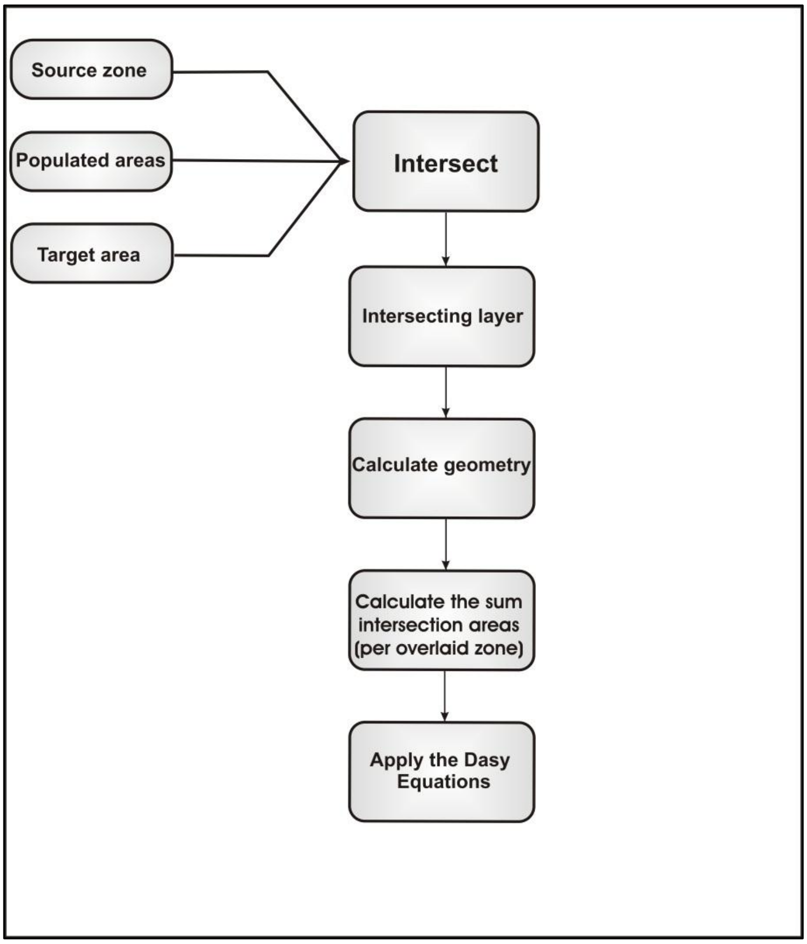


Figure 3.3: Implementation steps for the Dasy method

3.5 Location-allocation models

There are many types of models, as previously discussed. However, heuristic approaches are the most common and include many optimisation solutions for evaluating supply and demand problems (Church and Murray, 2009). Thus, in order to study the interactions and explore the impact of the inherent assumptions for the use of the results of these three areal interpolation techniques on the objectives functions of the location-allocation models and operations of each model, four heuristic models were chosen. These were: the MI model of the p-median problem, the MC model of the maximal covering location problem, the MF model of the location set covering problem and the MA model. These models were chosen because they have been used and reviewed by many authors to support the planning of facility locations (for example: Hakimi, 1964; Teitz and Bart, 1968; ReVelle and Swain, 1970; Toregas et al., 1971; Holmes et al., 1972; Church and ReVelle, 1974; Rahman and Smith, 1991; Schilling et al., 1993; Love and Lindquist, 1995; Serra and Marianov 1999; Cromley and McLafferty, 2002; Dessouky et al., 2007; Church and Murray, 2009; Tomintz et al., 2013). Therefore, these models were considered to be suitable for supporting the overall research aims.

The differences between the four models related to how each model searches for and evaluates possible solutions. The different models each have their own particular statistical and mathematical foundations which are associated with different objectives and inherent operations in terms of minimising the total weighted distance between supply and demand, maximising the coverage for demand, minimising facilities and maximising attendance. Before reviewing the models used in this research, a simple explanation of the demand and supply points is given, to be used with the location-allocation models. The demand points are for the weights of population estimations that were areally interpolated through the use of each areal interpolation method. This study created layers of the centroid point for the target areas for each method across the case studies using 'ArcMAP 10 - Toolbox - Data Management Tools - Features - Feature to Point'. The supply points comprised the GPs or PHCCs in each case study.

The application of different location-allocation models requires use time or distances to be added to the impedance cut-off between the demand and the facilities. The study applied the standards from the Services Planning Standard Manual (2005) in the KSA, which stipulates that the distance between the demand point and a PHCC should be within 800 metres. A distance of 800 metres between demand and facilities was therefore evaluated in the MI, MC and MA models over three case studies. In contrast, the analysis of the MF model was applied using distances and sensitivity to the facility and demand selection. This was achieved by varying the distances used from 600 to 1000 metres at 50-metre intervals for the three demand surfaces in each case study. The location-allocation models used in this study are described as follows:

3.5.1 The MI model

The MI p-median model is a longstanding location-allocation model which seeks to minimise the total weighted distance aggregated over all of the supply and demand locations (Hakimi, 1964; Teitz and Bart, 1968). In terms of the operations, this model depends upon the interchange or substitution of the number of locations that are required to select the chosen and candidate locations capable of minimising the weighted distances between the supply and demand locations (Church and Sorensen, 1994). In this study, the MI model was applied with maximum distance constraints (800m) in order to identify a different subset of facilities in each demand surface across the case study. The p-median problem with maximum distance constraints was applied in a number of previous studies (Toregas et al., 1971; Khumawla, 1973; Hillsman and Rushton, 1975; Rahman and Smith, 1991; Chaudhry et al., 1995; Algharib, 2011).

The objective function of this model, as has been described by Teitz and Bart (1968) and written in Cromley and McLafferty (2002) and it can be specified as:

The objective function of this model IS to:

$$\text{Minimise } Z = \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \qquad \textit{Equation } (8)$$

Given the following constraints:

1) A facility has to be allotted with a separate demand site: $x_{ij} \leq x_{jj}$ for all (i, j)

2) An open facility must be allotted a demand:

$$\sum_{j \in J} x_{ij} = 1 \text{ for all } i \qquad \textit{Equation } (9)$$

3) Only the p facilities are to be located:

$$\sum_{j \in J} x_{jj} = p \text{ for all } j \qquad \textit{Equation } (10)$$

4) The sum of the LSOAs or neighbourhoods assigned to them equals the number of facilities to be located.

The total demand from a separate demand site is given as:

$x_{ij} = (0, 1)$ for all (i, j) is allotted to only one facility, where:

Z = objective function;

I = all the demand areas where the nodes on the network along the subscript i are an index signifying a specific demand area;

J = the collection of candidate facility sites when the nodes on the network along with the subscript j are frequently an index which signifies a particular facility site;

a_i = the number of people who are present at the demand site i;

d_{ij} denotes the distance in terms of the travel cost and separates place i from candidate facility site j; but

$d_{ij} \leq 800m$;

x_{ij} is equal to 1 when demand at place i is allotted to a facility opened at site j, or is equal to 0 when the demand at place i is not allotted to that site; and

p = the number of facilities that need to be located.

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3.5.1.1 Implementation of the MI model

The MI model was applied in order to select different subsets of facilities in each demand surface for each of the case studies, using ArcInfo. The results were calculated and displayed for each subset of facilities over the demand surfaces, which resulted from the use of areal interpolation techniques.

3.5.2 The MC model

The MC model aims to maximise coverage for the number of possible demand points within a certain distance or travel time (Church and ReVelle, 1974; ReVelle and Hogan, 1989b; Spaulding and Cromley, 2007; Murawski and Church, 2009). This model is considered to be appropriate when there are a small number of suppliers and it is necessary to cover maximum demand in an area (Church and Murray, 2009; Gu et al., 2010). Thus, the operations of the MC model are different to those of the MF model. In terms of facility selections, the MC model does not minimise the number of facilities needed to serve all the demand points over a certain distance or time, as was the case with the MF model. However, the MC model provides solutions to cover the largest possible area of demand according to certain distance requirements, or the time elapsed between supply and demand.

The objective function of the MC model has been written in a number of studies (Church and ReVelle, 1974; Cromley and McLafferty, 2002; Murawski and Church, 2009), as follows:

$$\text{Minimise } Z = \sum_{i \in I} a_i y_i \qquad Equation\ (11)$$

S.T

$$\sum_{j \in N_i} x_j + y_i \geq 1 \text{ for all } i \in I \qquad Equation\ (12)$$

$$\sum_{j \in J} x_j = p \qquad Equation\ (13)$$

$$x_j = (0, 1) \text{ for all } j \in J$$

$$y_i = (0, 1) \text{ for all } i \in I$$

When:

Z = objective function;
I denotes the set of demand nodes;
J is the collection of the facility sites;
S signifies the distance; when it is past the demand point it is thought to be uncovered (you can select a value of S as per your choice for each demand point);
d_{ij} specifies the shortest distance amid the node i and the node j;
x_j = 1 when the facility is assigned to the site j, or 0 when the facility is not assigned to the site j;
$N_i = \{ j \in J \mid d_{ij} \leq 800m \}$;
a_i specifies the population which is to be serviced at the demand node i;
y_i= 1 when demand is fulfilled at the site i, or 0 if it is not fulfilled;
p refers to the total facilities that are to be located.

3.5.2.1 Implementation of the MC model

The MC model was applied in order to select different subsets of facilities in each demand surface across the case study using ArcInfo 10. The results were calculated and displayed for each subset of facilities over the demand surfaces which resulted from the use of areal interpolation techniques.

3.5.3 The MF model

The MF model seeks to minimise the number of facilities that cover or serve all demand within a certain distance or travel time (Toregas et al., 1971; Daskin and Stern, 1981; Schilling et al., 1993; ReVelle and Hogan, 1989a; Church and Murray, 2009; Straitiff and Cromley, 2010 and Algharib, 2011). This model has been used and developed by many authors to study service locations, (for example Toregas and ReVelle, 1973; ReVelle and Hogan, 1989a; Marianov and ReVelle, 1994; Rajagopalan et al. 2008). This model differed from others that seek to optimally fit a set number of facilities to a demand surface in that it identified the number of facilities needed to satisfy a particular distance constraint. The MF model was similar to the MC model in terms of handling or allocating the demand points, but differed in terms of the number of facilities allocated depending on the distance used. It can be written (Schilling et al., 1993; Cromley and McLafferty, 2002) as follows:
The objective function of this model is to:

$$\text{Minimise } Z = \sum_{j \in J} x_j \qquad Equation\ (14)$$

The range of an individual demand site has to be either the critical service distance or the time to at least one open facility site.

$$\sum_{j \in N_i} x_j \geq 1 \text{ for all } i \qquad Equation\ (15)$$

A candidate facility site has to be closed or open: $x_j = (0, 1)$ for all j

Were:

Z denotes the objective function;

I specifies the collection of demand areas which are mostly nodes on a network, plus the subscript i is an index that reports a specific demand area;

J identifies the collection of candidate facilities which are mostly nodes on a network, plus the subscript j is an index that indicates a specific facility site;

x_j takes the value 1 in a situation where a facility is opened at candidate site j, otherwise its value will be 0 with the facility unopened at candidate site j;

N_i represents the collection of facilities when the distance between demand site i and candidate facility site j is less than the critical distance or time, or $d_{ij} \leq s$;

d_{ij} refers to the distance between the demand site i and the candidate facility site j, but in this study the distance was specified as:

$d_{ij} \leq$ 600 to 1000 metres at 50 metre intervals; and

s is the symbol of important service response time or the distance.

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3.5.3.1 Implementation of the MF model

The MF model was applied in order to select different subsets of facilities for each demand surface across the case study areas, using ArcInfo 10. The results were calculated and displayed for each distance over the demand surfaces that resulted from the use of the areal interpolation techniques.

3.5.4 The MA model

The MA model aims to maximise the attendance of the demand within the distances used and travel time. The demand weight for each demand point is partially allocated in those areas that are close to the majority of demand (Holmes et al., 1972 and Algharib, 2011). This is another kind of coverage problem and is different to that for previous models. The main difference in the MA model is that it covers a ratio of the demand weight for each demand point and does not provide complete coverage. It was helpful to investigate the results of this model when applying different demand surfaces in the case studies. The objective function of this model was written by Holmes et al. (1972) as follows:

$$Z = \sum_{i=0}^{n}\sum_{j=0}^{n} a_i\left(S - d_{ij}\right) x_{ij} \qquad Equation\ (16)$$

Suppose that the demand or need exists in the *i*th areal unit, then $i = 1, 2\ldots n$ is usually symbolised as the total number of people;

Suppose d_{ij}, j = 1, 2... n, specifies the distance between the areal units i and j, an appropriate metric is required to measure it;

S signifies the threshold distance; in this study $d_{ij} \leq 800m$.

The variables used to make choices are as follows (when the variables are n^2 in number):

x_{ij} = 0 when the areal unit i is not attended by a facility in j;

$0 < d_{ij} \leq 1$ when the areal unit i is attended by a facility in j.

3.5.4.1 Implementation of the MA model

The MA model was applied using ArcInfo 10, in order to select different subsets of facilities at each demand surface, across the case studies. The results were calculated and displayed for each subset of facilities over the demand surfaces, which resulted from the use of the areal interpolation techniques.

3.5.5 Multiple the GPs location

When there are multiple GPs in one location, the location allocation models used in this study will consider those GPs as all representing a single location. In fact, this is one of the disadvantages of these models. Other location allocation models, such as Maximize Capacitated Coverage can overcome this disadvantage by selecting the limited number of people located for each GP.

3.6 The statistical analysis

This study used the Chi-square test to detect the statistically significant differences between the results of sensitivity demand selection for the interaction of each location-allocation model with the three demand surfaces. The Chi-square test was applied using GraphPad Prism 6 software.

3.7 Summary

Three areal interpolation techniques and four location-allocation models were selected in order to explore the interactions between the location-allocation models and the different surfaces resulting from the use of the areal interpolation techniques. These were chosen in order to explore the impact of the inherent assumptions for the use of the results of the three areal interpolation techniques on the objective function and operation of each of the location-allocation model when applied to different case studies with different characteristics in terms of the degree of homogeneousness and heterogeneous distribution of the population in the census area, census area size, the land use and the numbers of facilities. Efficient and informed public and health planning strategies are important but are particularly difficult to implement in countries that lack spatially detailed census data. Therefore, the study of these interactions between the models and different demand surfaces provides the scientific rationale for this work.

Chapter Four: Results of Areal Interpolation Techniques

4.1 Introduction

The overall aim of this research was to consider the effects of the interactions of different areal interpolation techniques with different location-allocation models and identify lessons that could be learnt from their analysis. In order to achieve this aim, the study applied three areal interpolation techniques; Areal Weighting (AW), Pycnophylactic (Pycno) and Dasymetric (Dasy) methods. These methods have been previously utilised and commentated on in many studies (see for example Tobler (1979) Goodchild and Lam (1980), Lam (1983), Martin (1989), Langford et al., (1991), Fisher and Langford (1995), Langford (2006), Mennis (2003), Comber et al. (2008) and Kim and Yao, (2010)). The three different methods incorporate their own unique estimations that can be associated with their different assumptions. For example, the AW method assumes that the population distribution is homogeneous within the areas that overlap between a source zone and target areas (Lam, 1983; Hawley, 2005; Hawley and Moellering, 2005; Brindley et al., 2005; Cromley et al., 2009 and Qiu et al., 2012). In contrast, the Pycno method relies on heterogeneous estimations for the population within the target areas, adjusting the smooth density function based on volume-preserving for source zones. The Dasy method uses ancillary data, acquired from supervised classifications for satellite images. Therefore, it relies on more realistic information as regards population location within target areas and so is able to estimate the population based on known populated regions of the target area only. These differences in the assumptions made by the three areal interpolation techniques deliver different population estimations based on the spatial characteristics of a specific problem, as demonstrated in each case study.

The three areal interpolation techniques were applied to three case study sites: Leicester, Buraydah and Unayzah. The source zones represented the Lower Super Output Areas (LSOAs) in Leicester and the neighbourhoods in Buraydah and Unayzah. The target areas were represented by a specified grid cell size (90-metres) inside each of the LSOAs, or neighbourhoods. The methodology chapter has described the implementation of each areal interpolation technique.

The aim was to estimate the total population of each of the LSOAs, or neighbourhoods, within the 90-metre grid cell. Then, subsequently to use centroid points for each grid cell based on the data obtained from each of the three methods in order to identify demand points to analyse the interactions of different areal interpolation techniques with different location allocation models.

There are many tests that can be used to validate the accuracy of results for areal interpolation techniques, for example; the Root Mean Square Error and R squared. These tests can provide information about the error rates between the variables being tested; in this case comparing the actual population with the estimated population. However, the study did not apply these tests, due to the use of the 90-metre grid cell size as there was no population data for these grids for any of the locations.

The chapter proceeds as follows: the results of the areal interpolation techniques are presented in Section 4.2. Section 4.2.1 provides the results of the AW methods. Section 4.2.2 provides the results of the Pycno methods and Section 4.2.3 presents the results of the Dasy methods. An example of the calculations made using three areal interpolation techniques is presented in Section 4.2.4. Results showing the differences between the findings of all three methods are presented in Section 4.3. Section 4.3.1 provides the results showing the differences between the three methods when used in Leicester. Section 4.3.2 provides the results of the differences in the three methods when used in Buraydah. Section 4.3.3 provides the results of the differences in the three methods when used in Unayzah. Finally, Section 4.4 provides a summary in light of the results from the three areal interpolation techniques for all three case studies.

4.2 Results of the Areal Interpolation Techniques

The techniques that were applied related to the AW method from Lam (1983); the Pycno method from Tobler (1979) and the Dasy method which has been used by many authors.

4.2.1 Results of the AW method

The AW method was applied to estimate the population of source zones for all the case studies to the target areas which were a grid with a cell size of 90-metres inside the LSOAs or neighbourhoods. This technique estimated the population of LSOAs and neighbourhoods in a homogeneous form within the target areas. Figure 4.1 shows the results of the AW method with regards to the three case studies. Through the results of the AW method the homogeneous distribution for the population within the target areas was clear from the adoption of this method. The study noted that there was an increase in the estimated population in the target areas of Leicester (up to 253 people) inside some of the target areas. In contrast, there was about 129 and 44 people in some of the target areas for Buraydah and Unayzah. This was due to the small areas for the source zones in Leicester and the large areas for the source zones in Buraydah and Unayzah. The assumptions of the AW method, the LSOAs or neighbourhood area sizes and the population densities are key factors which affect the weight of the population estimations inside each target area.

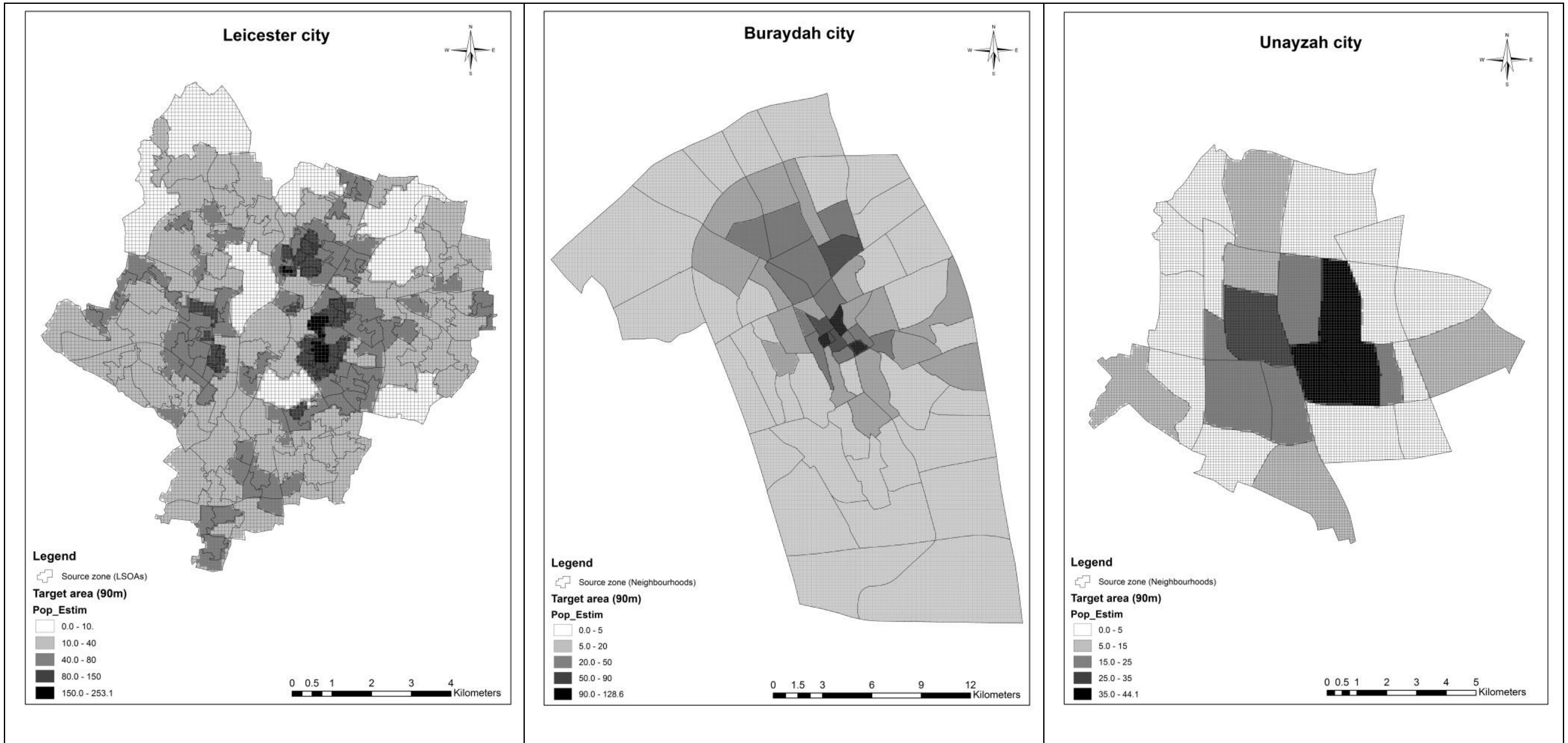


Figure 4.1: Results of the AW method on the three case studies. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

4.2.2 Results of the Pycno method

This technique has estimated the population of neighbourhoods and LSOAs based on Tobler's method (1979). The Pycno method provides estimates of the target area with the assumption of the smooth density function in order to determine the volume-preserving property (Kim and Yao, 2010). Thus this technique provides a heterogeneous estimation for the target areas with the volume-preserving for the LSOAs and neighbourhoods borders. Figure 4.2 shows the results of applying the Pycno method on the case studies.

From the results of the Pycno method the study noted that there was a smooth and gradual density for the population density in the target areas which started from some of the LSOAs and neighbourhoods which had high population densities in the middle and some parts of the city and gradually decreased to the parties. The high population density for some neighbourhoods in the middle of Buraydah and Unayzah led to the gradual population density for the target areas and tended to be these neighbourhoods and smoothly decreased to the neighbourhoods which had low population densities in parts of those cities (see Figure 4.2). Also, the large areas in the source zones in Buraydah and Unayzah had an effect on the results of target areas for these cities.

In contrast, with the homogeneous distribution for the population of LSOAs in Leicester, the study noted that the results of smooth and gradual population density for the target areas were distributed to all the areas of the city. Compared to the AW method, the study noted that there was an increase in the estimated population (up to about 341 people) inside some of the target areas in Leicester. Additionally, in Buraydah and Unayzah there was about 170 and 66 people in some of the target areas. Generally, it can be argued that the Pycno method may be closer to the representation of the population with greater accurately than the AW method; because it was unacceptable that the population was distributed homogeneously in any geographic area as happens with the AW method. Thus, the Pycno method overcomes the weakness of the spatial aspects and the adoption of the AW technique to estimate the population in a homogeneous form within the target area.

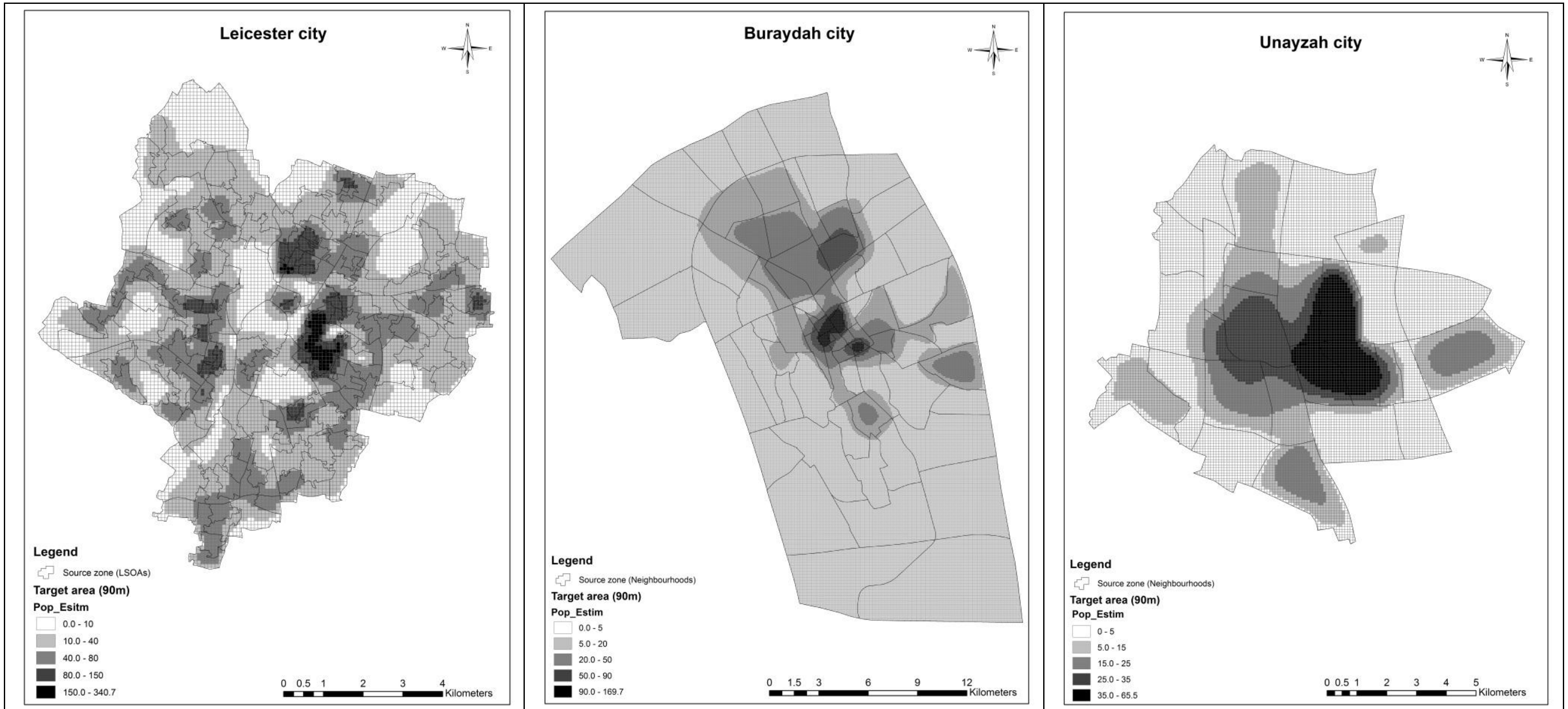


Figure 4.2: Results of the Pycno method on the three case studies. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

4.2.3 Results of the Dasy method

This technique classified satellite images to identify the extent of the urban areas in order to estimate the population of source zones to those areas as has been used by many other authors. Figure 4.3 shows the results of applying the Dasy method on the three case studies. The adoption of the Dasy method using the ancillary information through the use of satellite images helped this technique to provide more realistic data in order to estimate the population in the targeted areas. The results in the figure represent the total population for all the pixels inside each target area. More details for the supervised classification for the three case studies are available in Appendix 1 (see Figures 1.1 to 1.3).

The results showed that there were relatively heterogeneous distributions for the estimated population in the target areas for each case study. Additionally, the study noted that there were concentrations for the majority of the estimated population in the target areas in central of Buraydah and some parts of Unayzah. However, in Leicester there was a wide distribution for the estimated population in the target areas which covered most parts of the city. This was due to the assumptions of the Dasy method which depend on the use of satellite imagery to estimate the population to the artificial and built areas and the exclusion of all other areas that may have been included in the estimated population for the other two methods.

The study also noted that there was an increase in the estimated population in the target areas of Buraydah and Unayzah, up to about 364 people inside some of the target areas compared to AW and Pycno surfaces in Buraydah, and up to about 61 people inside some of the target areas compared to AW surface in Unayzah. These increasing numbers in the weight of the target areas were because in some cases there were large areas for the source zones with a high population density and in contrast there were limited artificial and built areas within some of those zones. Here the effectiveness of the Dasy method can be noted in these kinds of case studies compared to the other two methods. However, if there are wide areas for artificial and built areas inside the source zones, the role of the Dasy method will be less effective. The existence of the large areas of source zones with a smaller population, especially in the suburbs of cities, is a situation which may affect the results of the population estimation for these zones in Buraydah. However, the assumptions of the Dasy method helped this technique to provide the spatial information for the sites of population inside the target areas through the use of remote sensing data.

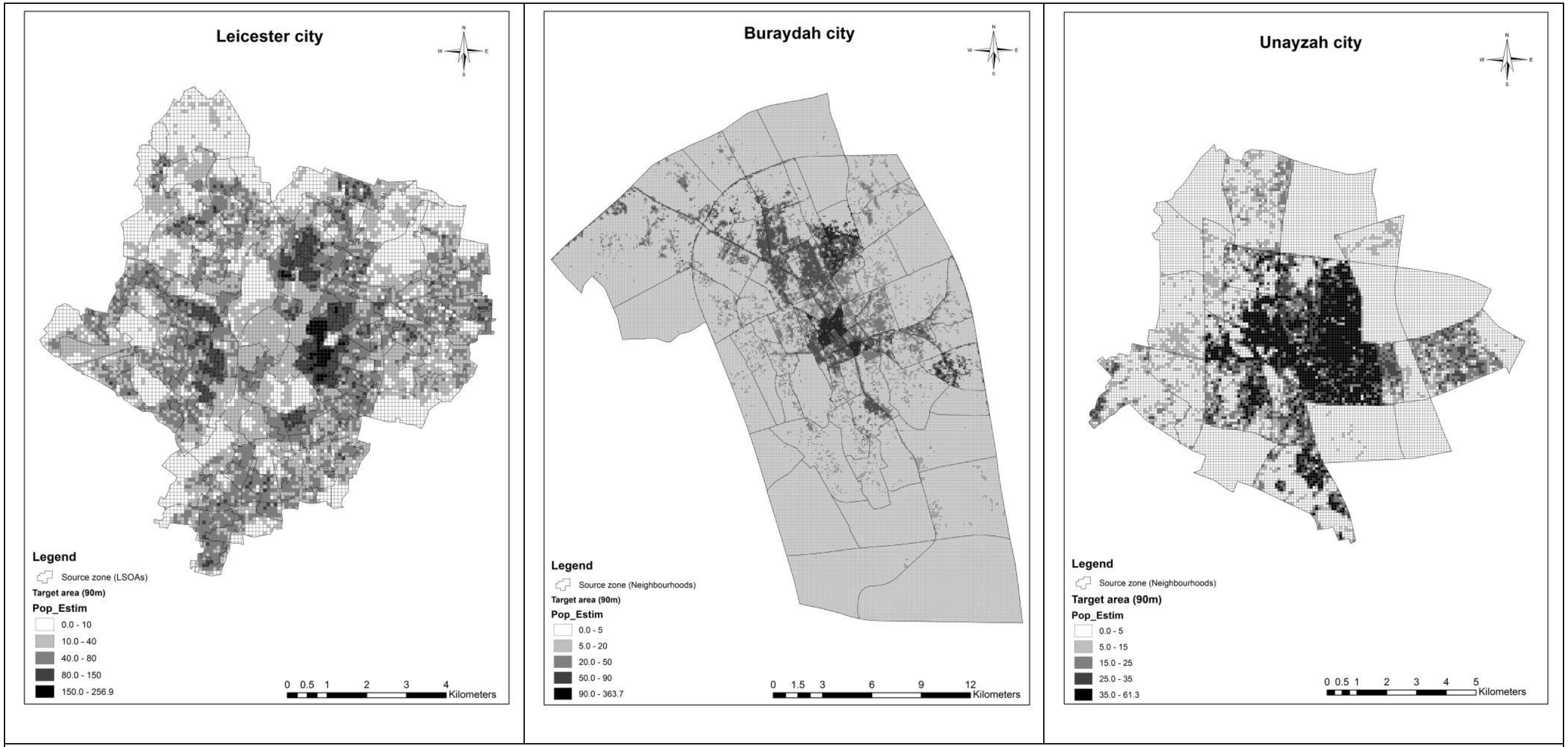
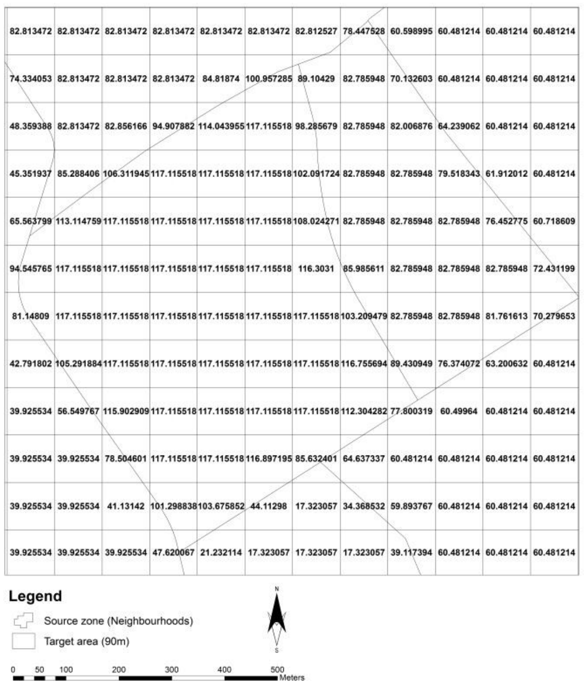


Figure 4.3: Results of the Dasy method on the three case studies. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

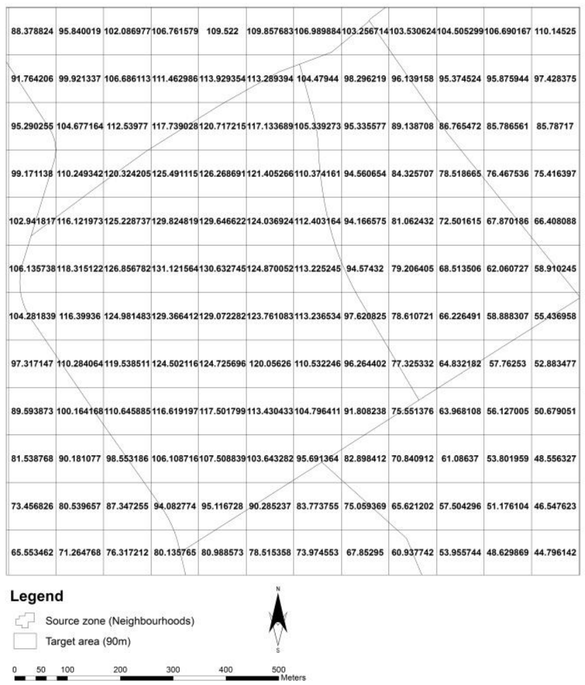
4.2.4 An example of the calculations made using three areal interpolation techniques

This study provides examples of the calculations made when applying the three areal interpolation techniques in order to estimate the population to the target areas in one case study. Figure 4.4 shows the results when applying the three areal interpolation techniques to two polygons in the middle of Buraydah city. The results reflect the role played by assumptions for each areal interpolation technique when estimating the population within the target area. For example, the AW method concerns the homogeneous distribution of the population within the target area, as was evident in the target areas inside the two polygons in Figure 4.4. In contrast, the assumption of a smooth density function for the Pycno method played a clear role in the creation of heterogeneous estimations for the target areas within the two polygons.

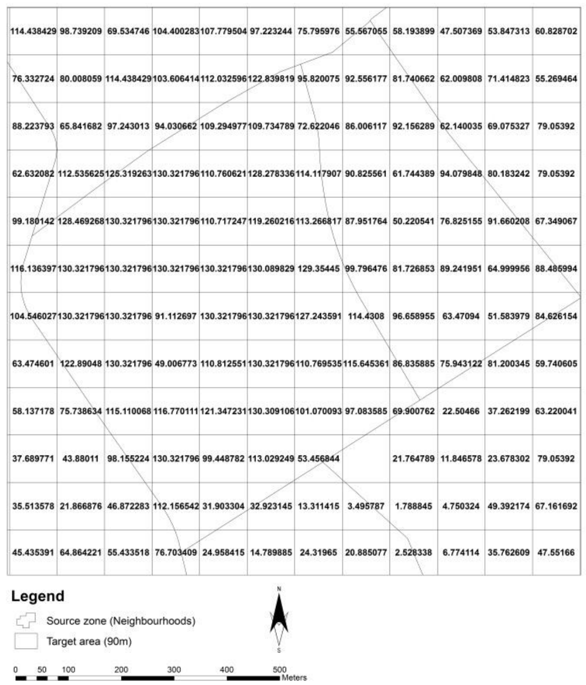
The use of ancillary information for the Dasy method produced relatively heterogeneous distributions for target areas within the two source zones. This depends on the populated or built-up areas within each source zone. Figure 4.4 shows large populated areas in the middle of Buraydah. In this case, there were no empty spaces within the two source zones; although, the differences in population estimation results between the target areas were dependent on the size of the built-up areas within each target area.



a) AW



b) Pycno



c) Dasy

Figure 4.4: An example of the calculations made using three areal interpolation techniques in two polygons in the middle of Buraydah city.

4.3 Results of the differences between the three methods

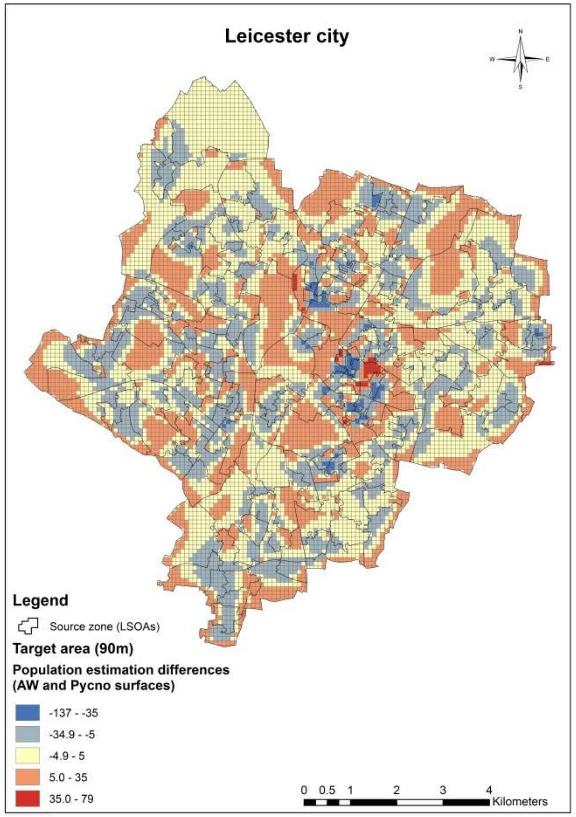
This section presents the differences in the population estimation results for the three methods within the target areas in each case study. The objective in mapping the differences between the three methods for each case study was to calculate the differences in the weights of population estimations for each grid cell between the methods within the target areas. Thus, the study first calculated the differences between the AW and Pycno methods; second, the differences between the AW and Dasy methods; and finally, the differences between the Pycno and Dasy methods. The results illustrate clear differences between the findings using the three methods in each case study, especially in the central areas of the KSA case studies and some parts of the Leicester area. These results are presented in the next sections.

4.3.1 Results of the differences between the three methods in Leicester

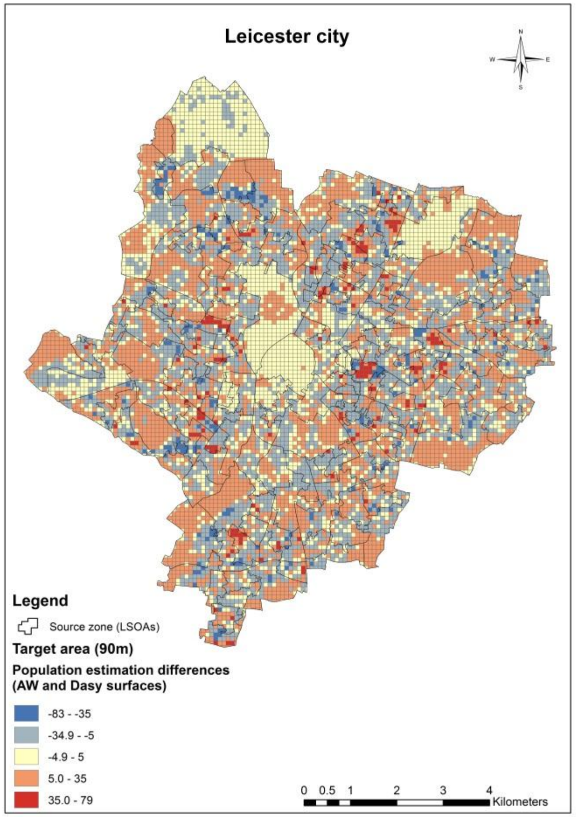
The results when mapping the differences between the three surfaces in Leicester show that there were clear differences between the AW when compared to Pycno and Dasy surfaces; also in the Pycno surface when compared to the Dasy surface (see Figure 4.4). For example when the study compared the weights of population estimation for each grid cell between the AW surface and the Pycno surface there were clear differences between the two surfaces in the centre of Leicester and other parts of the city (see the blue, light blue, orange and the red colours in Figure 4.5a). This was due to the different assumptions made by the two methods in terms of homogeneous estimations for AW method and heterogeneous estimations for the population within the target areas requiring the smooth density function in the Pycno method.

The results also showed that there were clear differences in population estimation between the AW surface and the Dasy surface (see Figure 4.5b). Different weights of population estimations for each grid cell between the two surfaces were clear in most parts of the city, except for in central Leicester (see the blue, light blue, orange and the red colours in Figure 4.5b). This was due to the use of the ancillary data, which provides the Dasy method with more realistic information on for the populated areas which to base population estimates.

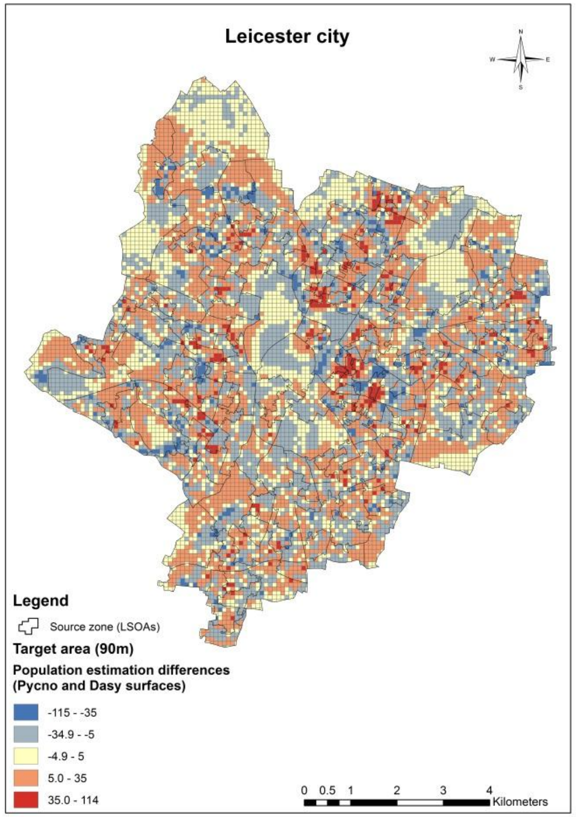
Additionally, the different assumptions for the Dasy and Pycno methods are as described above, and produced different weights of the population estimations results within the target areas (see Figure 4.4c, the results of comparing Pycno and Dasy surfaces). There were clear differences between the two methods, which were represented by significantly different numbers within the target areas, as shown in the blue, light blue, orange and red colours in Figure 4.5c.



a) AW surface when compared to Pycno surface



b) AW surface when compared to Dasy surface



c) Pycno surface when compared to Dasy surface

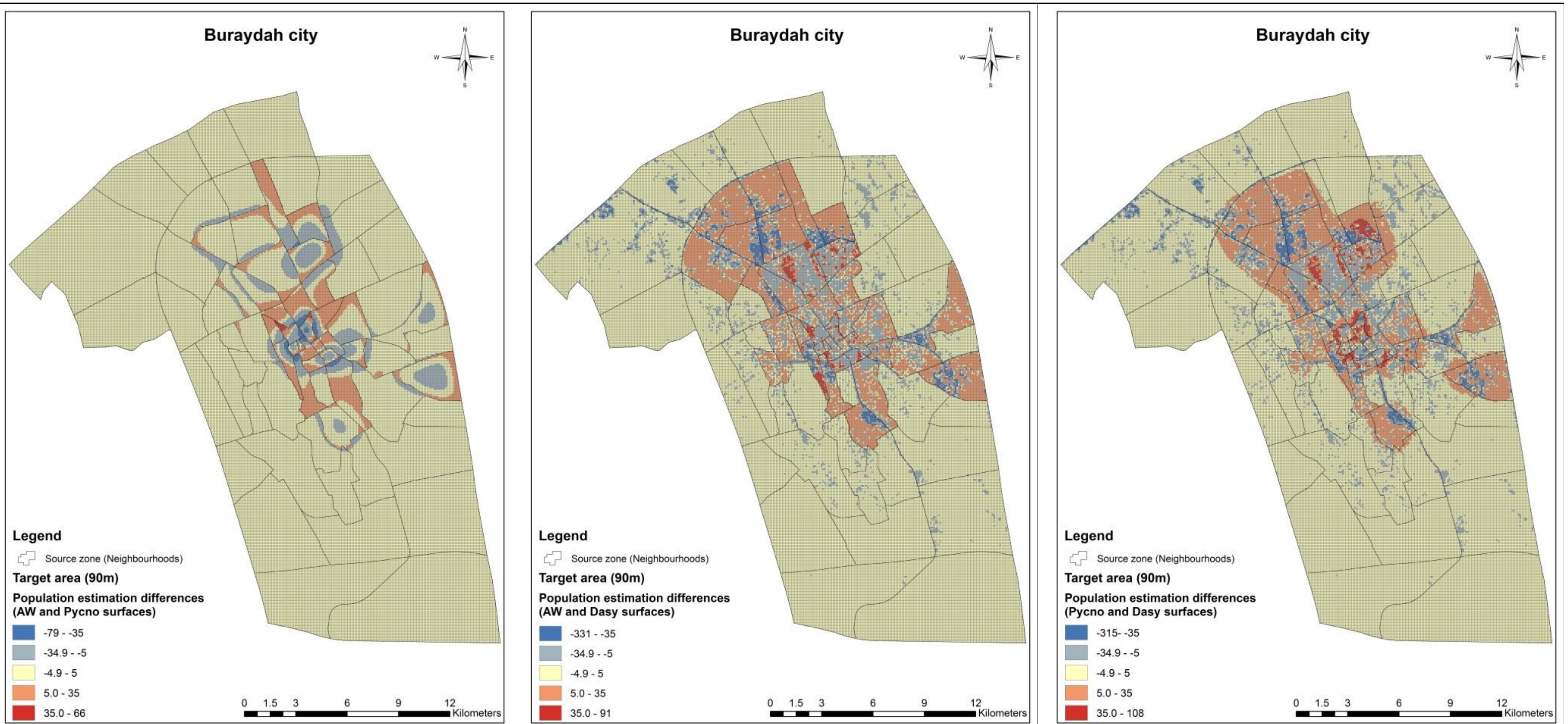
Figure 4.5: Results of mapping the differences between the three surfaces in Leicester: a) AW and Pycno surfaces; b) AW and Dasy surfaces; and c) Pycno and Dasy surfaces. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

4.3.2 Results of the differences between the three methods in Buraydah

The results of mapping the differences between the weights of population estimations for each grid cell for the three surfaces in Buraydah reveal clear differences between the AW surface and the Dasy surface, and also between the Pycno surface and the Dasy surface especially in the central region and some areas east and north of Buraydah (see Figure 4.6b and c). However, the differences were less between the AW surface when compared to the Pycno surface (see Figure 4.6a). The large area size for some of the source zones with low population densities, and the assumptions of the AW and Pycno methods, depend on providing a population estimation for all of the target areas that intersect within the source zone, reducing the difference between the two surfaces (see beige colour in Figure 4.6a).

In contrast, the benefits of using ancillary data mean that the Dasy method provides more realistic information for built-up areas, especially where there is a large area size for the source zone. It can provide different weights for population estimation results within the target areas (see the blue, light blue, orange and the red colours in Figure 4.6 b and c). The study also noted significantly different numbers between the weights of population estimations for each grid cell when comparing the Dasy with the two other surfaces (see Figure 4.6).

Mapping the differences between the three methods used in this study revealed that with the impacts of the assumptions for each areal interpolation method, as previously described, the size of the source zones and the degree of the population densities for those zones played an important role in the results. This was clear in the results for Leicester and Buraydah.



a) AW surface when compared to Pycno surface	b) AW surface when compared to Dasy surface	c) Pycno surface when compared to Dasy surface

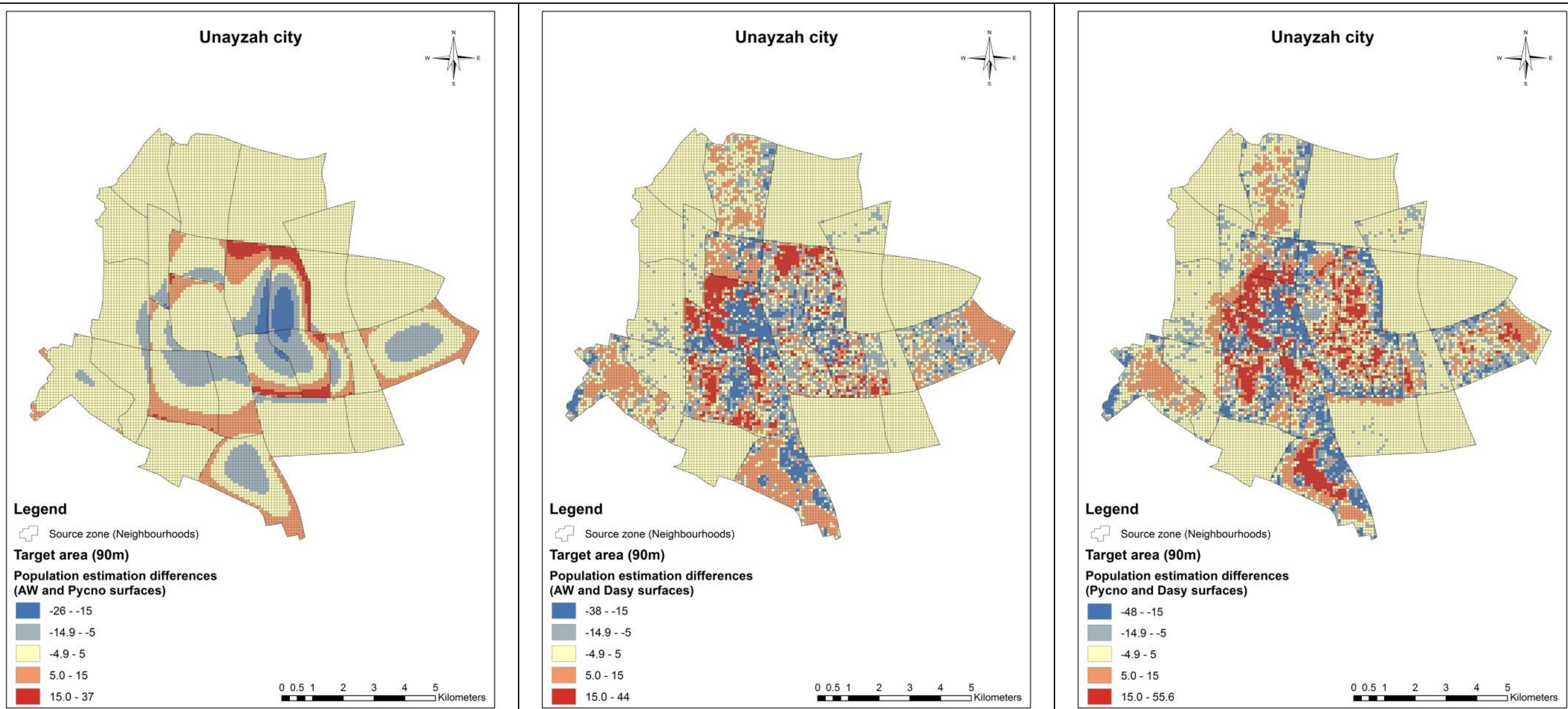
Figure 4.6: Results of mapping the differences between the three surfaces in Buraydah: a) AW and Pycno surfaces; b) AW and Dasy surfaces; and c) Pycno and Dasy surfaces.

4.3.3 Results of the differences between the three methods in Unayzah

The results when mapping the differences between the three surfaces in Unayzah, in terms of the weights of population estimations within the target areas, show clear difference, especially in those source zones with high population densities in the central, eastern, northern and southern areas of the city (see Figure 4.7). However, the study noted that the differences between the results for the AW surface and Pycno surface were less than those that originated from other comparative results, especially in the larger sized source zones with high population densities in the western parts of central Unayzah and some of those zones in the north and west of the city (see beige colour in Figure 4.7a). This was due to the adoption of AW and Pycno methods to estimate the population in all the target areas, which produced population estimation weights that were lower than when using the Dasy method.

The results also shown that the Dasy surface produced different weights of population estimations for each grid cell, when compared to the results of AW and Pycno surfaces (see the blue, light blue, orange and the red colours in Figure 4.7 b and c). Additionally, the degree of differences for the Dasy surface, when compared to Pycno surface, was greater than for the AW surface. This was due to assumptions of heterogeneous estimations with the effect of neighbours for the Pycno surface and high weightings for the population estimations for populated areas only arising from the Dasy surface.

By mapping the differences for the three case studies, it was demonstrated that the differences between AW and Pycno surfaces will be lessened if the size of the source zone is large and the population density for the zone low. However, in a similar situation, if the size of the source zone is large and the population density for this zone was low, then the Dasy surface will produce different estimation results when compared to AW or Pycno surfaces.



a) AW surface when compared to Pycno surface	b) AW surface when compared to Dasy surface	c) Pycno surface when compared to Dasy surface

Figure 4.7: Results of mapping the differences between the three surfaces in Unayzah: a) AW and Pycno surfaces; b) AW and Dasy surfaces; and c) Pycno and Dasy surfaces.

4.4 Summary

Three areal interpolation techniques were applied to three case studies in order to estimate the population of the source zones in the target areas. The results revealed that there were different distributions of population estimation results for the target areas, based on the assumptions made by each technique. However, there were additional spatial factors which affected the differences in results for each case study. For example in Leicester, because there was homogeneity in the population density for the source zones and small areas and larger built up areas throughout most of the source zones in some parts of the city, the weights of population estimations for each target area differed less between the AW and Dasy methods when compared with the other case studies. In contrast, the Pycno method produced a number of differing results in terms of the weights of estimated population for the target areas; this was due to the heterogeneous estimation for the target areas, combined with the volume-preserving for the LSOAs (see Figures 4.1 to 4.3).

In Buraydah and Unayzah, the different distributions of population estimation results between the three techniques within the target areas were very clear, for a number of different reasons. Firstly, as a consequence of the assumptions previously made for each technique. Secondly, because of the great disparities in population densities and the larger areas in the source zones. Finally, because of the limited artificial and built areas within the source zones. These reasons contributed to the differences between the three techniques in terms of the population density in each target area (see Figures 4.1 to 4.3). Additionally, these led in some cases to double the population figures for some of the target areas in Buraydah when contrasting the results of the AW with the Dasy method.

The different assumptions between the techniques used, in terms of the homogeneous distributions for the AW method, the heterogeneous distribution for Pycno method and the use of the ancillary data for Dasy method, played an important role in producing the population estimations for the target areas. Thus, the results of mapping the differences between the three surfaces in terms of the weights of population estimation for each target area in Leicester, Buraydah and Unayzah have revealed that clear differences between the AW when compared to Pycno and Dasy surfaces, and the Pycno surface when compared to Dasy surface (see Figures 4.5 to 4.7). However, in Buraydah and

Unayzah the study noted that with the large size of the some of the source zones the degree of the difference between the AW surface when compared to the Pycno surface were less than those from elsewhere.

To validate these results and their accuracy, the results need to be compared with the actual population data for the target areas. However, as stated above, it was not possible to validate these results due to the use of grid cells of 90-metres. The results of the population estimations for the target areas that have been obtained in this chapter represent the demand points for facilities in the analysis of interactions for the different areal interpolation techniques using the different location-allocation models. Differences in population densities between the three techniques are the main factors leading to the creation of some of the differences in the location allocation model and the three demand surfaces.

Chapter Five: Results of Interaction between Location-Allocation Models and Areal Interpolation Techniques

5.1 Introduction

Four location-allocation models, including the Minimise Impedance p-median problem (MI), Maximise Coverage (MC), Minimise Facilities (MF) and Maximise Attendance (MA) models, were used to determine the optimal location of GPs in the UK and PHCCs in the KSA, and their results were compared. Each of the four models was applied to different population (demand) surfaces resulting from three areal interpolation techniques: areal weighting (AW), pycnophylactic (Pycno) and dasymetric (Dasy), and three case studies, in Leicester, Buraydah and Unayzah. The aim was to explore the interactions of these four models with three areal interpolation demand surfaces being used to quantify and optimise public health facility locations and their access, in order to provide a deeper understanding for these models and techniques and support the optimal facility locations. The results were used to explore the impact of inherent assumptions for the three areal interpolation techniques and the spatial characteristics of each case study on the results of population estimations for the surfaces and the results of optimal facilities selection for each location-allocation model when apply on three demand surfaces. A secondary aim was to provide a deeper understanding and advancing knowledge regarding the objective function and the operations embedded in each of the four location-allocation models when applied to the different case study characteristics and to the results of three areal interpolation techniques. Finally, the study aims to fill the gap in the literature regarding choosing a suitable interpolation surfaces to fit the characteristics of the problem and the location-allocation model.

This study applied the MI, MC, MF and MA models in all three case studies. As described in the previous chapter, the demand points representing the census data were areally interpolated to 90-metre grid cells in each study area. The facilities' points represent GPs in the UK case study and PHCCs in the KSA. There were 31 PHCC locations in Buraydah city and 15 PHCCs in Unayzah city. In Leicester, there were 66 GP locations. As discussed in the literature review and methodology chapters, the use of location-allocation models frequently depends upon use of the road networks dataset to determine the distances or times between demand points and facilities. The Services

Planning Standard Manual (2005) in the KSA stipulated that the distance between demand and PHCC should be within 800 metres. A distance of 800 metres between the demand and facilities was therefore evaluated in all three case studies.

The four location-allocation models and the parameters needed were described in the methodology chapter. However, in the results for each model, the study provided some information about the aim of the models and the parameters to be applied. Analysis of the MI, MC and MA models was applied for each case study by varying the number of facilities to be selected; this ensured that the results provided a more in-depth understanding of the sensitivity of demand selection, interactions of the three demand surfaces used and assumptions embedded in each model. In contrast, analysis of the MF model was applied using distances and sensitivity to the facility and demand selection by varying the distances used from 600 to 1000 metres at 50 metre intervals for the three demand surfaces in each case study.

Before presenting the results, the following terms used to describe them are defined below:

- **Distances**: different or specified distance limits in metres between facilities and demand points.
- **Chosen facility**: selection of a facility by the user as falling within the accessibility solution subset and the distance used.
- **Candidate facility**: a facility that has not been chosen and that may contribute to accessibility solutions within the distance used.
- **Lines**: indicate the demand points covered by the selection of facilities.
- **Covered**: the demand points (demand selection) falling within the distance used.
- **Uncovered**: the demand points falling beyond the distance used.

This chapter is structured as follows. Section 5.2 presents the interactions between the four location-allocation models and the three areal interpolation techniques. Some figures showing these interactions are presented in this chapter, while others are displayed in Appendix 2. It was found that there were similar results between the MI and MC models. This is because the MI model was applied with maximum distance constraints. Thus, Section 5.2.1 presents the results of the MI and MC models, Section 5.2.2 gives the results of the MF model and Section 5.2.3 provides the results of the MA model. Section 5.3 presents a summary in light of the interaction results between the four location-allocation models and the three areal interpolation techniques. Finally, Section 5.4 presents some generalised points arising from the results of the interactions.

5.2 Results of Interaction between Location-Allocation Models and Areal Interpolation Techniques

5.2.1 The results of the MI and MC models

The aim of the MI model is to deliver solutions that minimise the distance between facilities and demand points (Hakimi, 1964; Teitz and Bart, 1968). In this model, the analyst must select the number of facilities – namely, the GP locations (in the UK case study) and the PHCC locations (in the KSA) – and the distance used if the model is applied with maximum distance constraints. The model consequently selects the facilities chosen to minimise the distance between them and the demand points (the centroid points for the 90-metre grid cell which has been areally interpolated using three areal interpolation methods).

The aim of the MC model is to maximise the coverage for the demand for each facility within the distance specified (Church and ReVelle, 1974; ReVelle and Hogan, 1989b; Spaulding and Cromley, 2007; Murawski and Church, 2009). This model will choose GPs or PHCCs according the numbers of facilities selected and the distance of 800 metres, specified by the analyst in order to maximise coverage for the demand points.

The process involved in the MI model depends upon the interchange or substitution of the locations required to select chosen and candidate locations capable of minimising the weighted distance between the supply and demand locations (Church and Sorensen, 1994). The MC model seeks to cover the largest possible area of demand in order to maximise the coverage for that demand (Church and ReVelle, 1974; Church and Sorensen, 1994). These two models differ from the MF model which seeks to minimise the number of facilities needed to cover all demand within a certain distance or timeframe (Schilling et al., 1993). The MA model is also different, aiming to maximise attendance and allocate a ratio from the demand weight in areas that are close to the majority of demand within a certain distance or travel time (Holmes et al., 1972).

5.2.1.1 The results of the MI and MC models for Leicester

The MI and MC models were parameterised to select the best 1, 5, 10, 20, 30, 40, 50 and 60 of 66 GP locations to serve the three demand surfaces within the distance of 800 metres. In terms of facility selection, the results showed that the MI and MC models provided similar selection results between the two models (see, for example, Figures 5.1, 5.2 and 5.3 for the results of the MI and MC models which selected the best 10, 20 and 30 GPs based on the three demand surfaces within 800 metres). The remaining results for the best 1, 5 and 40 to 60 GP locations for the MI and MC models are presented in Appendix 2 (see Figures 2.1 to 2.5). The similarity between the results of the MC and MI models was due to their similar operation in terms both of minimising the total weighted distances between the GPs and demand points and of handling demand if the MI model was applied with maximum distance constraints. The following points describe the similarities between the MI and MC models in terms of operation as described in ArcInfo 10 and the methodology chapter:

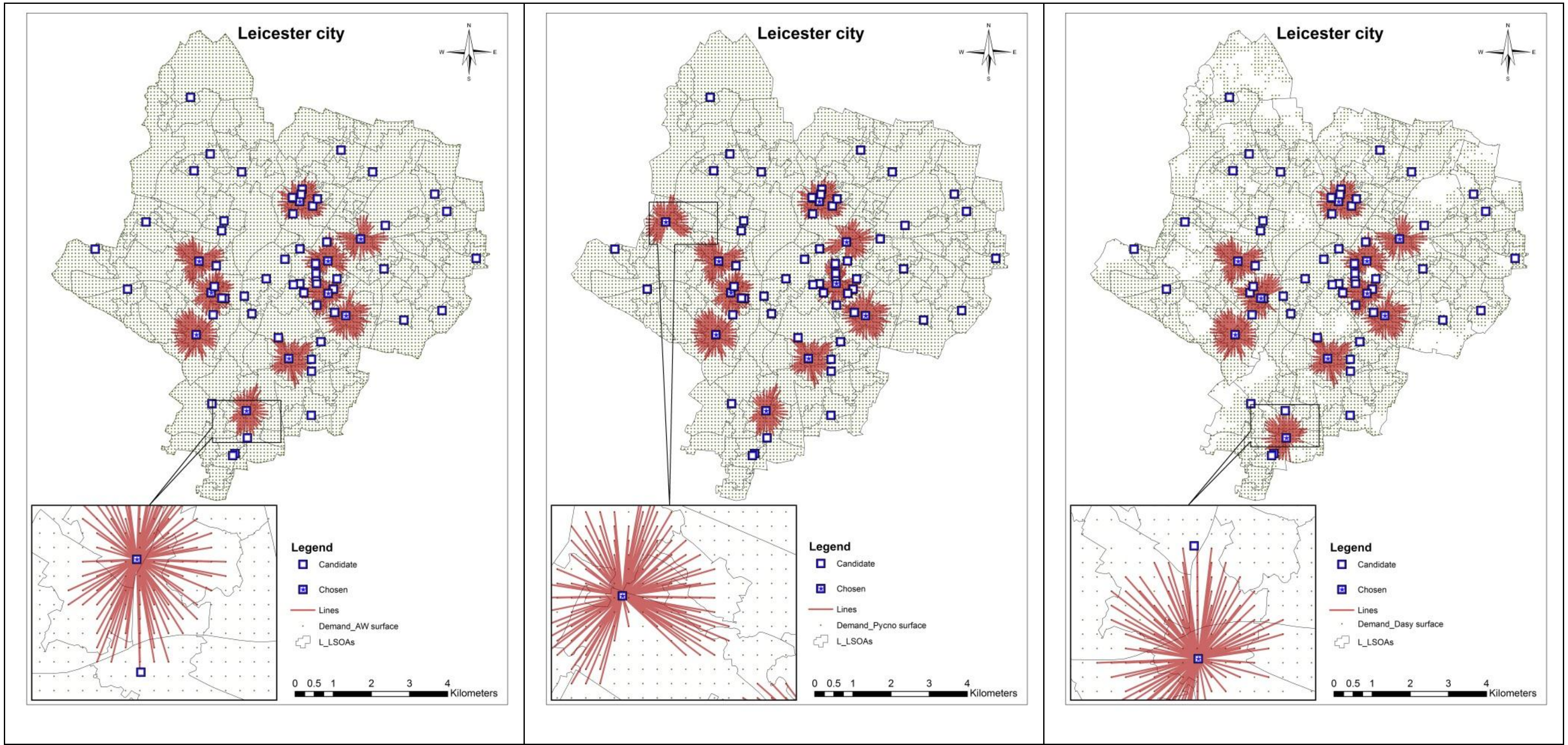
1. Within the distance used, any demand point outside the specified distance is not allocated.
2. If the demand point is within the distance used, the total weight for that demand point is allocated to one facility.
3. If the demand point is within the distance used for more than one facility, the total weight for that demand point is allocated to the nearest facility only.

As a consequence of the similarities in the assumptions of the MI and MC models, the two models results were similar in terms of facilities and demand selection.

Some of the interaction results for the MI and MC models show some differences in terms of facility selection when they were run on the three demand surfaces (see Figures 5.1, 5.2 and 5.3 for the differences in terms of facilities selection for the best 10, 20 and 30 GP locations in Leicester; see Appendix 2, Figures 2.1, 2.3 and 2.4 for the best 1, 40 and 50 GP locations). From the interaction results between the MI and MC models and the three demand surfaces, the study noted that the results of the population estimates obtained through the use of the AW, Pycno and Dasy methods had an effect on the selection of the best 1, 10, 20, 30, 40 and 50 GP locations in Leicester. These interactions resulted from the objectives functions and the operation of the two models as described above and the implicit assumptions of each technique. For example, the AW method provides a homogeneous and unified distribution for the population within the target area, while the Pycno method provides heterogeneous estimation for the population within the target areas with the smooth density function in order to determine the volume-preserving property (Lam, 1983; Kim and Yao, 2010). Meanwhile, the Dasy method relies upon areas of urban land use from a remote sensing analysis for the distribution of the population in the target area.

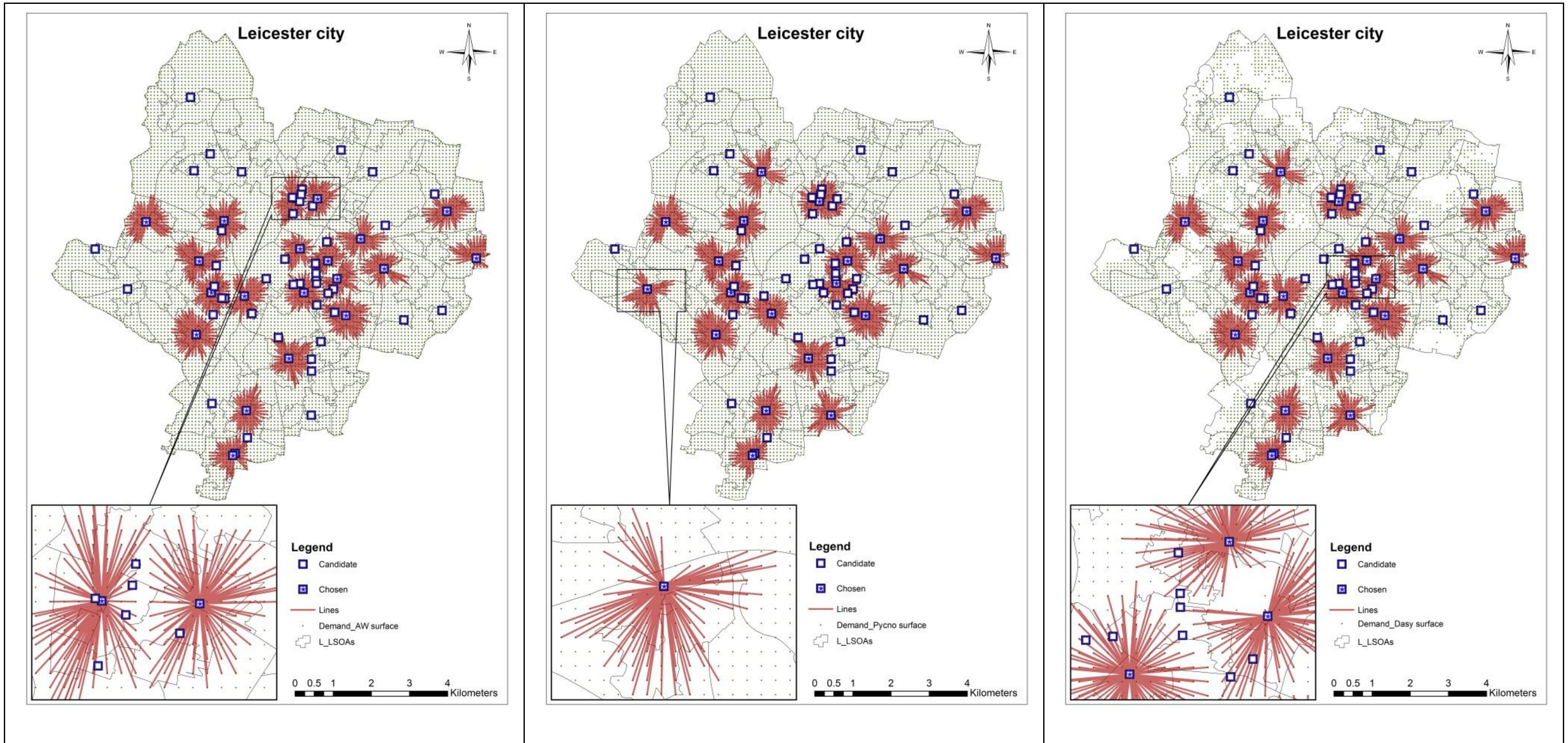
The main factor affecting the two models and the three demand surfaces is the demand weight. When the demand weight was changed based on the assumptions of each areal interpolation technique, the MI and MC models provided different facilities selections between the three demand surfaces to cover the demand needs. Some of the results of the interactions depicted in Figure 5.1 suggest that the Pycno surface produced some different facility selections for the AW and Dasy surfaces (see the two new facilities selections in the central and west of Leicester in Figure 5.1). There were also some differences in the facilities selection when the MI and MC models were run to select the best 20 and 30 GP locations on the three demand surfaces (see Figures 5.2 and 5.3 the differences in facilities selection results in the north, south, central, east and west of Leicester). Different facilities selection results were obtained for the best 40 and 50 GP locations (see Figures 2.3 and 2.4 in Appendix 2).

In contrast, some other results for MI and MC models identified similar facilities selections between AW and Dasy surfaces (see the best 1 GP location in Figure 2.1 in Appendix 2). Also, there were similar facilities selections between the three demand surfaces (see the best 5 and 60 GP locations in Figures 2.2 and 2.5 in Appendix 2). It is to be expected that the differences in determining the best GP locations were not very clear. This is firstly due to the differences in the population estimations for each surface, which were within the boundaries of the LSOAs only and secondly, due to the adoption of the MI and MC models to minimise the distances and allocate the GPs based on demand weight within the areas of high population density for LSOAs. Whilst the high population densities were the same between the three demand surfaces, there were differences between the demand weights for each point inside the LSOAs.



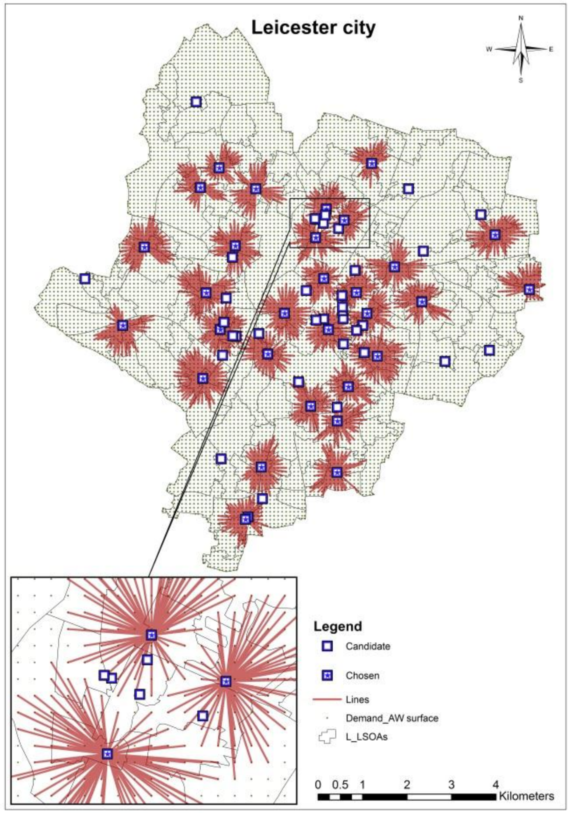
a) AW	b) Pycno	c) Dasy

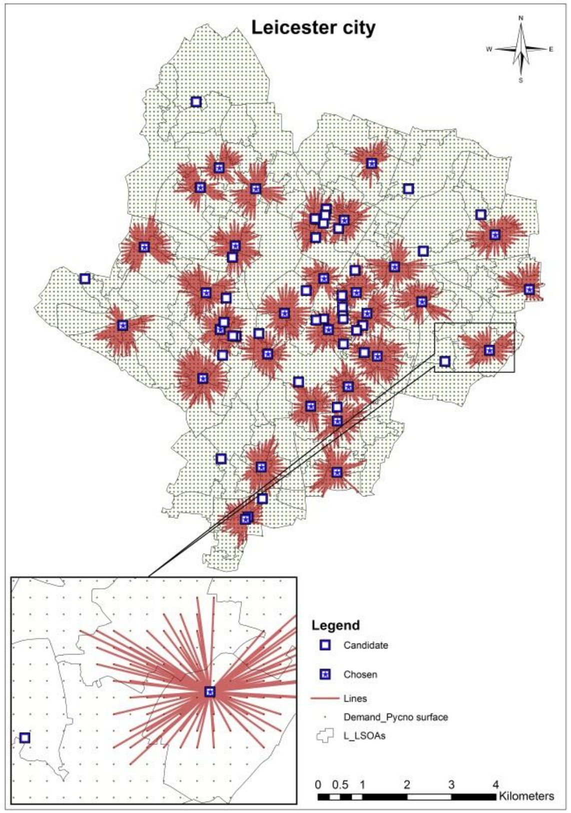
Figure 5.1: Results of applying the MI and MC models in Leicester to select the best 10 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

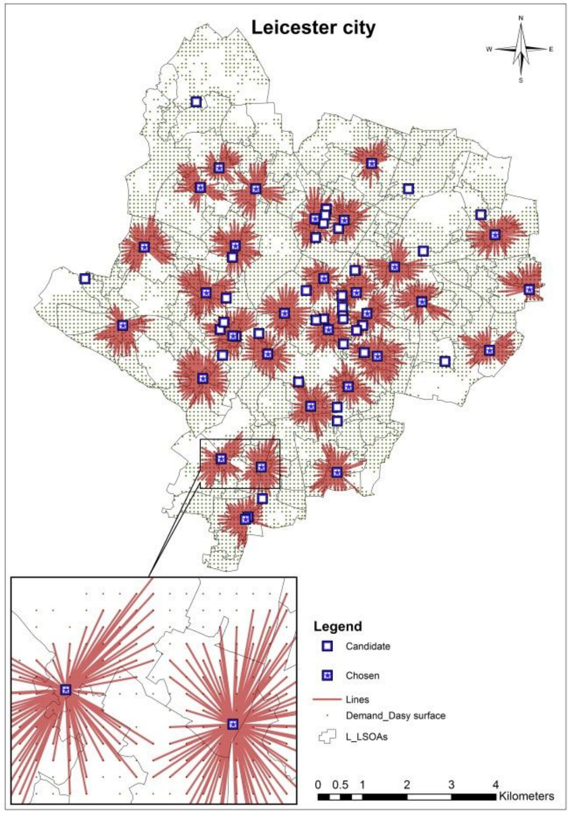


a) AW	b) Pycno	c) Dasy

Figure 5.2: Results of applying the MI and MC models in Leicester to select the best 20 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.







a) AW	b) Pycno	c) Dasy

Figure 5.3: Results of applying the MI and MC models in Leicester to select the best 30 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

In terms of demand selection, the MI and MC models also provided similar results. This was dependent upon the number of GP facilities to be chosen from the total to serve the demand points for each surface within the distance of 800 metres (see Figure 5.4). This was due to the similarity between the operation of the MI and MC models in handling the demand points, as described above. However, the results of the interactions between the MI and MC models and the three demand surfaces from the areal interpolation techniques were different in Leicester, in terms of serving the weight of the demand for each point. The results for the MI and MC models show that the Pycno surface provided better performance in terms of geographical coverage for the weight of demand in the best 1, 5, 10 and 20 GP locations, of the three surfaces when covering demand within 800 metres (see the points indicated in blue in Figure 5.4). The Dasy surface also provided better performance in terms of geographical coverage for the best 30, 40, 50, 60 and 66 GP locations (see the points indicated in green in Figure 5.4). In contrast, the AW surface achieved the worst results (see the red points in Figure 5.4).

It may be noted that there was substantial convergence between the three demand surfaces in terms of the size of the geographical coverage in determining the best 1, 5 and 10 GP locations (see Figure 5.4). However, this convergence gradually decreased as the number of facilities selected increased. The facilities are mainly distributed in areas close to centres of population and the Pycno method of estimating the population is gradual, heterogeneous and close to the LSOAs border, which have a high population density: these factors may impact on the results of the demand selection size for this technique in determining the best 1 to 20 GP locations. However, the assumptions of the Dasy surface depended upon the use of remote sensing data to select the built up areas, (then estimating the population only in those areas) and this had an effect on the performance in terms of demand selection in determining the best 30 to 66 GP locations. From the results of the MI and MC models, it may also be noted that there was saturation, with a small increase in the weight of the demand occurring upon selecting the best 50, 60 and 66 GP locations for the three surfaces (see Figure 5.4). It may be argued that the large number of GPs, and the short distances between them, may have affected the weight of the demand selection for the MI and MC models.

The interaction results provided some different solutions for the MI and MC models when applied to the three demand surfaces. The main aim of the location-allocation models is to minimise distances and cover demand needs. Thus, the interaction results show that the Dasy surfaces achieved the best geographical coverage for the weight of the demand when the models were run to select 30 or more facilities that were distributed in all parts of the city, there being many empty spaces in terms of population (built up areas) in the north, east and west of Leicester. In this case, the Dasy surface might be considered the best surface to select the facilities and allocate the demand points when there were many empty spaces from built up areas. However, the adoption of the Pycno method to estimate the gradual and heterogeneous population close to the LSOAs border, which has a high population density, had an effect in terms of leading to differences in facilities selection and, in fact, provided a better performance in terms of geographical coverage for the weight of the demand in determining the best 1 to 20 GP locations (see Figure 5.4). This was due to the use of the MI and MC models to minimise distances, selecting most of the facilities from 1 to 20 in the LSOAs border with a high population density in the central of the city. In this case, the role of the Dasy surface was less effective because the empty spaces of the population were limited to the central of Leicester.

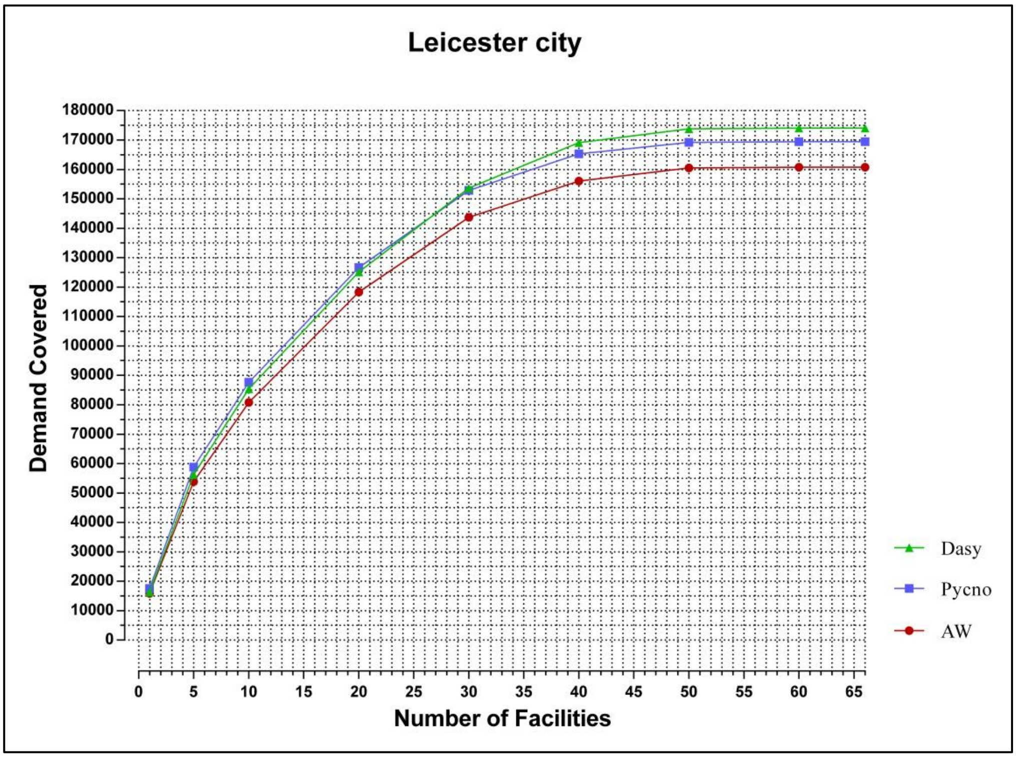


Figure 5.4: Results of the sensitivity demand selection from the MI and MC models for the three demand surfaces in Leicester

The study used the Chi-square test to determine whether significant differences between the results of MI and MC models and the sensitivity demand selection existed for the three demand surfaces in Leicester. The results of Chi-square test showed that there were statistically significant differences between the results of sensitivity demand selection for the AW surface when compared with Pycno, for the AW surface when compared with Dasy and for the Pycno surface when compared with Dasy as the P value was < 0.0001 (see Table 5.1). It seems that the assumptions of the AW, Pycno and Dasy surfaces as described above had a clear impact on the MI and MC models and, therefore, on the determination of the best GP locations.

Table 5.1 Analysis of the results of the sensitivity demand selection from the MI and MC models in Leicester

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	71.50, 8	86.57, 8	317.8, 8
P value	< 0.0001	< 0.0001	< 0.0001
Statistically significant? (alpha<0.05)	Yes	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represent the sensitivity demand selection for the best 1, 5, 10, 20, 30, 40, 50, 60 and 66 GP locations. **The number of columns represents the two surfaces tested.

The results of applying the MI and MC models on the three demand surfaces in this case study may be summarised as follows:

1. The MI and MC models produced similar facilities and demand selections when applied on the same surfaces with the same selected numbers of facilities.
2. The interaction results showed that there were some differences in terms of facility selection when the two models were run on the three demand surfaces.
3. The results of the population estimates obtained through use of the AW, Pycno and Dasy methods affected the selection of the best GP locations and there were interactions between the two models and the three demand surfaces.
4. The Pycno surface produced some different facility selections for the AW and Dasy surfaces; in contrast, in some results there was similarity in facility selection between the three demand surfaces.

5. The Pycno and Dasy surfaces provided better performances in terms of geographical coverage for the weight of the demand, depending upon the number of GP facilities to be chosen from the total.
6. There were statistically significant differences when comparing the results of sensitivity demand selection for the three demand surfaces.

5.2.1.2 The results of the MI and MC models for Buraydah

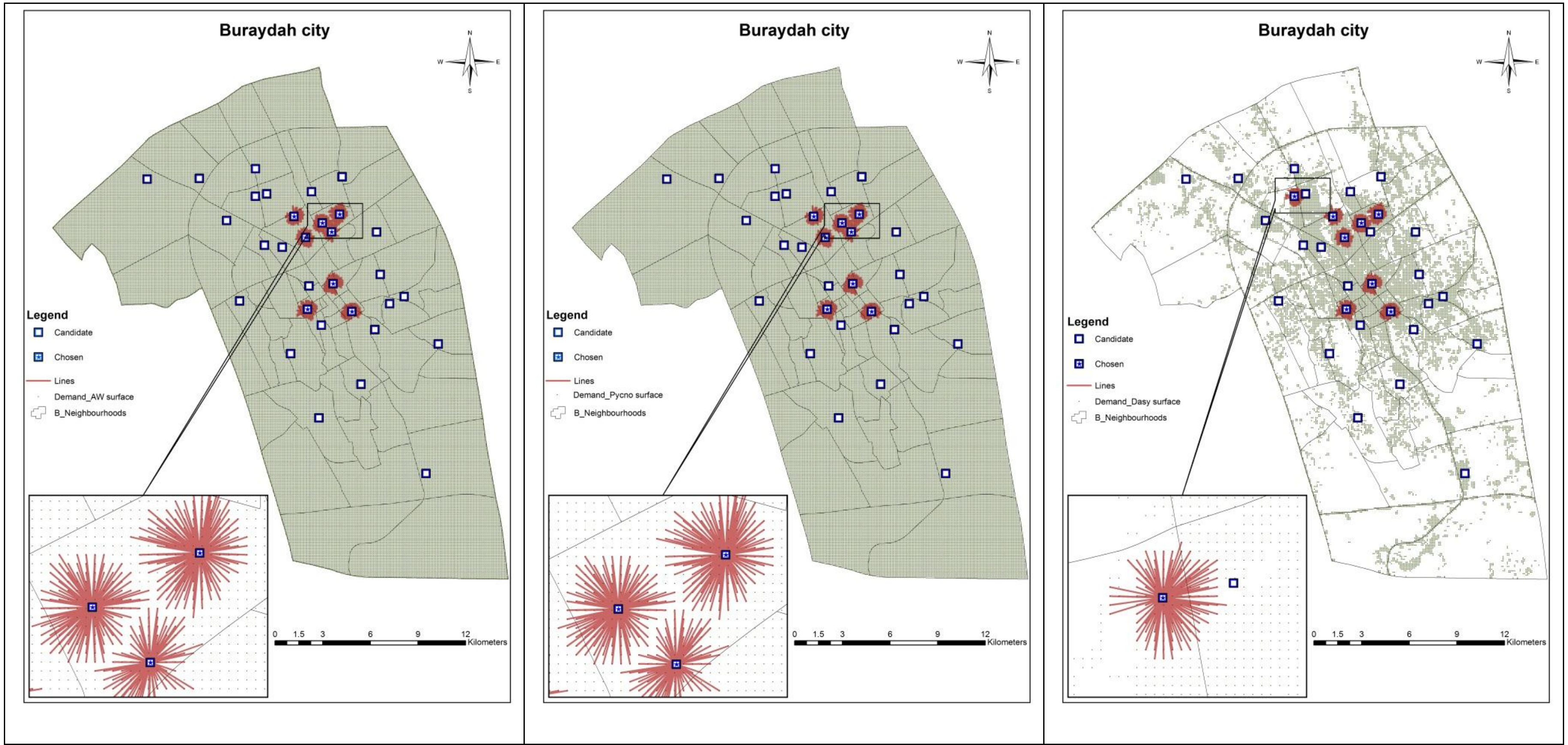
The MI and MC models were run to select the best 1, 4, 8, 12, 16, 20, 24 and 28 of 31 PHCC locations to serve the three demand surfaces within the distance of 800 metres. In terms of facility selection, the results of the MI and MC models show that there were similar selection results between the two models (see, for example, Figures 5.5, 5.6 and 5.7 show the results of the MI and MC models to select the best 8, 16 and 24 PHCCs; for other interaction results for the best 1, 4, 12, 20 and 28 PHCCs, see Figures 2.6 to 2.10 in Appendix 2). These results demonstrate that the MI and MC models provided similar results even when applied to a new case study with different facility locations and demand surfaces. This, again, was due to the use of maximum distance constraints for MI model and the similarity between the operation of the MI and MC models in terms of handling the demand points and selecting the facilities, as mentioned above. The similarity in results between the MC and MI models in terms of facility and demand selection can also be seen in other studies (see Algharib, 2011).

Some of the interaction results between the surfaces and the MI and MC models show that there were both similar and different results were obtained in terms of facility selection. Figures 2.6 and 2.7 in Appendix 2 reveal similar results for the application of the two models to select the best 1 and 4 PHCC location of the total of 31 on three demand surfaces. In addition, Figures 5.5 and 5.6 in the results section and Figure 2.8 in Appendix 2 also show similar results between the AW and Pycno surfaces when the two models were applied to select the best 8, 12 and 16 PHCC locations. In contrast, the Dasy surface produced some differences in the facilities selection results (see the different facility selections for the Dasy surface in the north of Buraydah city in Figure 5.5 and in the east of the city in Figure 5.6). Figure 5.7 reveals the differences in terms of facility selection for the best 24 PHCC locations of the total in Buraydah when applied to the three demand surfaces. There were also differences in terms of facility selection between the three demand surfaces in certain other results (see Figure 2.9 in

Appendix 2). The Pycno surface produced some different facilities selection results with regard to the MI and MC models in selecting the best 28 PHCC locations (see Figure 2.10 in Appendix 2).

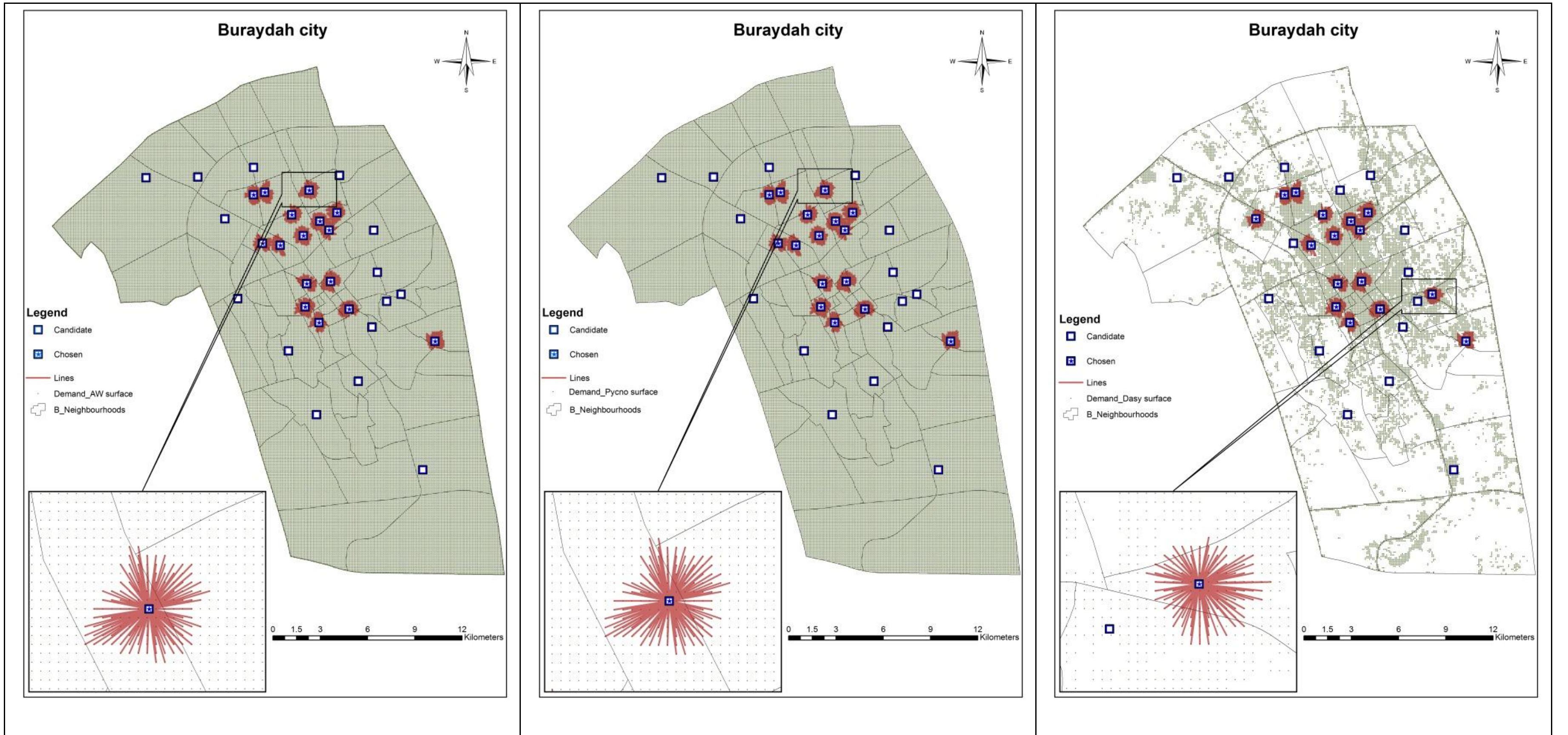
The similarity of the pattern of results in Buraydah between the three demand surfaces was only observed when a small number of PHCCs were selected to serve the demand points. The high population density of some neighbourhoods in the central and northern parts of Buraydah had an impact on the results of the interactions between the two models and three demand surfaces, as shown in Figures 2.6 and 2.7 in Appendix 2 where the results of the two models have produced the same facility selection on the three demand surfaces. The selection of the best locations to serve the demand points thus depends upon the availability of the appropriate number of facilities to cover both the entire city and the demand points. Where there were few facilities in Buraydah, the accessibility solutions for the MI and MC models were minimal.

However, when 8 or more PHCC locations were selected, there were clear differences in the facility selection. For example, it was noted that there were few differences between the results of the MI and MC models when applied on the AW and Pycno surfaces but, when applied on the Dasy surface, there were very different results (see, for example, Figures 5.6 and 5.7). The results of the MI and MC models with the Dasy surface produced some new facility selections in the north, east and north-west of Buraydah (see Figures 5.5, 5.6 and 5.7). This may have been due to the large areas for neighbourhoods in KSA cities, the operations of the MI and MC models that distances should be minimised and maximise the coverage and the high weight allocated only within the built areas with the Dasy surface.



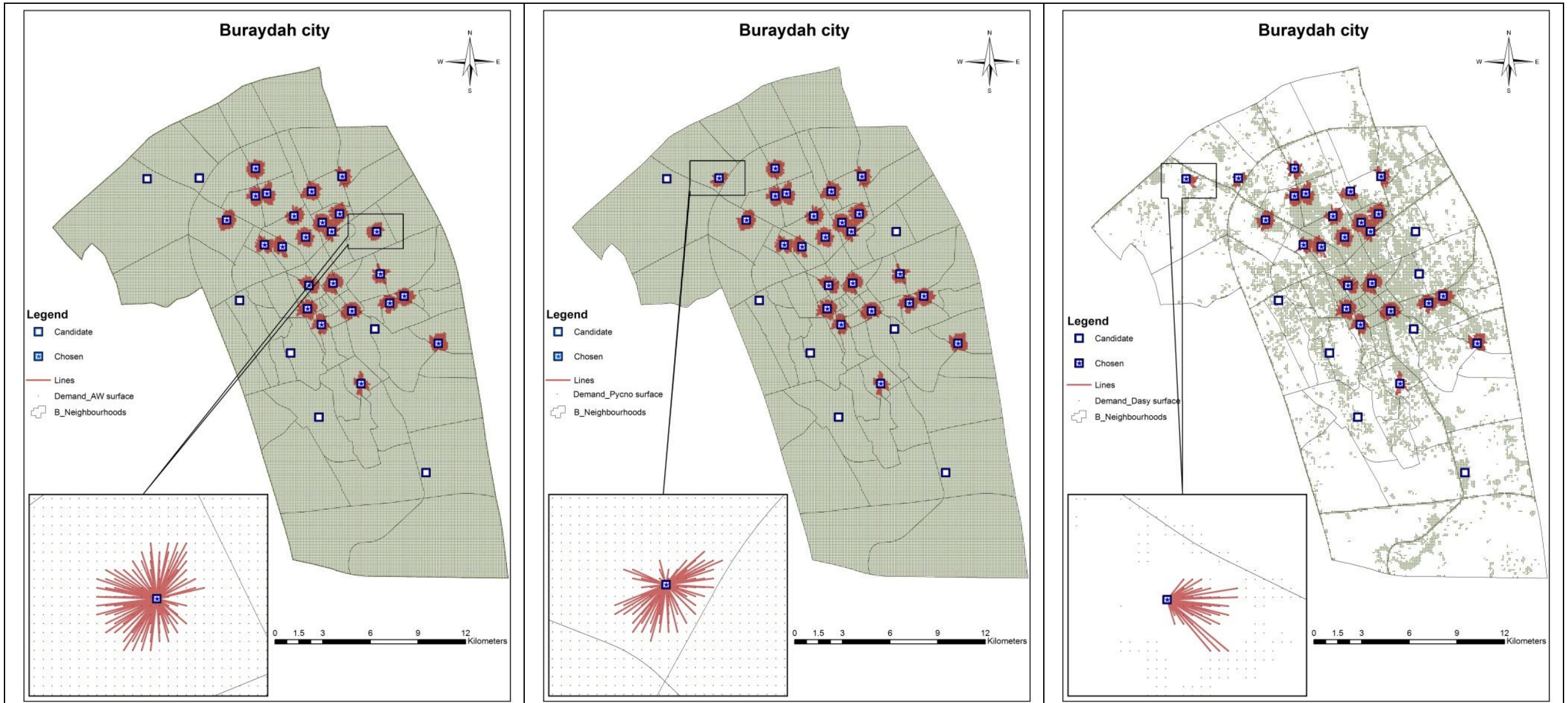
a) AW | b) Pycno | c) Dasy

Figure 5.5: Results of applying the MI and MC models in Buraydah to select the best 8 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.6: Results of applying the MI and MC models in Buraydah to select the best 16 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.7: Results of applying the MI and MC models in Buraydah to select the best 24 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

The results of the demand selection for the MI and MC models respectively were also similar, depending upon the number of PHCC facilities to be chosen from the total to cover the demand points for each surface within the distance of 800 metres (see Figure 5.8). However, the interaction results between the two models and the three demand surfaces using the areal interpolation techniques differed between Buraydah and Leicester in terms both of covering the weight of the demand points and of selecting the best 1, 4, 8, 12, 16, 20, 24, 28 and 31 PHCC locations. The results show that, of all the techniques, the Dasy surface achieved the best geographical coverage for the weight of demand to serve the demand points within 800 metres (see the green points in Figure 5.8). In contrast, the AW surface produced the worst results for geographical coverage of the demand points, while the Pycno surface ranked in the middle (see the red and blue points respectively in Figure 5.8). Additionally, the Pycno surface achieved the greatest geographical coverage for the weight of the demand in the best 1 and 4 PHCC locations. There was substantial convergence between the Dasy and Pycno surfaces in the weight of geographical coverage (demand) and in determining the best 1, 4 and 8 PHCC locations; however, this convergence gradually decreased when determining the best 12, 16, 20, 24, 28 and 31 locations (see Figure 5.8).

The limited numbers for the (31) PHCCs were only available for the large areas and high population density of some neighbourhoods in Buraydah; this had an effect on some of the interaction results between the MI and MC models and the AW, Pycno and Dasy surfaces. Additionally, the horizontal extension of Buraydah had a clear impact on the distribution of PHCCs and the results of the two models in terms of allocating the demand weight. Thus, it was noted that there was a large disparity between the three surfaces in terms of demand selection for the best 20, 24 and 28 PHCCs in the city. The Pycno and AW surfaces were affected by their own assumptions in terms of the need to estimate the population in all the areas inside the neighbourhood borders, despite the fact that there were large areas in the neighbourhood with no inhabitants, as shown by the results for the Dasy surface. In contrast, the Dasy surface provided the best geographical coverage for the weight of the demand as it was based on the use of remote sensing data, which providing information for the built areas within the neighbourhoods. Therefore, the demand weights resulting from this surface were greater than the other two surfaces near the PHCCs. Thus, the study noted that the Dasy surface was better in the analysis of minimising the distances and maximise the coverage of demand points.

In terms of facilities and demand selection, it was noted that results for the MI and MC models differed between Buraydah and Leicester. The Dasy surface produced some different facilities selection results in Buraydah, because the size of the neighbourhoods was too large and built areas within them were few (see Figures 5.5 to 5.7).

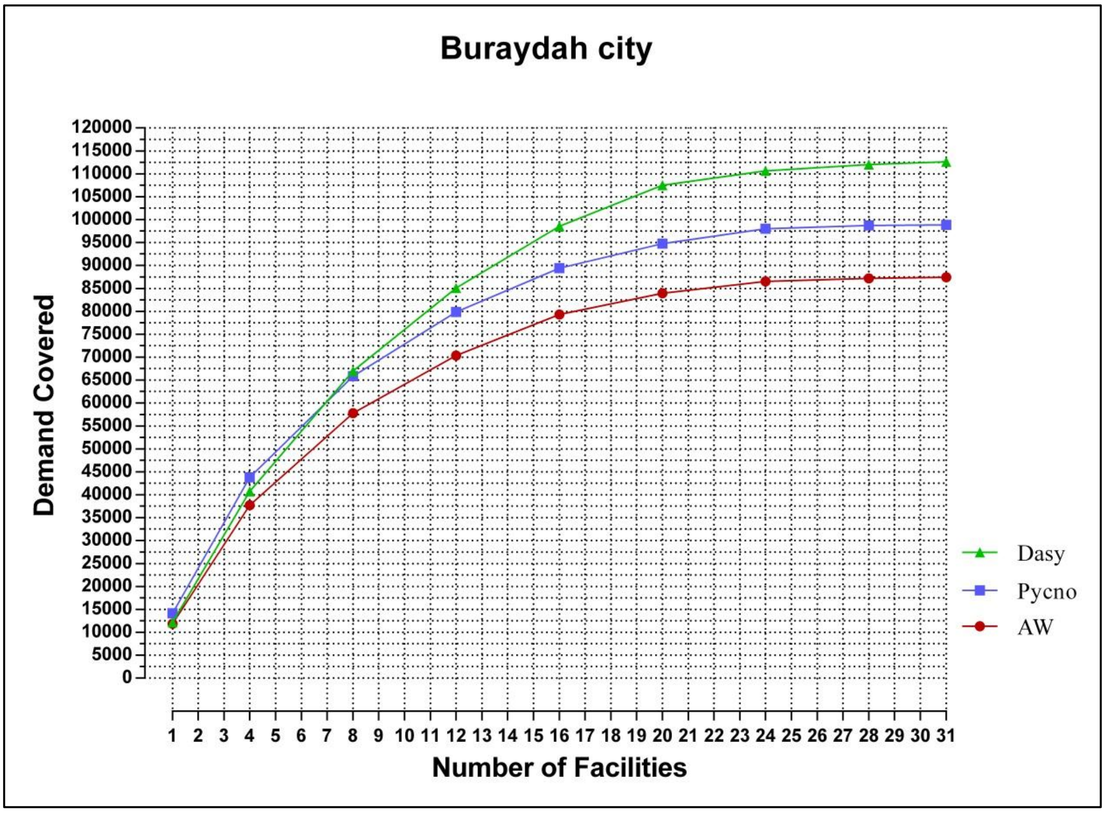


Figure 5.8: Results of the sensitivity demand selection from the MI and MC models for the three demand surfaces in Buraydah

The Chi-square test was used to analyse differences between the results of the MI and MC models and the sensitivity demand selection for the three demand surfaces in Buraydah. These results are shown in Table 5.2. There were statistically significant differences between the results of sensitivity demand selection for the AW surface when compared with Pycno, for the AW surface when compared with Dasy and for the Pycno surface when compared with Dasy (because the P value was < 0.05). In Buraydah, it could be argued that the horizontal extension and large area sizes for the neighbourhoods had a clear impact on the differences in sensitivity demand selection for the MI and MC models. On this basis, the assumptions regarding the three demand surfaces, as previously noted, were statistically different and influenced the weight of demand allocated by using MI and MC models.

Table 5.2 Analysis of the results of the sensitivity demand selection from the MI and MC models in Buraydah

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	31.03, 8	987.7, 8	1421, 8
P value	0.0001	< 0.0001	< 0.0001
Statistically significant? (alpha<0.05)	Yes	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represent the sensitivity demand selection for the best 1, 4, 8, 12, 16, 20, 24, 28 and 31 PHCC locations. **The number of columns represents the two surfaces tested.

In summary, the results of applying the MI and MC models on the three demand surfaces in this case study demonstrated the following points:

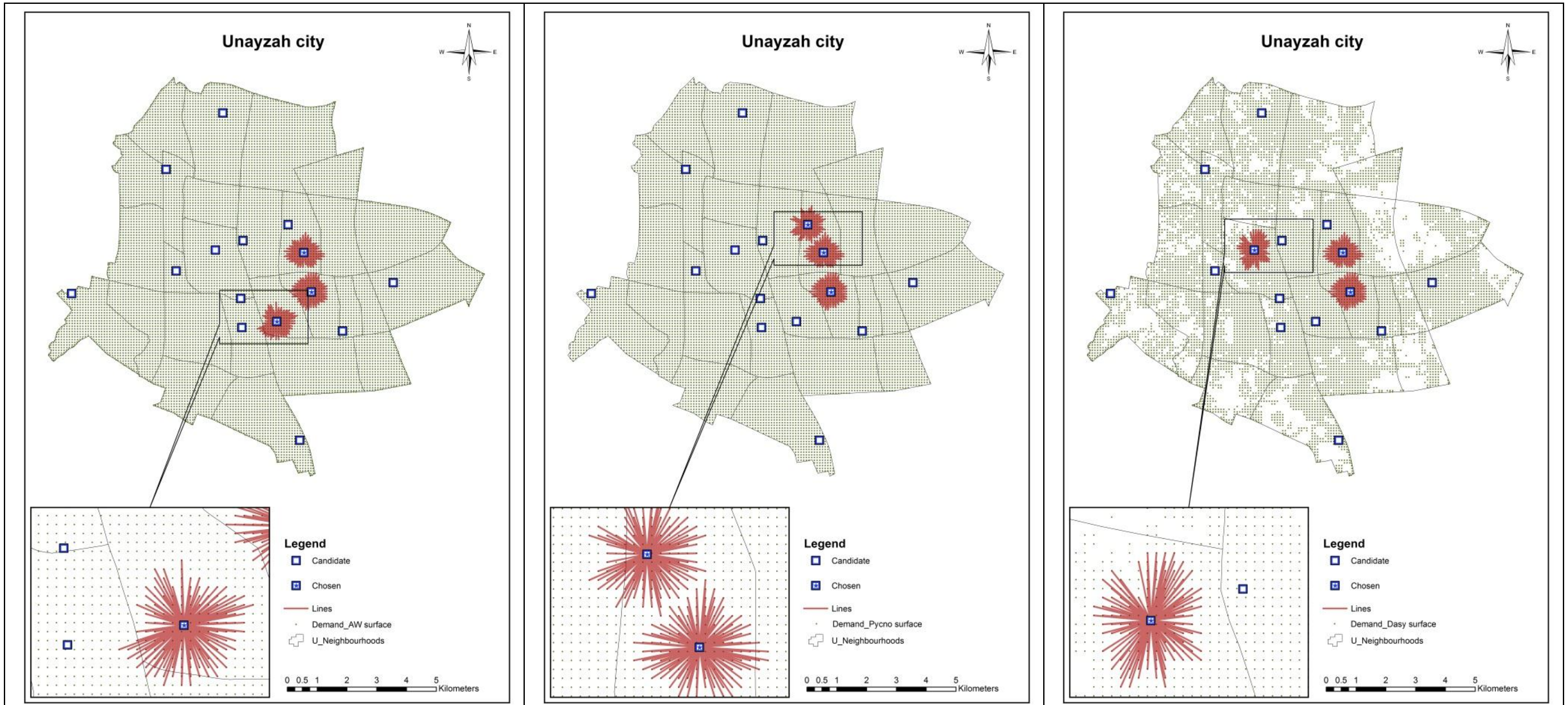
1. Some different facilities selection results were obtained in terms of facility selection when these models were applied on the three demand surfaces.
2. The high population density of some neighbourhoods in the central and northern parts of Buraydah had an impact on the results of interactions between the models and the demand surfaces.
3. There were few differences between the results of the MI and MC models when applied on the AW and Pycno surfaces.
4. The Dasy surface produced some new facilities selections when compared to the AW and Pycno surfaces.
5. In terms of geographical coverage for the weight of the demand, the Dasy surface provided a better performance.
6. There was a large disparity between the three surfaces in terms of the demand weight selection for the best 20, 24 and 28 PHCCs in this city.
7. In the case of the horizontal extension and large area sizes of the neighbourhoods, there were statistically significant differences between the results of sensitivity demand selection for the three demand surfaces.

5.2.1.3 The results of the MI and MC models for Unayzah

The MI and MC models were applied to select the best 1, 3, 5, 7, 8, 9, 11 and 13 of 15 PHCC locations serving the three demand surfaces in Unayzah within the distance of 800 metres. As shown by the results for the MI and MC models in Leicester and Buraydah, similar results were obtained for these models in Unayzah when applied to the same demand surface and selecting the same number of locations. Some of the results for these models (those applied to select the best 3, 7 and 13 PHCCs based on the three demand surfaces within 800 metres) are shown in Figures 5.9, 5.10 and 5.11. For the interaction results for the best 1, 5, 8, 9, and 11 PHCCs, see Figures 2.11 to 2.15 in Appendix 2.

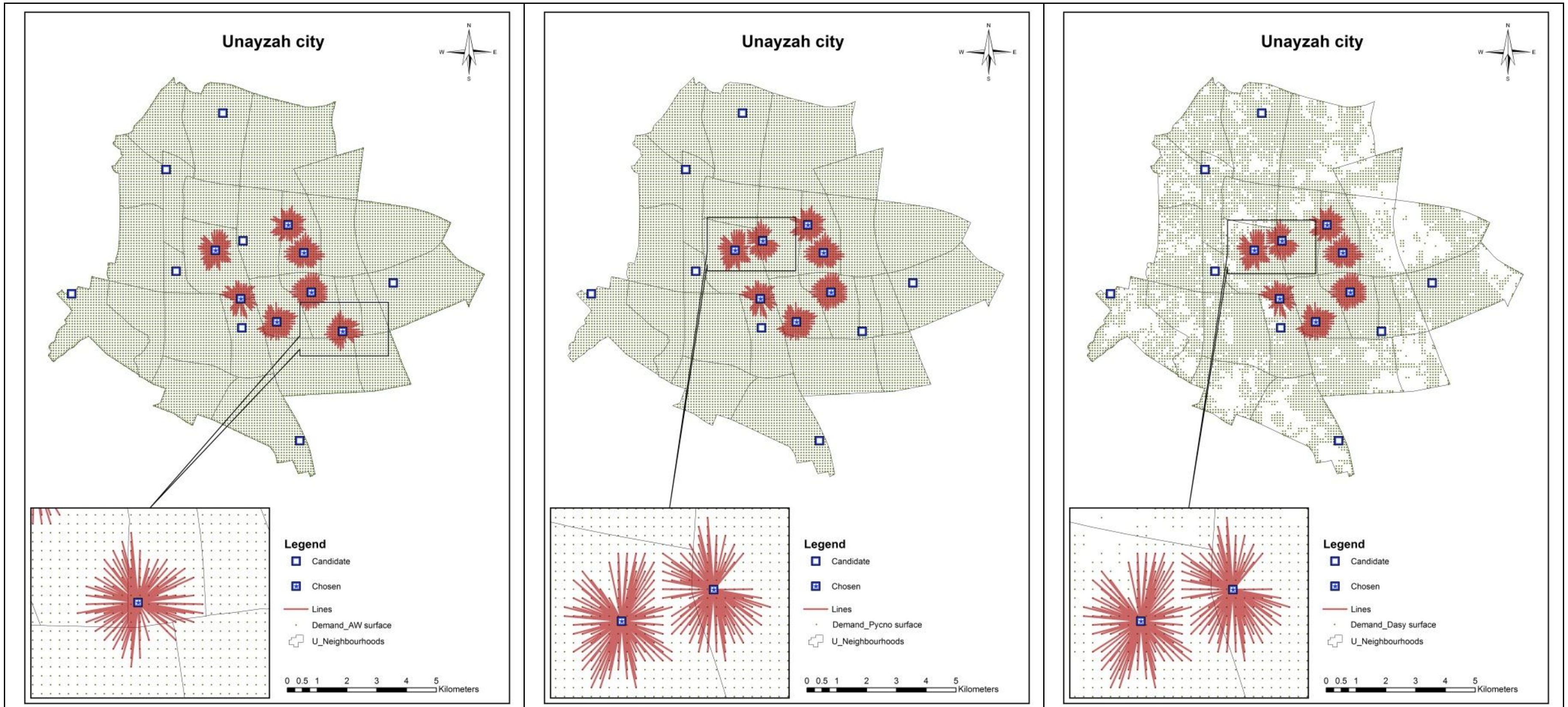
Some of the interaction results for the MI and MC models reveal some different facility selections between the three demand surfaces for the best 3 and 13 PHCC locations (see Figures 5.9 and 5.11). The MI and MC models with the AW surface produced some different facility selections compared to the other two surfaces (see Figure 5.10 for the best 7 PHCC locations. Additionally, the two models on the Dasy surface identified some different facility selections compared to the other two surfaces (see the best 9 PHCC locations in Figure 2.14 in the Appendix 2). In contrast, other results for the MI and MC models show that there were similarities in facility selection based on the three demand surfaces (see Figures 2.11 to 2.13 and 2.15 in Appendix 2).

The limited number of PHCCs and their concentration in certain neighbourhoods with a high population density in this study of Unayzah may have affected some results for interactions between the models and the three demand surfaces. However, from these results, it was noted that the small number of PHCCs in Unayzah had an effect on the results for the best 3 PHCC locations as there were certain differences between the Pycno surface and the other two surfaces. For example, on the Pycno surface, there were two PHCC locations in one neighbourhood in the centre of Unayzah; conversely, for the AW and Dasy surfaces, there were three PHCC locations within different neighbourhoods (see Figure 5.9). This was due to the operations used by the MI and MC models in terms of allocating the demand points within 800 metres; for the AW and Dasy surfaces, the demand weights for the points near to the other two PHCC locations were greater than any other PHCC location, according to the results for the best 3 locations. Additionally, the differences in the weights of the demand based on the assumptions of each demand surface especially for the demand points inside the large source zone area contributed to produce some differences in the facilities selection results. This was a clear in the differences in the facilities selection results for the best 13 PHCC locations (see Figure 5.11 and the different facilities selections between the three demand surfaces in the north and west of Unayzah).



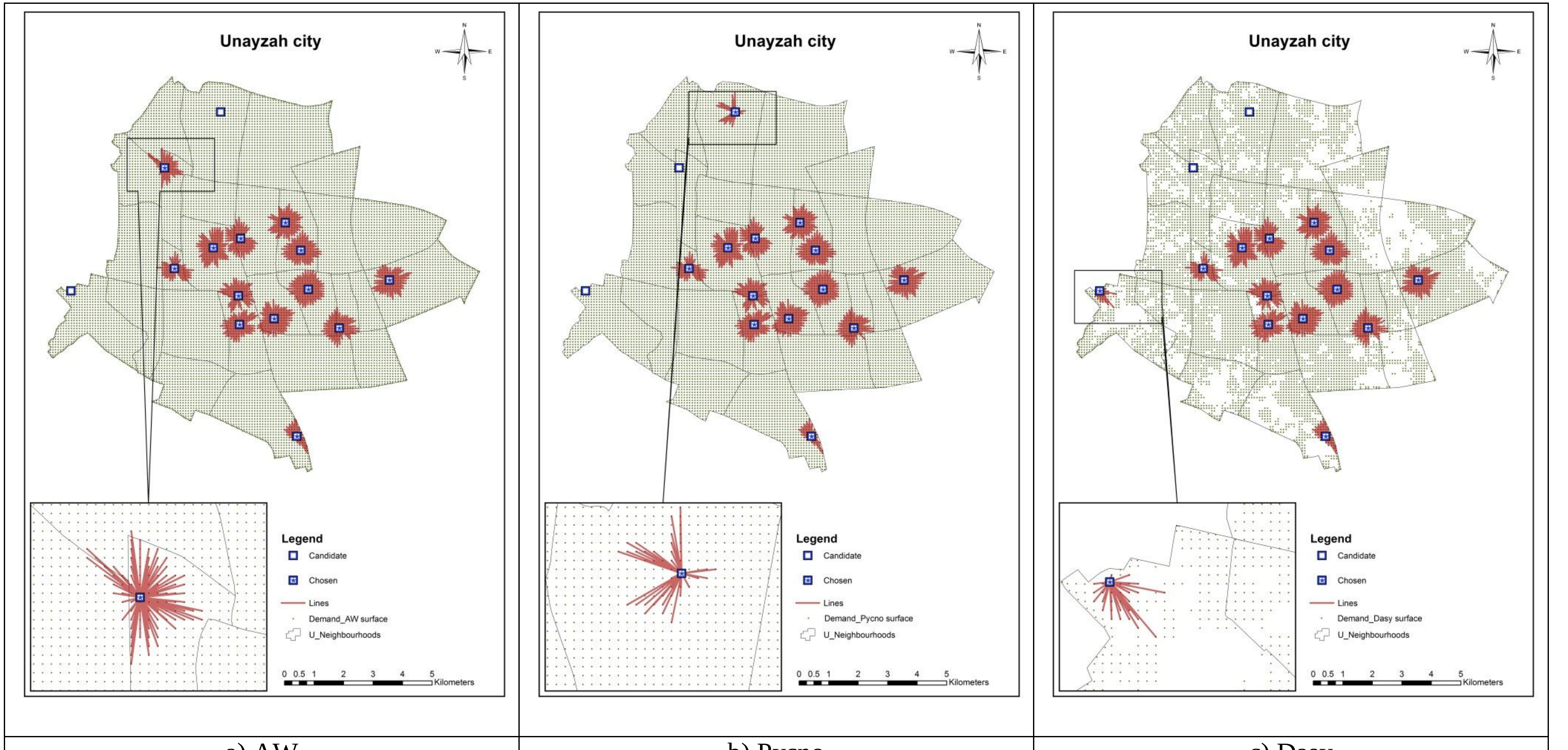
a) AW	b) Pycno	c) Dasy

Figure 5.9: Results of applying the MI and MC models in Unayzah to select the best 3 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.10: Results of applying the MI and MC models in Unayzah to select the best 7 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.11: Results of applying the MI and MC models in Unayzah to select the best 13 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

In terms of the demand selection, the MI and MC models also produced similar results depending upon the number of PHCC facilities chosen from the total of 15 in order to serve the demand points for each surface within the distance of 800 metres (see Figure 5.12). When selecting the best 1, 3, 5, 7, 8, 9, 11, 13 and 15 PHCC locations, the interactions between the MI and MC models and the three demand surfaces produced different results in Unayzah in terms of covering the demand points. The interaction results showed that, of all the surfaces, the Pycno surface achieved the best geographical coverage for the demand weight within 800 metres from the best 1 to 5 PHCCs (see the blue points in Figure 5.12). In contrast, the AW surface produced the worst results; the Dasy surface ranked in between for the best 1 to 5 PHCCs but achieved the best geographical coverage for the demand weight from the best 7 PHCCs (see the red and green points respectively in Figure 5.12).

The results show that there was substantial convergence for the demand weight between the Pycno, Dasy and AW surfaces in terms of the effect of the size of the geographical coverage (demand) in determining the best 1 and 3 PHCC locations (see Figure 5.12). However, this convergence gradually decreased on the AW surface when determining the best 5, 7, 8, 9, 11, 13 and 15 locations (see Figure 5.12). Where there were a few non-built areas in the neighbourhoods of central Unayzah, the performance of the Dasy surface was lower in terms of demand weight and sensitivity demand selection for both the MI and MC models. The demand surface resulting from the use of the AW method continued to produce the lowest weight of demand between the three demand surfaces. This may have been due to the assumptions behind this method, which depend upon homogeneous distribution and unification within the target area. On this basis, due to the large area sizes of the neighbourhoods in the KSA case studies, the results for the demand weight of each point inside the AW surface were lower than those for the Pycno surface, which uses the smooth density function in order to determine the volume-preserving property (Lam, 1983; Kim and Yao, 2010). The results were also lower than those for the Dasy surface, which depend upon the use of remote sensing data for population distribution in the target area. When the MI and MC models were run on the three demand surfaces and the three case studies, the study noted that the AW surface provided the worst interaction results in terms of demand selection.

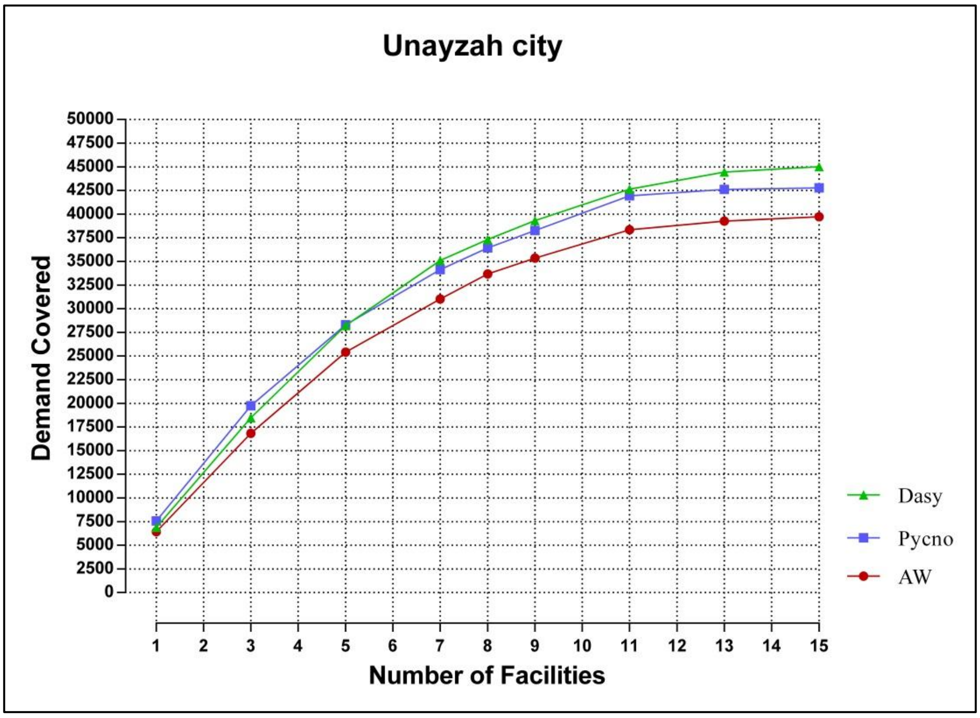


Figure 5.12: Results of the sensitivity demand selection from the MI and MC models for the three demand surfaces in Unayzah

The Chi-square test was used to compare the results of the three demand surfaces in terms of sensitivity demand selection; Table 5.3 shows the test results in Unayzah. The P value was <0.05, which means that there were statistically significant differences between the results of sensitivity demand selection for the AW surface when compared with Pycno and Dasy surfaces, and for Pycno when compared with Dasy surface (see Table 5.3). Despite the presence of these statistically significant differences in the sensitivity demand selection for certain surfaces, the results of the interactions between the two models and the surfaces in terms of facilities selections in Unayzah were lower than in Leicester and Buraydah.

Table 5.3 Analysis of the results of the sensitivity demand selection from the MI and MC models in Unayzah

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	77.75, 8	20.78, 8	158.7, 8
P value	< 0.0001	0.0077	< 0.0001
Statistically significant? (alpha<0.05)	Yes	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represent the sensitivity demand selection for the best 1, 3, 5, 7, 8, 9, 11, 13 and 15 PHCC locations. **The number of columns represents the two surfaces tested.

In summary, the results of applying the MI and MC models on the three demand in this case study surfaces showed the following points:

1. Some interaction results for the MI and MC models show similarities between facilities selections based on the three demand surfaces.
2. In some parts of the analysis, the AW and Dasy surfaces produced different facilities selections.
3. The differences in the weights of the demand based on the assumptions of each demand surface especially for the demand points inside the large source zone area contributed to produce some differences in the facilities selection results.
4. The limited numbers of PHCCs and the concentration of these facilities in certain neighbourhoods with a high population density had an effect on the interaction results between the models and the demand surfaces.
5. In terms of the demand coverage, the performance of the Dasy surface was better than the other surfaces where the most of the facilities were concentrated in the middle of the city.
6. The results of interactions between the two models and the surfaces in terms of different facilities selections in Unayzah were lower than Leicester and Buraydah.

5.2.2 The results of the MF model

The aim of the MF model is to minimise the distances and determine the minimum number of facilities needed to serve the demand (the centroid points for the 90 metre grid cell, which has been areally interpolated using three areal interpolation methods) within a certain distance or travel time (Schilling *et al.*, 1993). This model differs from others that seek to fit optimally a set number of facilities to a demand surface in that it identifies the number of facilities needed to satisfy a particular distance constraint. Consequently, the MF model will select from the chosen GP or PHCC locations according to distances and sensitivity to facility and demand selection by varying the distances used from 600 to 1000 metres at 50 metre intervals, using the three demand surfaces for each case study. The MF model was similar to the MC model in terms of handling or allocating the demand points as described in the methodology chapter but differed in terms of the number of facilities allocated, where this is determined by the analyst rather than the user depending on the distance used.

5.2.2.1 The results of the MF model for Leicester

The MF model was applied to select the minimum number of GP locations covering the three demand surfaces at 50 metre intervals from 600 to 1000 metre distances. In terms of the number of GPs needed to cover the demand points, the interaction results between the MF model and the three demand surfaces show that similar results were achieved between the three demand surfaces in all the distances used from 600 to 1000 metres (see Figure 5.13). Assuming that when the distance is increased the number of facilities will accordingly be decreased, the study noted that there was an increase in the number of facilities needed at 950 and 1000 metres, when compared to a distance of 900 metres in all three demand surfaces. This may be due to the small spacing between some of the GP locations.

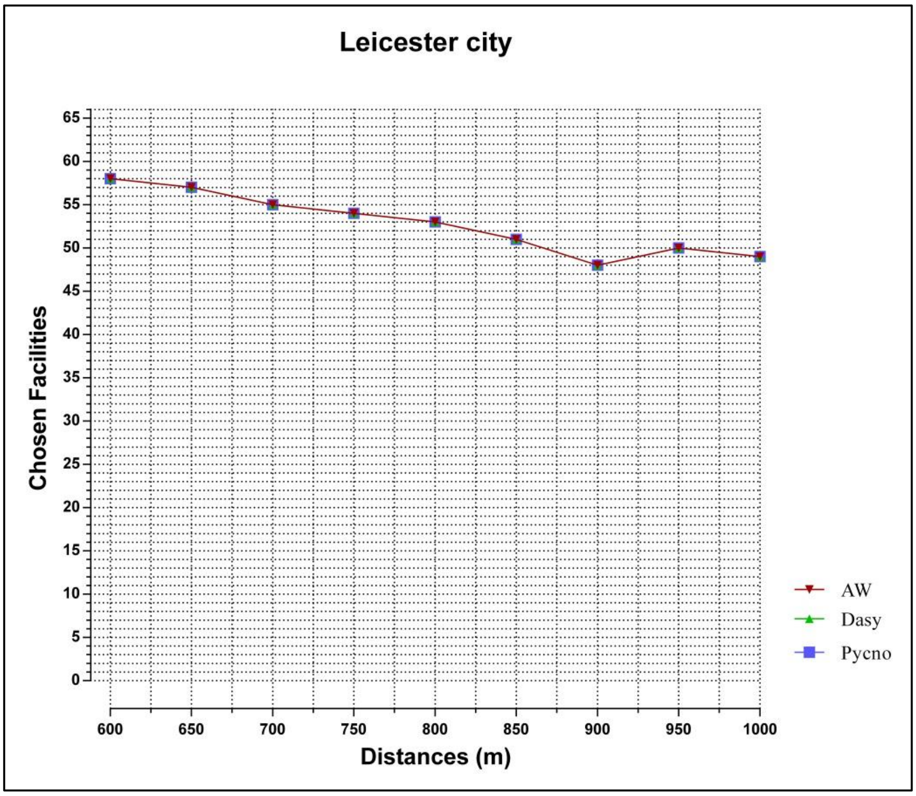
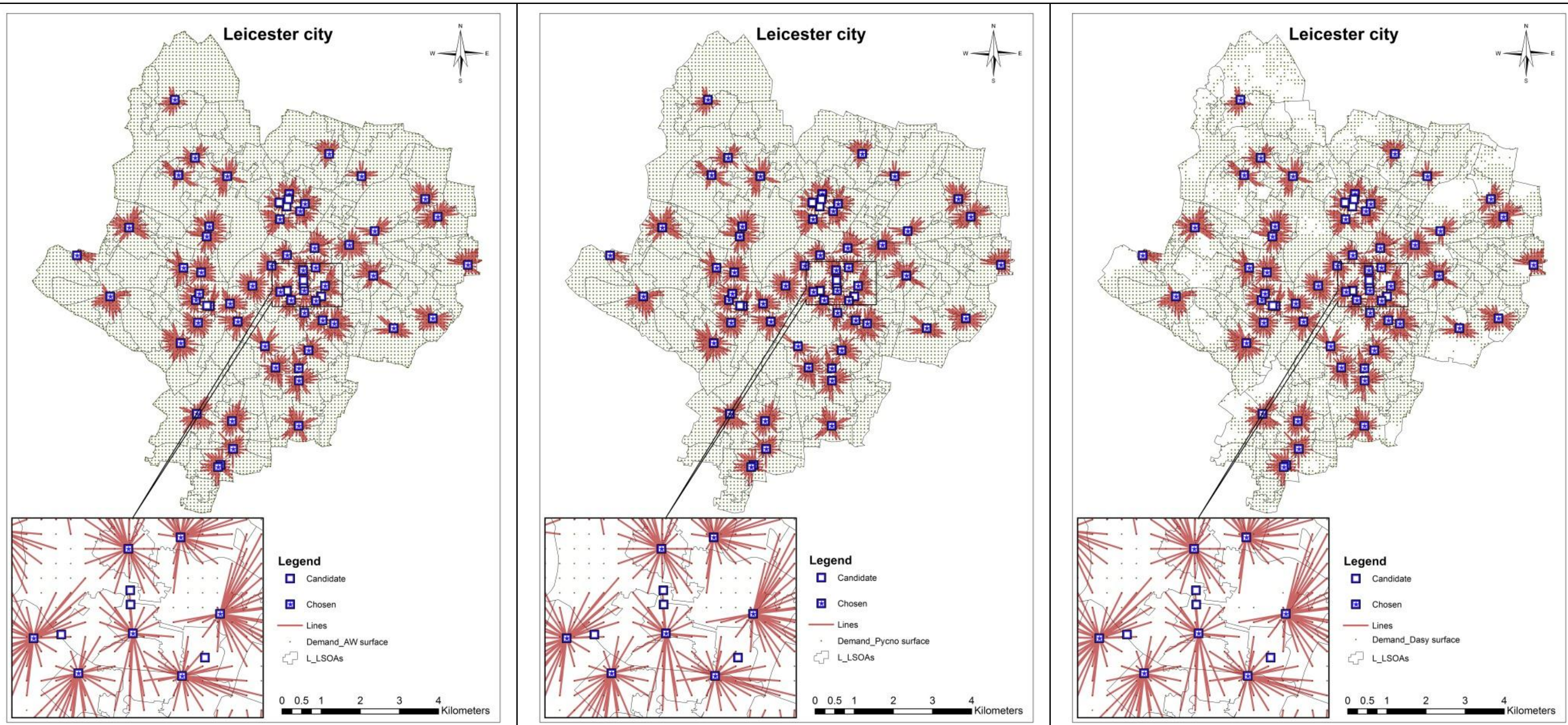


Figure 5.13: Results of the distances and sensitivity facility selection from the MF model for the three demand surfaces in Leicester

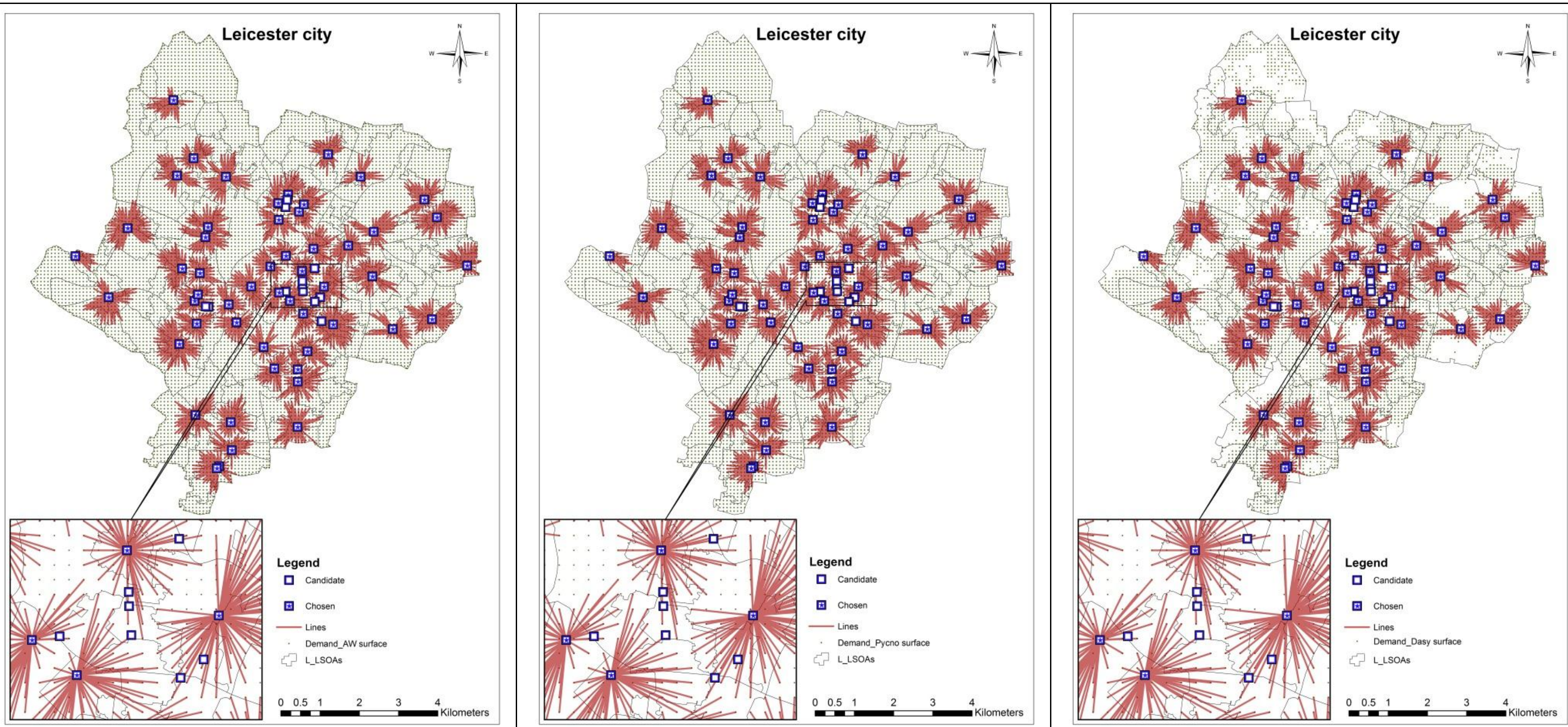
In contrast, in terms of facilities selection and interactions of the MF with the three demand surfaces, similar facilities selection results were obtained (for examples, see Figures 5.14, 5.15 and 5.16; the remaining results are presented in Figures 2.16 to 2.21 of Appendix 2). The availability of a large number of GP locations and the concentration of these facilities in particular areas, such as central and north-central Leicester, helped the MF model to minimise the number of facilities and determine the candidate GP locations on the three demand surfaces (see Figures 5.14 to 5.16).

From the results of the curves in Figure 5.13, it is clear that similar results were obtained between the three demand surfaces in terms of the number of GP locations selected in all the distances as mentioned above. The objective for use of the MF model is to provide the best coverage for the demand using the lowest number of facilities when resources are sufficient (Church and Murray, 2009). Thus, the model seeks to identify the number of facilities needed to satisfy a particular distance constraint. The study noted that there were no effects for the assumptions made by the three demand surfaces in terms of population estimations on the MF model because there were similar numbers between the three demand surfaces in terms of the chosen and candidate facilities. It might be that the concentration of most GP locations within small areas for LSOAs in Leicester had an impact on the differences between weights of demand inside each LSOA.



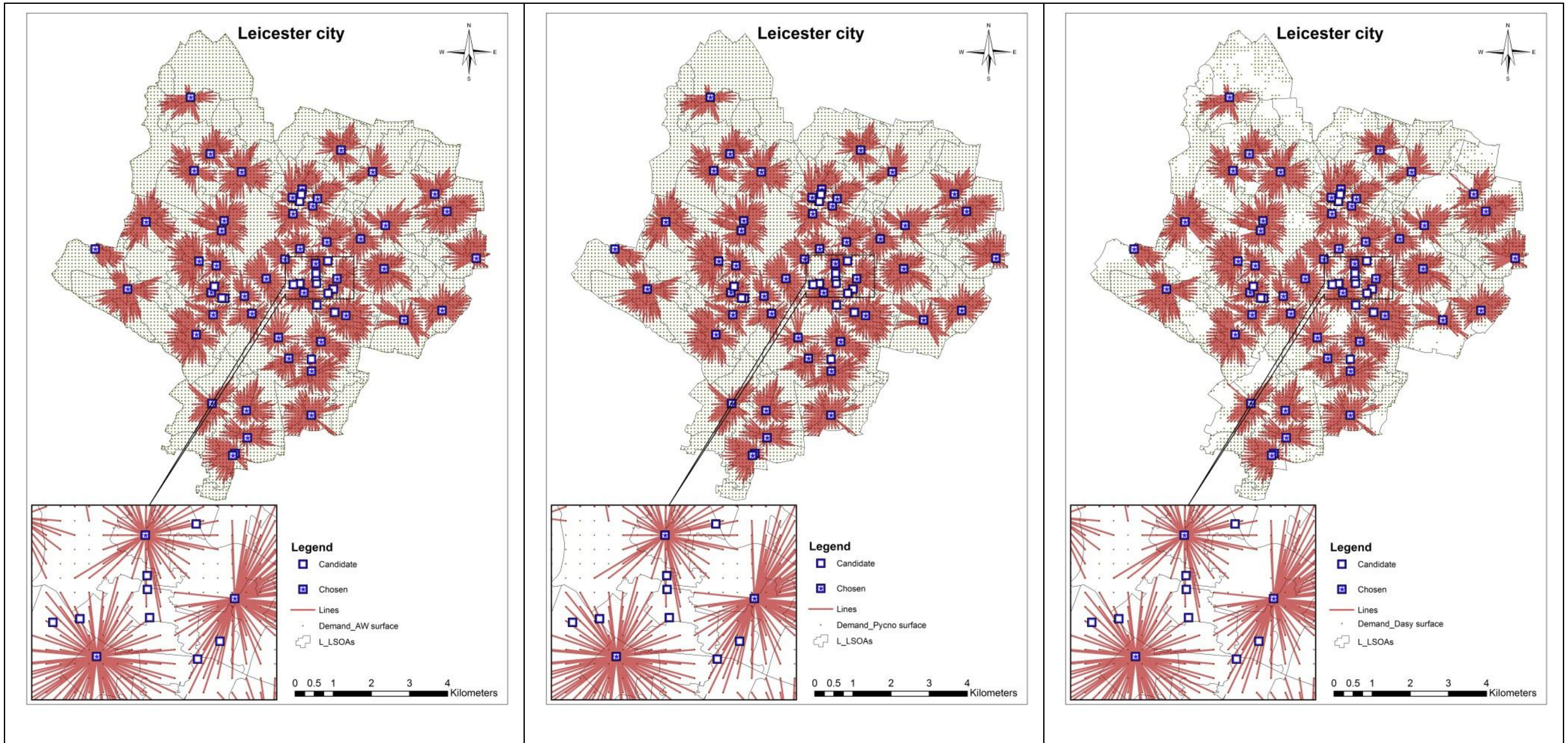
a) AW	b) Pycno	c) Dasy

Figure 5.14: Results of applying the MF model in Leicester within 600 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW | b) Pycno | c) Dasy

Figure 5.15: Results of applying the MF model in Leicester within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW	b) Pycno	c) Dasy

Figure 5.16: Results of applying the MF model in Leicester within 1000 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

In terms of demand selection, the interaction results for the MF model differed between the three demand surfaces as a result of using the AW, Pycno and Dasy methods. Figure 5.17 shows the differences between the results of the distances and sensitivity demand selection using the MF model for the three demand surfaces in Leicester. These results reveal that, of the three surfaces, the Dasy surface achieved the best geographical coverage for the weight of the demand in all distances used (see the green points in Figure 5.17). In contrast, the AW surface achieved the worst results, while the Pycno surface ranked in between (see the red and blue points respectively in Figure 5.17). For example, when applying the MF model within a distance of 800 metres, the weight of the demand selection resulting from the Dasy method was 174,047 people, 169,482 for the Pycno method and 160,780 for the AW method. The study noted that there was an increase in the weight of demand selection when using the MF model when the distances were increased. In relation to demand selection for the chosen facilities, there were also large differences compared with the other cases studied. However, despite these differences in sensitivity demand selection using the MF model, there were no differences between the three demand surfaces in terms of the numbers of facilities needed for all the distances used. The reasons for this are discussed in more detail in the discussion chapter.

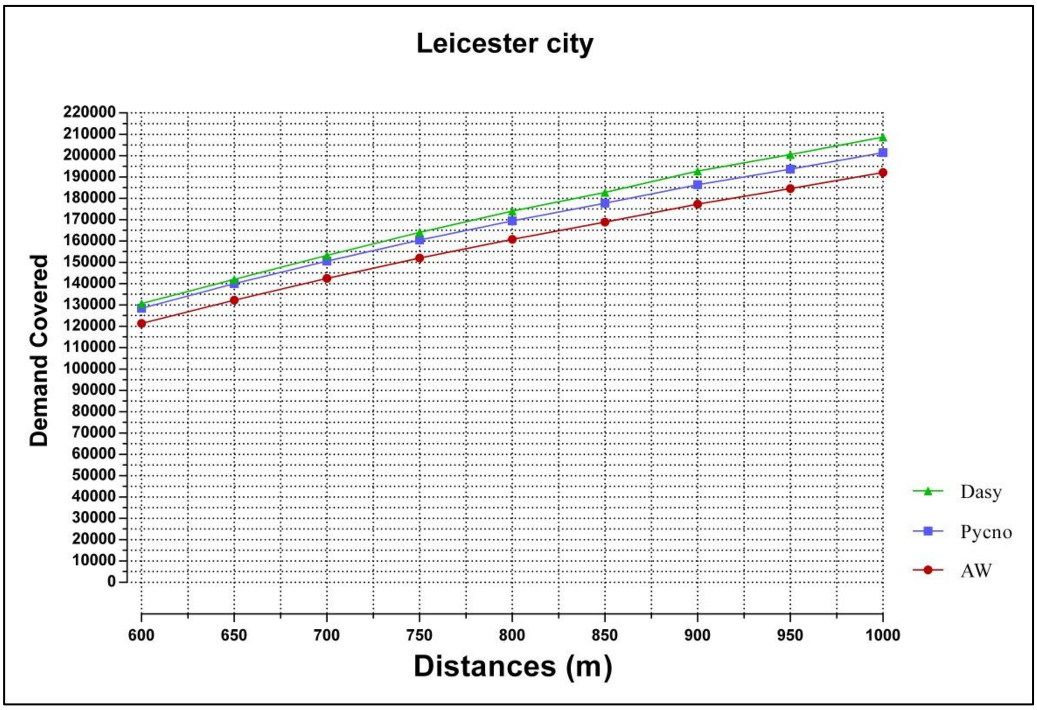


Figure 5.17: Results of the distances and sensitivity demand selection from the MF model for the three demand surfaces in Leicester

The Chi-square test for the results of sensitivity demand selection using the MF model showed that there were statistically significant differences between the results of the Pycno surface when compared with Dasy (see Table 5.4). However, there were no statistically significant differences between the AW and Pycno surfaces and AW with Dasy surfaces. There were no interaction between the three demand surfaces using the MF model compared to the MI and MC models in terms of facilities and demand selection. It seems that the small area sizes for the LSOAs, large built-up areas (especially in central Leicester) and the concentrations of most GP locations in the centre had a clear impact on the operation of the MF model in terms of selection of facilities and allocating the demand points between the three surfaces.

Table 5.4 Analysis of the results of the sensitivity demand selection from the MF model in Leicester

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	7.672, 8	14.33, 8	43.52, 8
P value	0.4661	0.0735	< 0.0001
Statistically significant? (alpha<0.05)	No	No	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represents the sensitivity demand selection from 600 to 1000 metres at 50 metre intervals. **The number of columns represents the two surfaces tested.

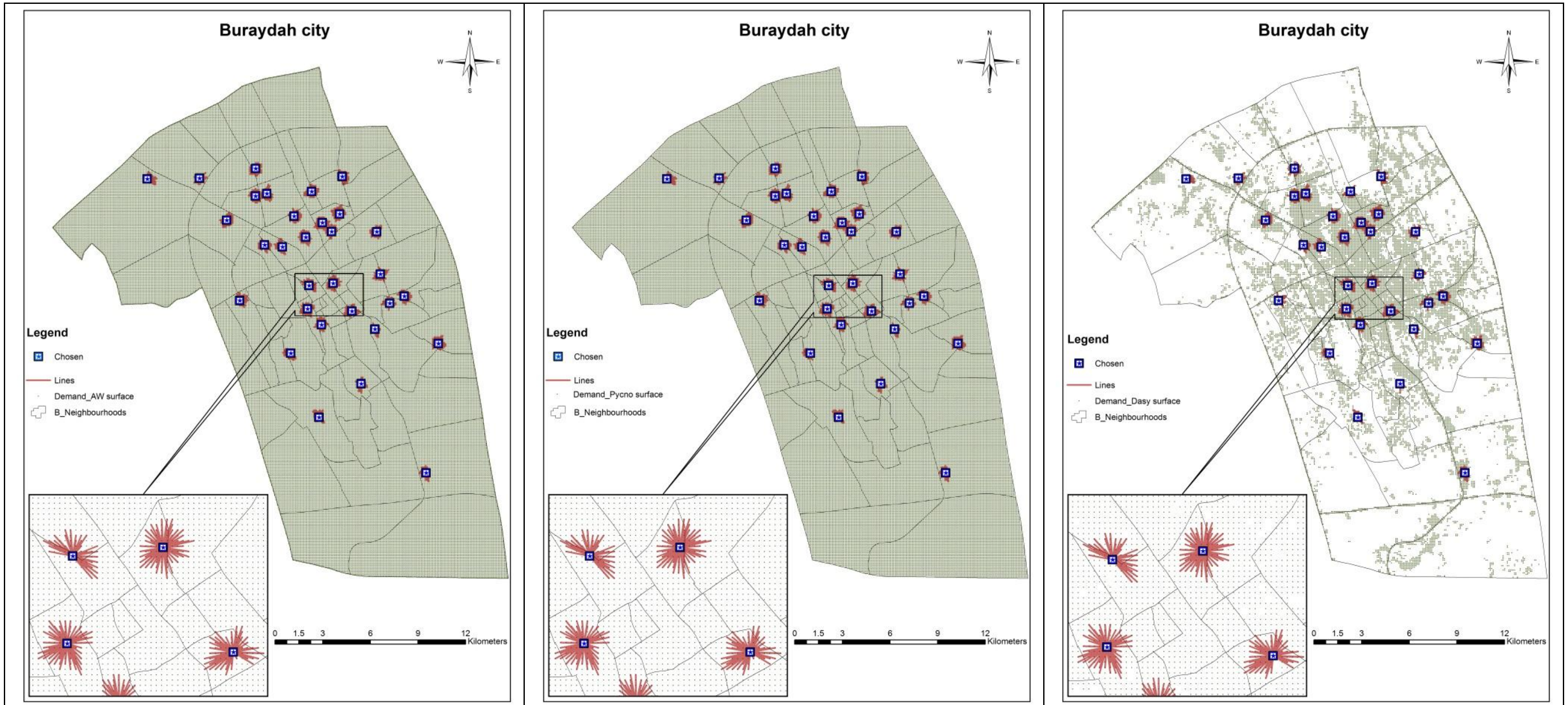
In summary, the results of applying the MF model on the three demand surfaces in this case study showed the following points:

1. In terms of the GP locations needed, similar results were obtained for the three demand surfaces in all distances used.
2. There was an increase in the number of facilities needed at 950 and 1000 metres, when compared to a distance of 900 metres in all three demand surfaces.
3. The results of the MF model reveal that the performance of the Dasy surface was better in terms of demand coverage.
4. The interaction results between the MF model and the three demand surfaces reveal that there were no interaction between the three demand surfaces using the MF model compared to the MI and MC models in terms of facilities and demand selection.

5.2.2.2 The results of the MF model for Buraydah

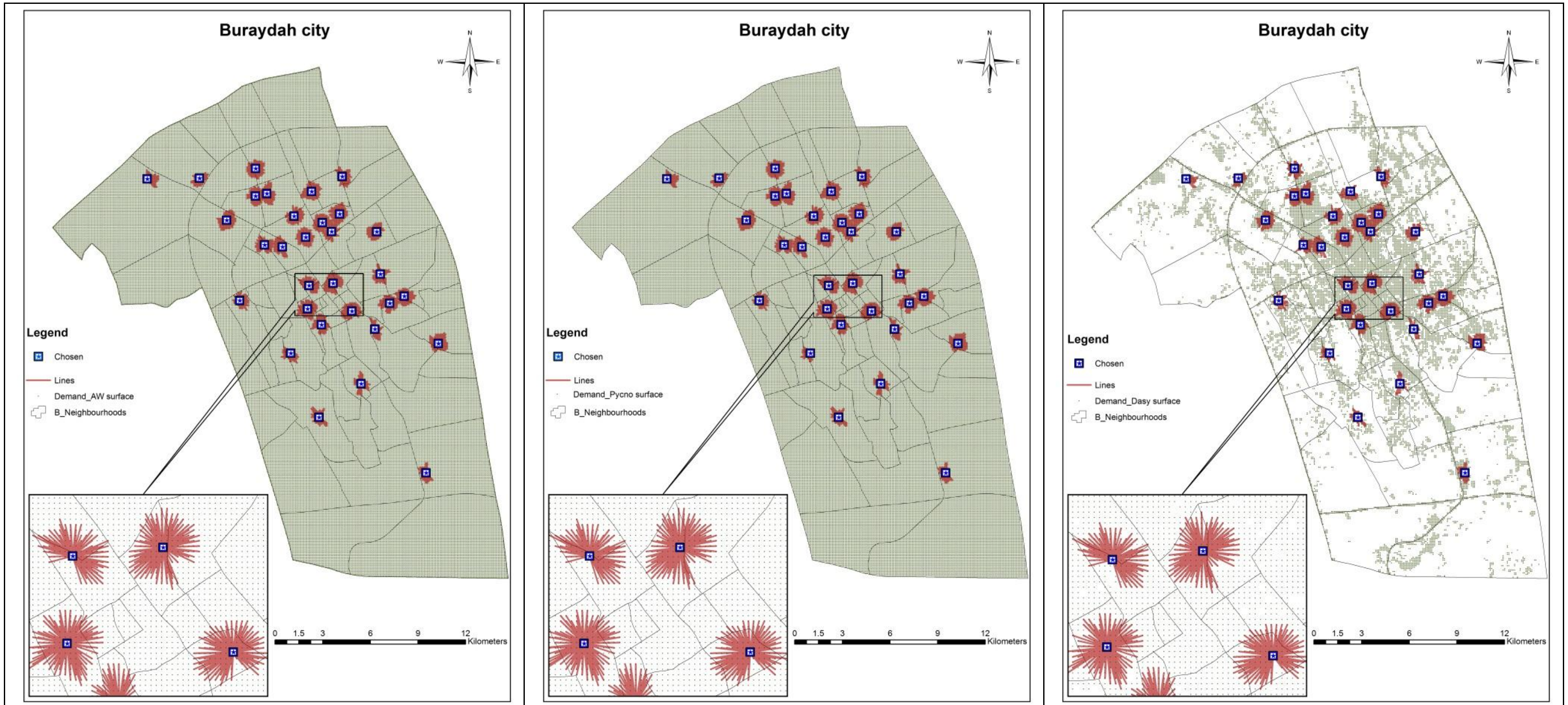
The MF model was parameterised to minimise the distances and to select the minimum number of chosen PHCC locations to cover each of the three demand surfaces at 50 metre intervals from 600 to 1000 metre distances. The interaction results for the MF model and the three demand surfaces show that, in terms of facility selections, there were no candidate facilities: all of the PHCC locations were chosen to cover the three demand surfaces in all distances used. Some of the MF model results are shown in Figures 5.18, 5.19 and 5.20, while the results for the remaining distances are presented in Appendix 2 (see Figures 2.22 to 2.27). These results mean that there were no candidate facilities in Buraydah, which may have contributed to accessibility solutions within the distances used.

As previously noted in the results for the MI and MC models, the large area of Buraydah city and the limited number of PHCCs also had an effect on the interaction results for the MF model. Figures 5.18 to 5.20 clearly show that there was wide spacing between the PHCC locations, particularly in those neighbourhoods with high population densities in the centre and north of Buraydah (see also the distribution of demand points outside the lines, which resulted from the use of the Dasy method, in Figures 5.18 to 5.20). On this basis, the MF model was not able to minimise the locations of the facilities as there were a large number of demand points in the centre and north of Buraydah, the demand weight of which had to be covered in those areas within those distances.



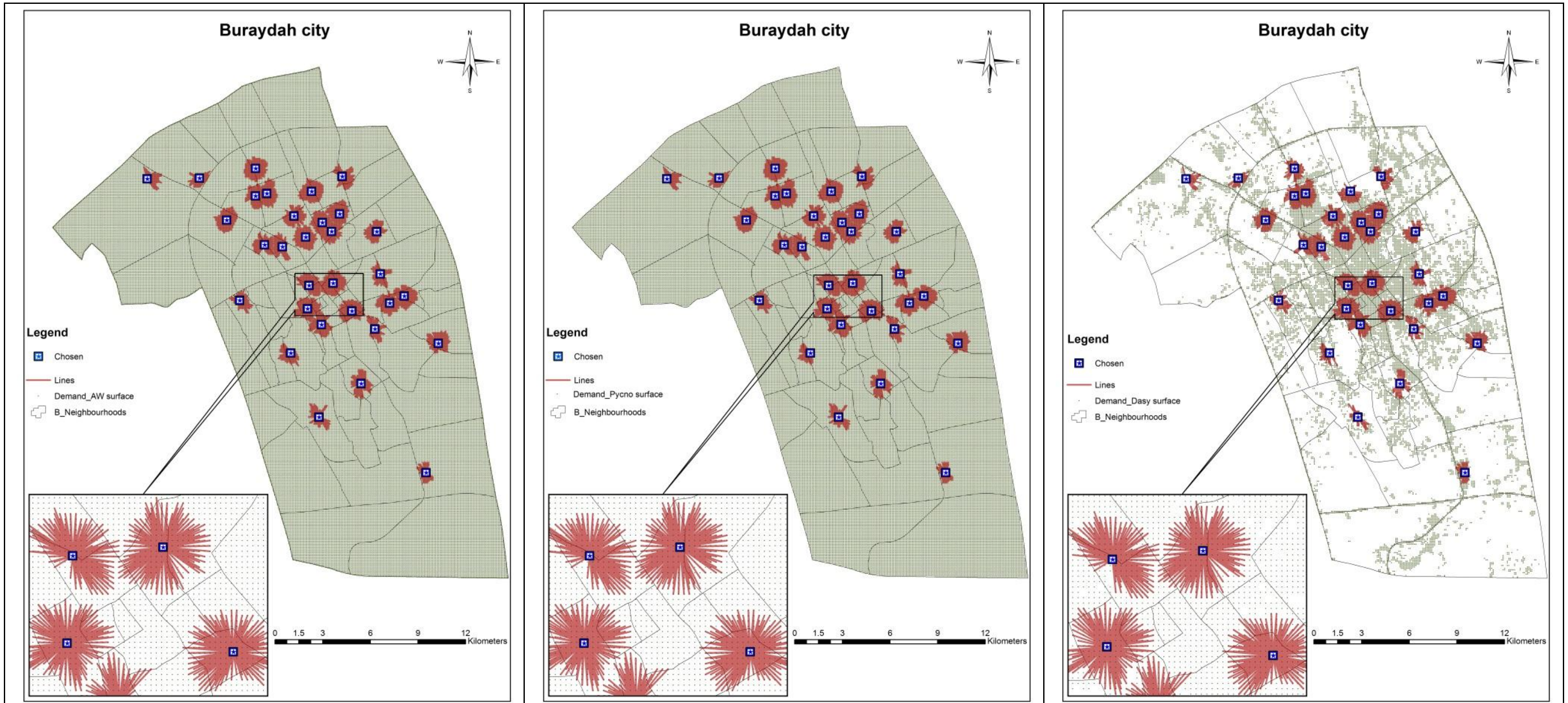
a) AW | b) Pycno | c) Dasy

Figure 5.18: Results of applying the MF model in Buraydah within 600 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW | b) Pycno | c) Dasy

Figure 5.19: Results of applying the MF model in Buraydah within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW | b) Pycno | c) Dasy

Figure 5.20: Results of applying the MF model in Buraydah within 1000 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

The demand selection results for the interactions of the MF model with the three demand surfaces produced different outcomes depending upon the distances used. Figure 5.21 illustrates the differences between the results of the distances and sensitivity demand selection using the MF model on the three demand surfaces in Buraydah. The interaction results show that, of the three surfaces, the Dasy surface achieved the best geographical coverage for the weight of the demand (see the green points in Figure 5.21), followed by the Pycno surface and the AW surface (see the blue and red points respectively in Figure 5.21). For example, when applying the MF model within a distance of 800 metres, the result of the demand weight selection for the Dasy surface was 112,609 people; the Pycno surface was 98,854 and the AW surface was 87,417. It can be noted from the results of the demand weight selection for the MF model that there was a relatively large variation in demand weight selection between the three surfaces. This may have been due to the wide spacing between the PHCC sites, the large size of the neighbourhoods and the assumptions of each areal interpolation technique, as previously noted.

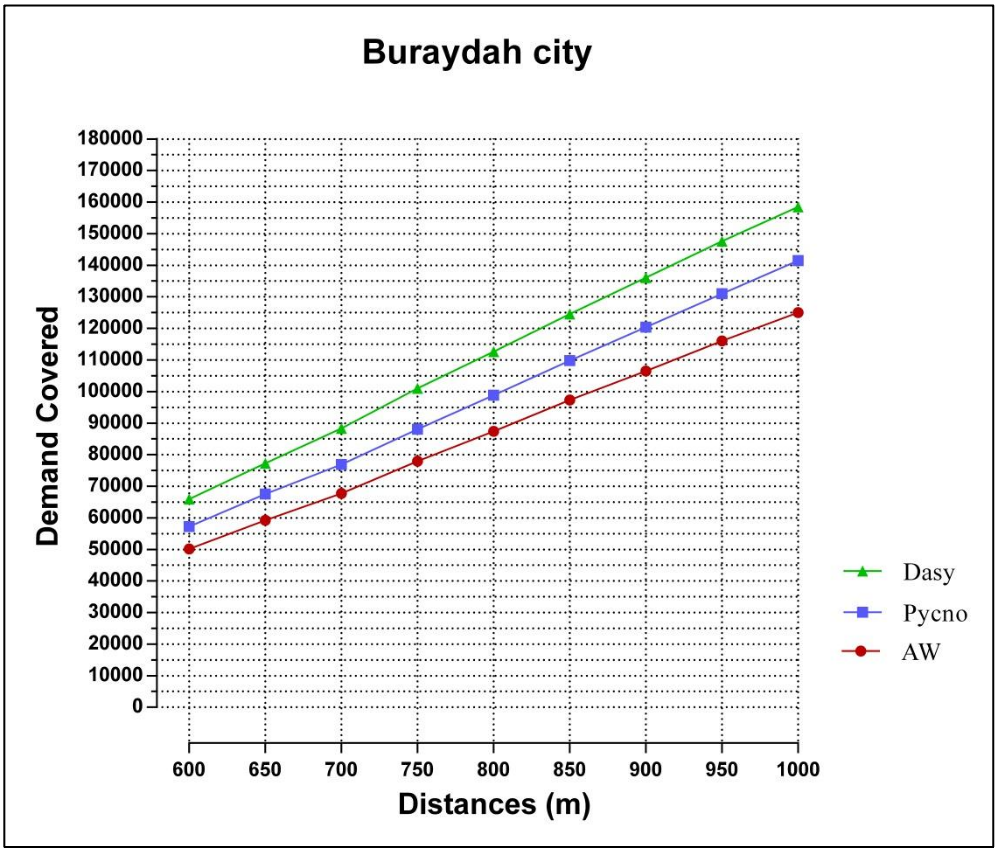


Figure 5.21: Results of the distances and sensitivity demand selection from the MF model for the three demand surfaces in Buraydah

The Chi-square test was used to analyse the large variation in demand selection size for the MF model between the three demand surfaces. The test results showed that the P value was < 0.0001, meaning that there were statistically significant differences between the results of sensitivity demand selection for the AW surface when compared with Dasy and also the Pycno surface when compared with Dasy. However, there were no statistically significant differences between the results of the AW and Pycno surfaces. As mentioned regarding the results of the MI and MC models in Buraydah, the large area sizes of the neighbourhoods and the assumptions made by the three demand surfaces had a clear role in influencing the demand and facilities selections; however, when applying the MF model, this study found that Dasy surface was statistically different in terms of allocating the demand weight only.

Table 5.5 Analysis of the results of the sensitivity demand selection from the MF model in Buraydah

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	5.101, 8	57.13, 8	38.00, 8
P value	0.7467	< 0.0001	< 0.0001
Statistically significant? (alpha<0.05)	No	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represents the sensitivity demand selection from 600 to 1000 metres at 50 metre intervals. **The number of columns represents the two surfaces tested.

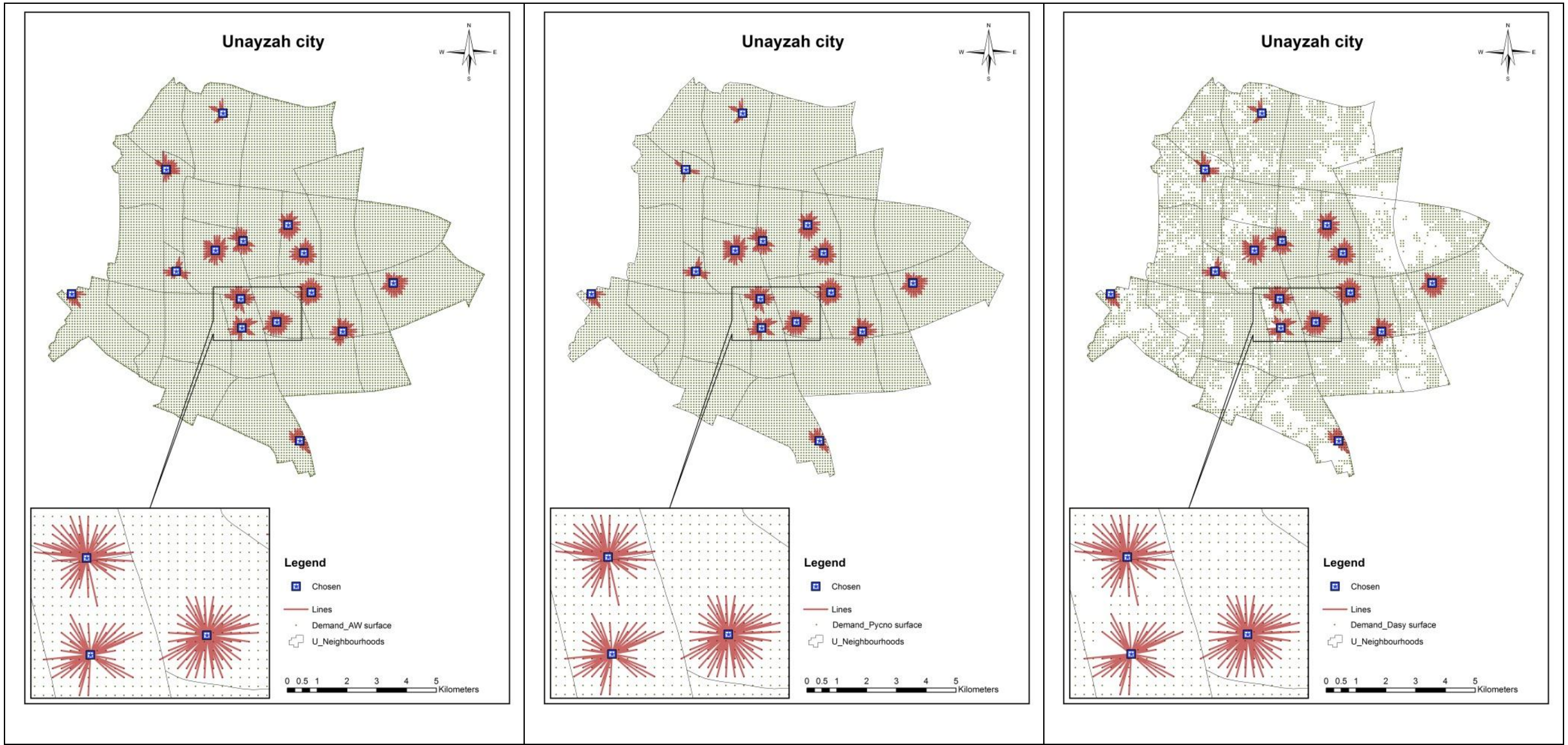
In summary, the results of applying the MF model on the three demand surfaces in this case study showed the following points:

1. There were no candidate facilities: all of the PHCC locations were chosen to cover the demand needs in the three surfaces within the distances used.
2. The large spacing between the PHCC sites, the large area of Buraydah city and the limited number of PHCCs also had an effect on the interaction results for the MF model.
3. The Dasy surface performed better in terms of demand coverage.
4. The MF model using the assumptions of the Dasy surface had a statistically different outcome in terms of allocating the demand weight only.

5.2.2.3 The results of the MF model for Unayzah

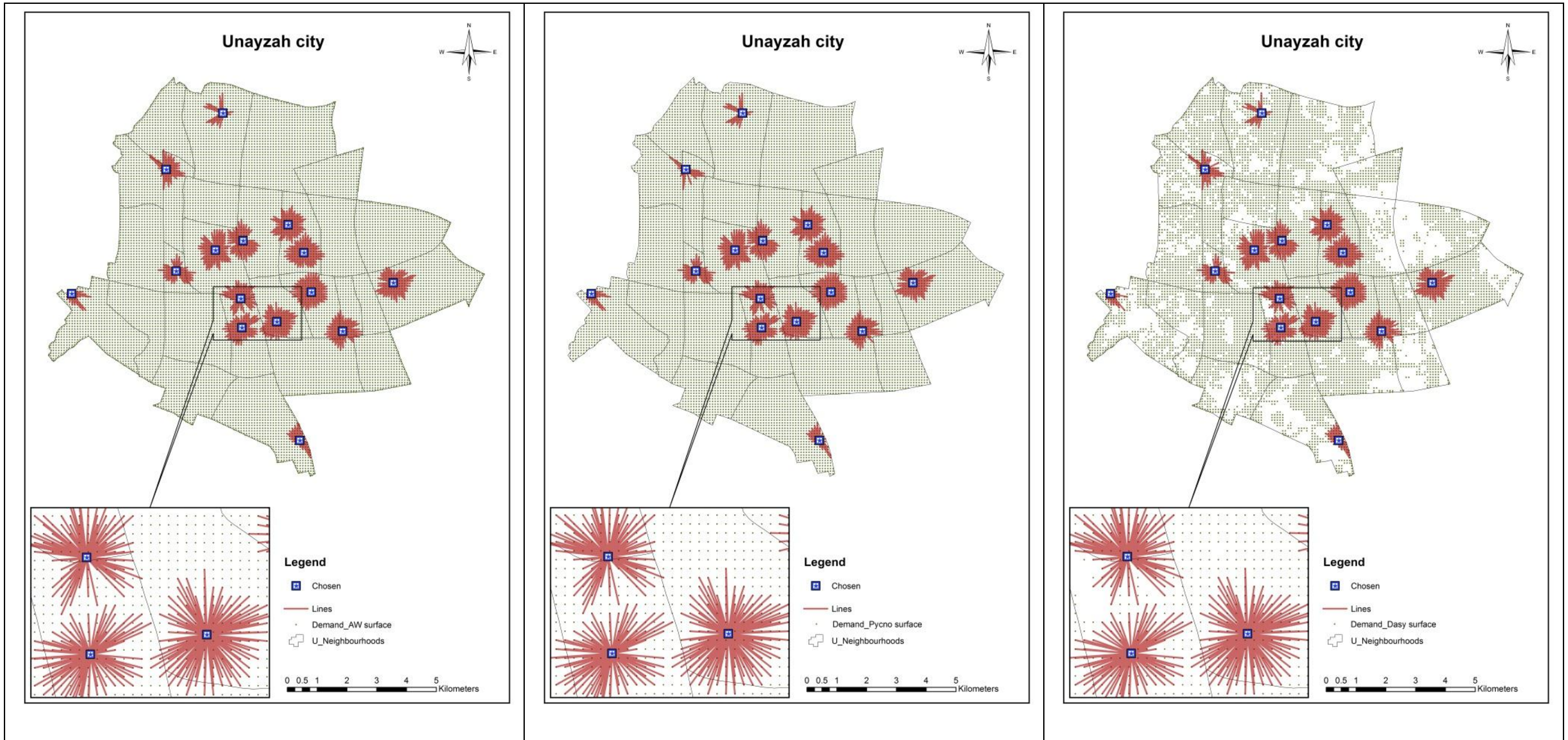
The MF model was run to minimise the distances between the PHCCs and the demand while, at the same time, selecting the minimum number of PHCC locations to cover the three demand surfaces at 50 metre intervals, from 600 to 1000 metre distances. In terms of facility selection, when applying the MF model on the three demand surfaces in Unayzah, the interaction results show that there were no candidate PHCC locations. The MF model facility selection results mean that all the facilities were chosen in each of the distances used in this study. Some of the MF model results are shown in Figures 5.22, 5.23 and 5.24, while the results from the remaining distances are presented in Appendix 2 (see Figures 2.28 to 2.33).

These results are similar to those for Buraydah, where the MF model was run on the three demand surfaces. The results demonstrate that the small numbers of PHCC locations and the large spacing between them in the KSA case studies had an effect on both the MF model and its interaction results. As noted in the previous case study, the wide spacing between PHCC locations in the centre and some other parts of Unayzah had the effect of minimising facilities and determining the candidate locations (see Figure 5.22). Even when the distance was increased to 800 metres and then further to 1000 metres, there was still large spacing between the PHCC locations (see the distribution of demand points outside the lines in the central and north-western Unayzah, resulting from the use of the Dasy method, in Figures 5.23 and 5.24).



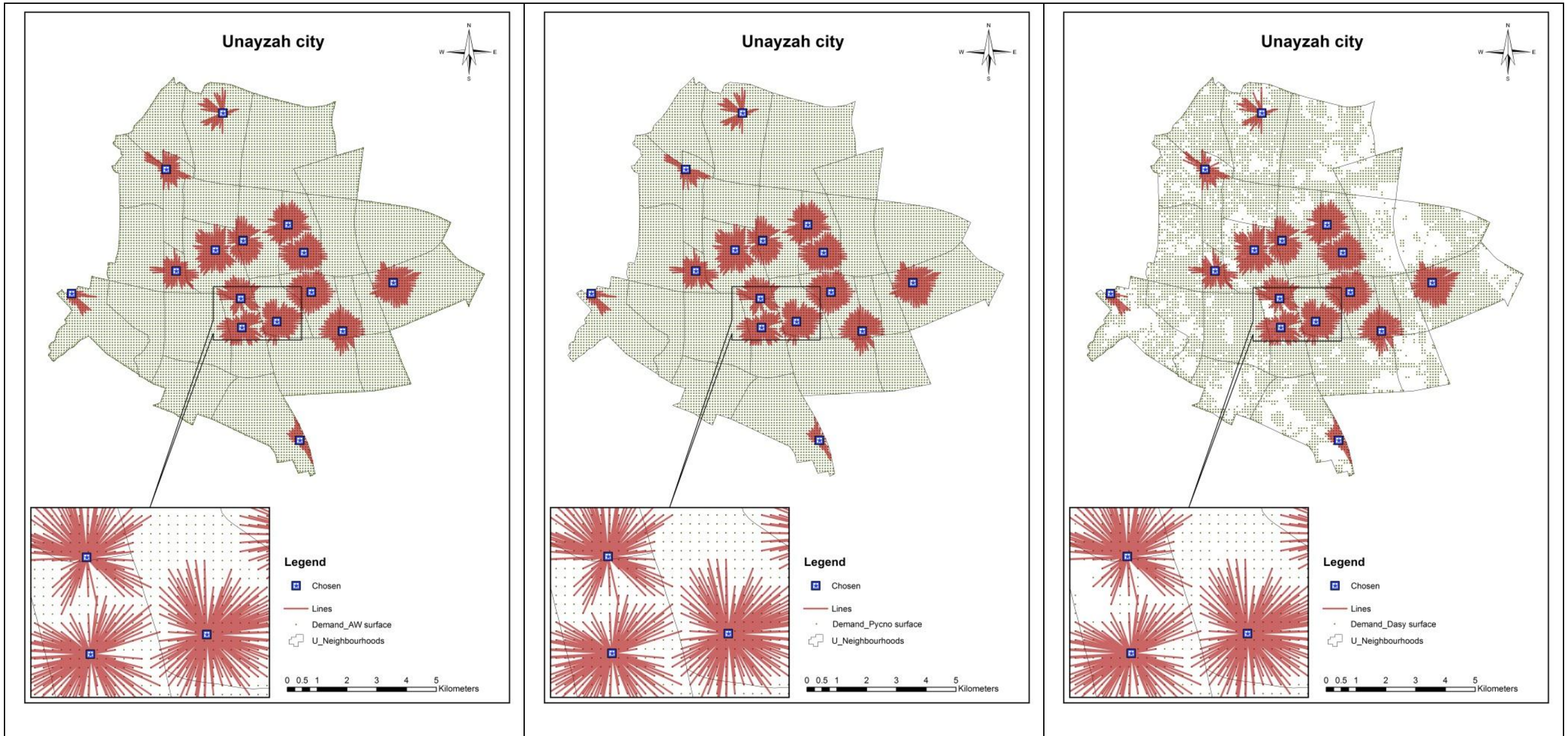
a) AW	b) Pycno	c) Dasy

Figure 5.22: Results of applying the MF model in Unayzah within 600 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.23: Results of applying the MF model in Unayzah within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.24: Results of applying the MF model in Unayzah within 1000 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

The interaction results for the MF model and the three demand surfaces show that demand coverage selection produced different results, depending upon the distances used. The distances and sensitivity demand selection by the MF model for the three surfaces in Unayzah are depicted in Figure 5.25. Of the three surfaces, the weight of demand selection by the Dasy surface achieved the best geographical coverage for the PHCCs (see the green points in Figure 5.25). The Pycno surface achieved the second best results, while the AW surface was deemed to be the worst method (see the blue and red points respectively in Figure 5.25). For example, when applying the MF model within a distance of 800 metres, the demand selection results show that 45,015.people were covered by using the Dasy method surface, 42,782.by the Pycno surface and 39,734.by the AW surface. The demand selection results show substantial convergence between the Dasy and Pycno surfaces for the distances from 600 to 1000 metres (see Figure 5.25). This may have been due to the concentration of most PHCCs in the middle of Unayzah, close to the population densities, and the fact that the assumptions made by the Dasy technique depended upon the estimated population in these areas.

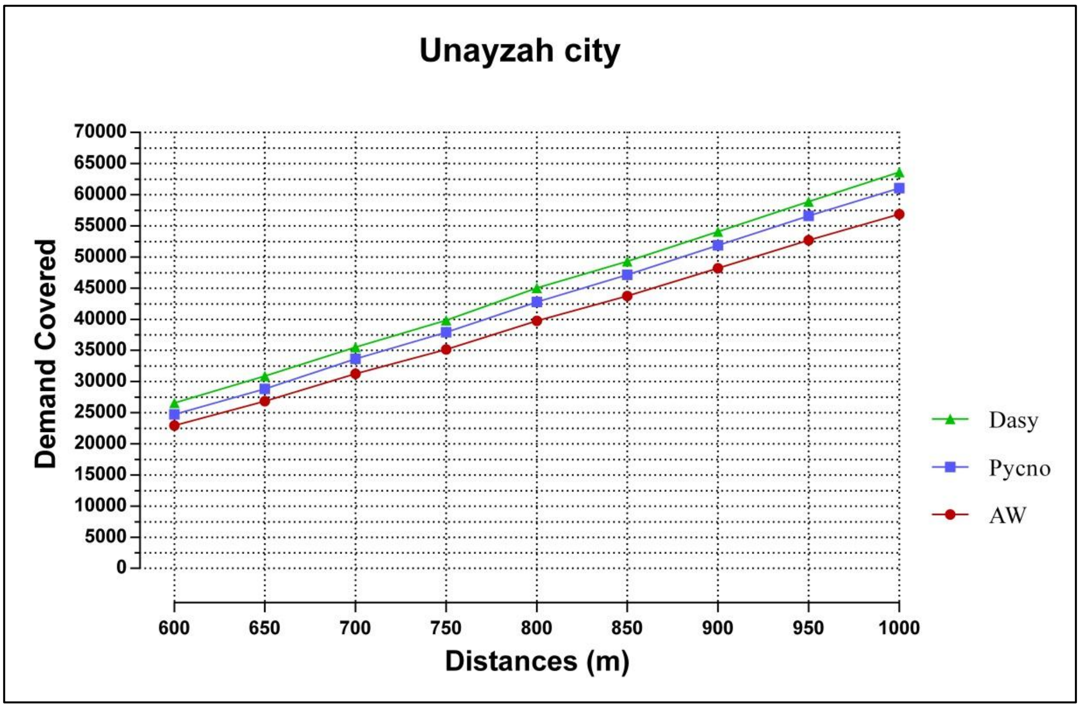


Figure 5.25: Results of the distances and sensitivity demand selection from the MF model for the three demand surfaces in Unayzah

The study used the Chi-square test to analyse differences between the results of the three demand surfaces in terms of sensitivity demand selection in Unayzah. The test results showed that there were no statistically significant differences between the results of the AW surface when compared with Pycno, however, there were statistically significant differences between the results of the AW surface when compared with Dasy surface and the Pycno surface when compared with Dasy surface (see Table 5.6). The comprehensive dealing for the MF model with the demand weights in order to minimise number of the facilities, and the adoption of the AW and Pycno methods to estimate the population in all the target areas within the source zone had an effect on the differences of the demand weights for each demand point between the two method and the sensitivity demand selection for MF model.

Table 5.6 Analysis of the results of the sensitivity demand selection from the MF model in Unayzah

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	0.5169, 8	21.28, 8	20.19, 8
P value	0.9998	0.0064	0.0096
Statistically significant? (alpha<0.05)	No	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represents the sensitivity demand selection from 600 to 1000 metres at 50 metre intervals. **The number of columns represents the two surfaces tested.

The results of applying the MF model on the three demand surfaces in this case study may be summarised as follows:

1. Within the distances used there were no candidate facilities: all of the PHCC locations were chosen to cover the demand needs in the three surfaces.
2. The wide spacing between the PHCC locations in the centre and some other parts of Unayzah had an effect on the ability to minimise of the facilities and determine the candidate locations.
3. The MF model on the Dasy surface produced a better performance in terms of demand coverage.

5.2.3 The results of the MA model

The aim of using the MA model is to maximise the attendance of demand for each service – namely the GPs (in the UK case study) and the PHCCs (in the KSA) – while simultaneously minimising the total distances between the facilities and the demand points (the centroid points for the 90 metre grid cell, which has been areally interpolated using three areal interpolation methods). The analyst needs to select the numbers of facilities to be chosen and the distance; the model then identifies the most likely GPs or PHCCs close to the majority of the demand weight. The MA model differs from the MI, MC and MF models in terms of the allocation of facilities and demand selection. The following points detail the operation of the MA model, as described in ArcInfo 10 and the methodology chapter:

1. Within the distance used, any demand point outside the specified distance is not allocated.
2. If the demand point is within the distance specified, a ratio of the total demand weight is partially allocated according to the distance to one facility.
3. If the demand point is within the distance specified for more than one facility, a ratio of the total weight for that demand point is allocated to the nearest facility only.

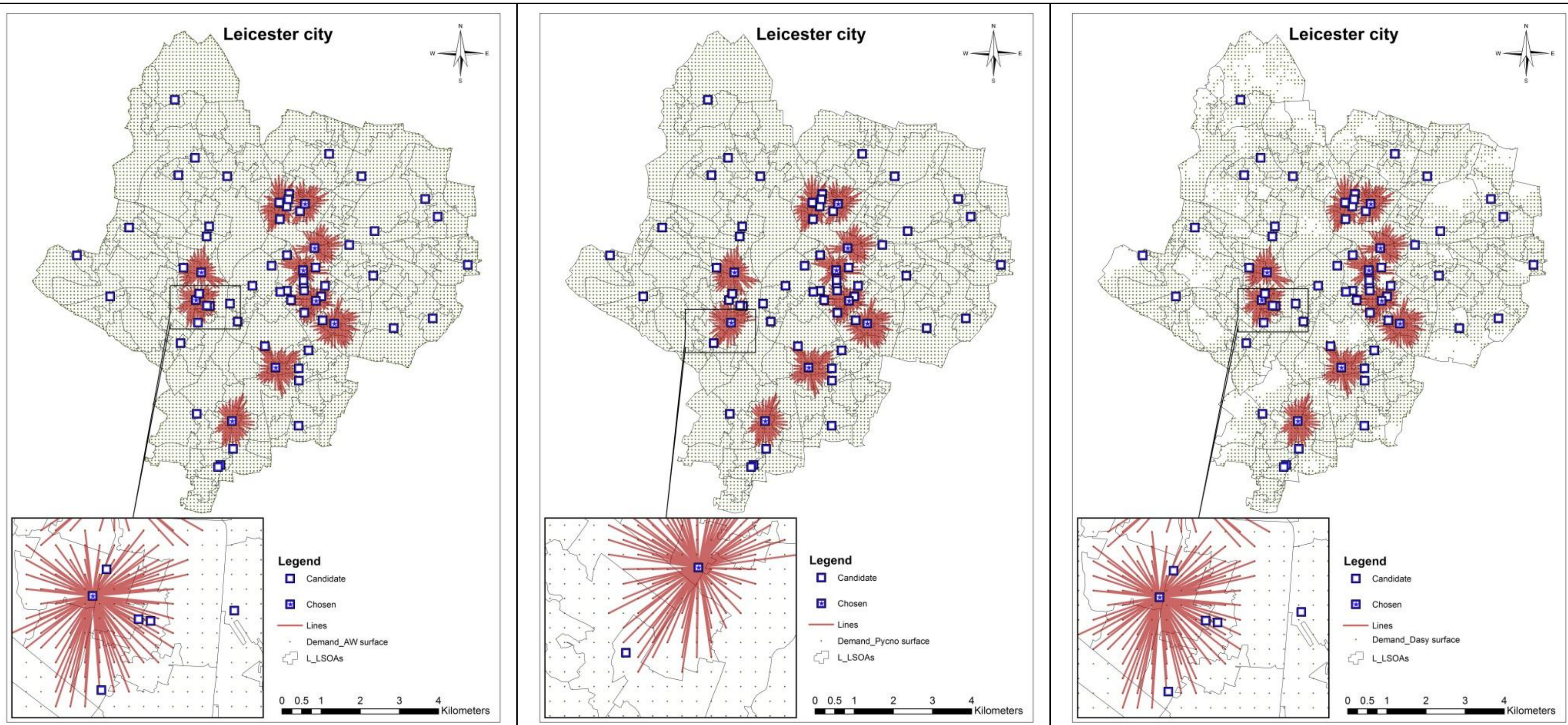
5.2.3.1 The results of the MA model for Leicester

The MA model was run to select the best 1, 5, 10, 20, 30, 40, 50 and 60 of 66 GP locations to cover each demand surface using the three demand surfaces within the specified distance of 800 metres. The interaction results for the MA model showed that there were some differences in terms of facility selection for the GP locations, depending on which of the three demand surfaces was used (some results are shown in Figures 5.26, 5.27 and 5.28, with the remainder shown in Figures 2.34 to 2.38 in Appendix 2).

Some of the interaction results for the MA model on the three demand surfaces show similarities between them when the analysis was undertaken in order to select a small or large number of GP locations, such as the best single and 60 GP locations (see Figures 2.34 and 2.38 in the Appendix 2). Additionally, there were similar selection results between the AW and Dasy surfaces in choosing the best 5 and 10 GP locations (see Figure 2.35 in the Appendix 2 and Figure 5.26 in the results chapter and the concentrations of the 5 and 10 GP locations in the middle of Leicester and the different selection results for the Pycno surface). This was due to the adoption of Pycno interpolation to provide a heterogeneous estimation for the target areas. Also, the objective function and the operations of the MA model in allocating the facilities close to the majority of the demand weight. On the basis of the operation of the MA model in terms of allocation of the facilities to the demand points as described above, it seems that the impact of LSOAs with a high population density was greater than the assumptions of the three demand surfaces in selecting small numbers of GP locations, such as the best single or 5 and 10 locations.

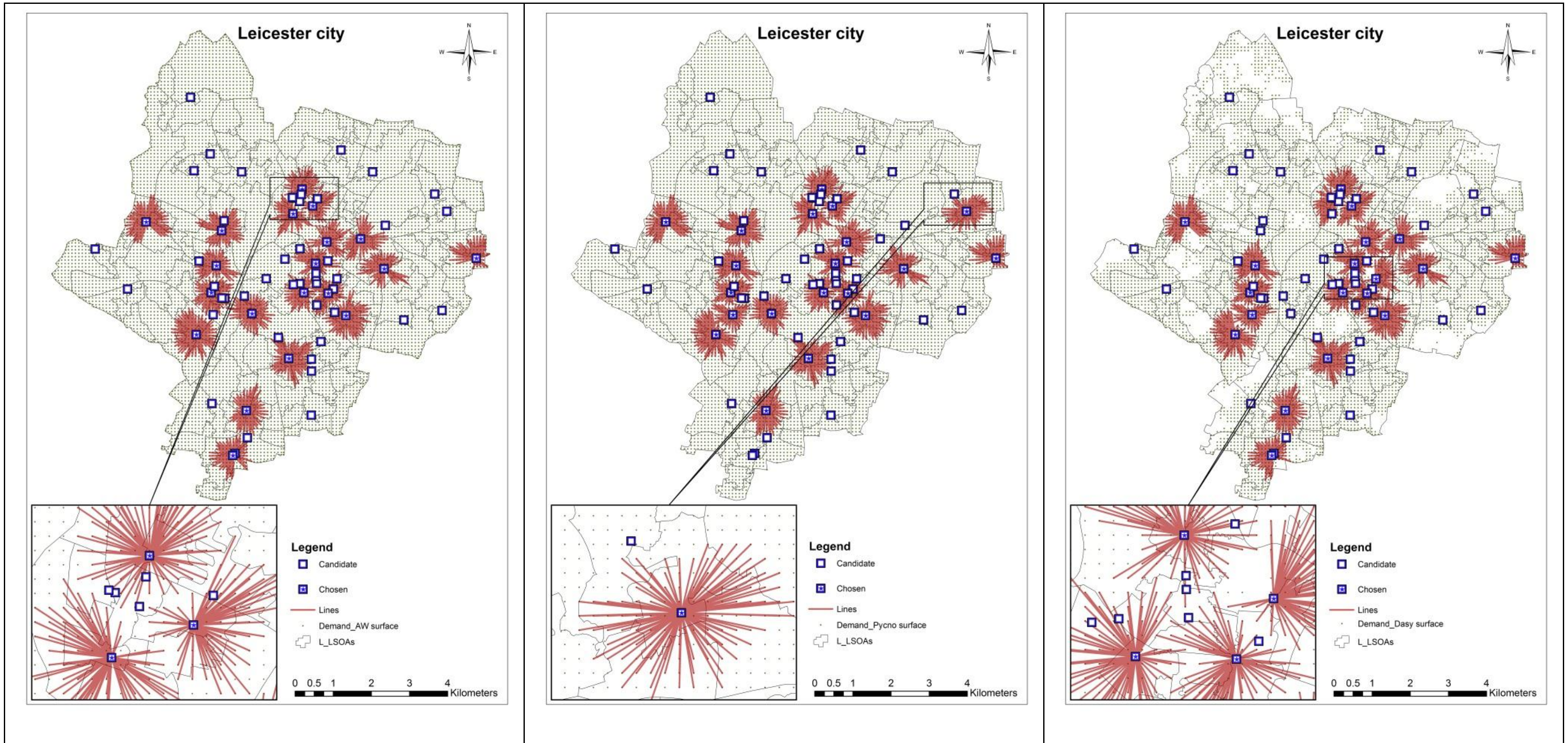
However, there were some differences in the facilities selection results between the three demand surfaces. For example, Figure 5.27 shows the different selection results for the MA model in selecting the best 20 GP locations on the three demand surfaces in the north, central and east of Leicester. Some differences between the surfaces also existed upon determining the best 30 GP locations to cover the demand points; these differences were clear to GP locations in the north, west and central of the city (as shown in Figure 5.28). There were another interaction results for the MA model on the three demand surfaces identified some differences in the facilities selection for the best 40 and 50 GP locations (as shown in Figures 2.36 and 2.37 in Appendix 2). The MA model results demonstrate that the population estimates obtained by using the AW, Pycno and Dasy methods had an effect on certain results for selection of the best GP locations in Leicester. These effects were a consequence of the implicit assumptions upon which each of these areal interpolation techniques is based.

Some of the GP selection results of the MA model also differed from those created by the MI and MC models, when those models were run to select the same number of GP locations as selected by the MA model (for example, see Figures 5.1 to 5.3). The results of the MA model suggest that it depends upon selecting the GP locations close to the majority of the demand. For example, Figures 5.26, 5.27 and 5.28 illustrate that there was a concentration of determined GP locations close to the majority of the demand. Thus, the MA model minimised the distances between the facilities and ensured that they were concentrated in those areas with the majority of the demand.



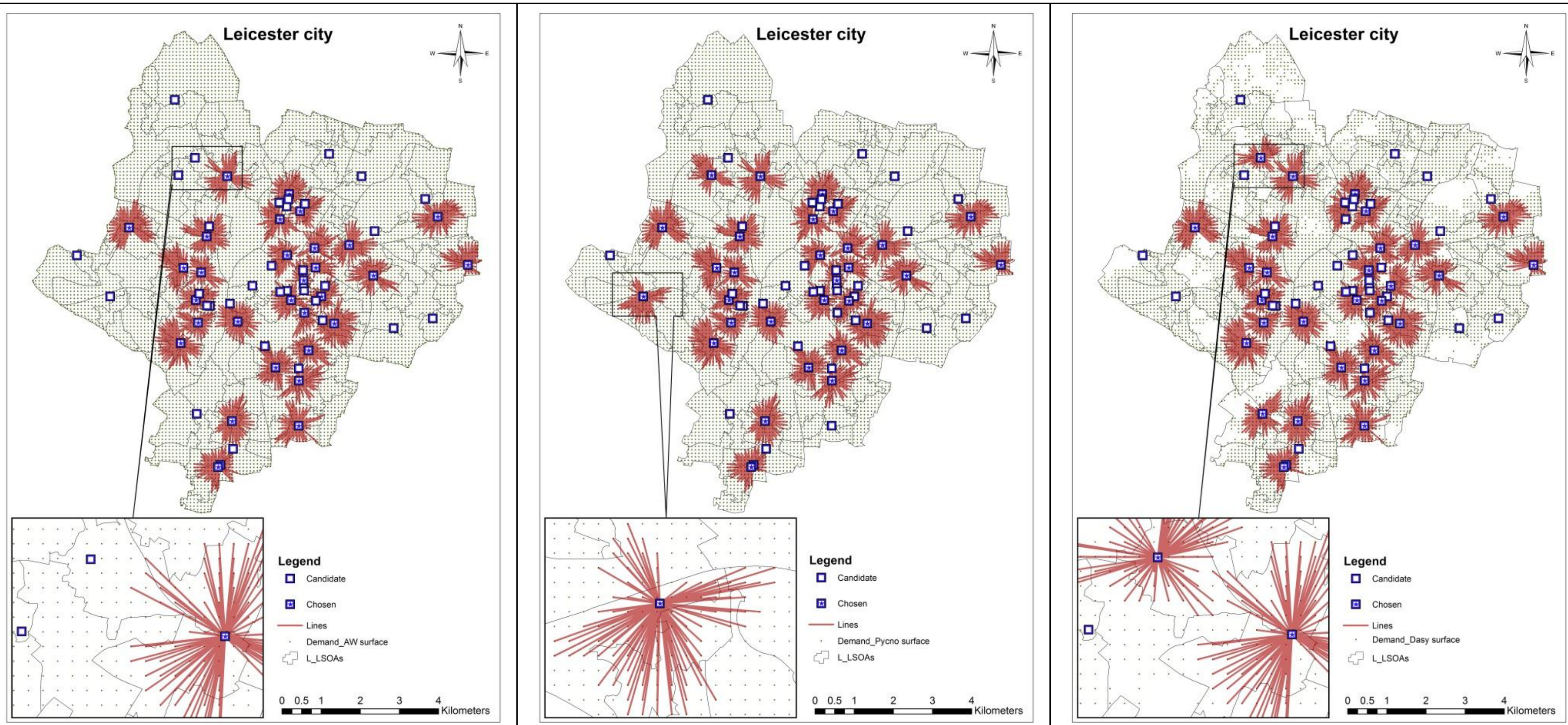
a) AW | b) Pycno | c) Dasy

Figure 5.26: Results of applying the MA model in Leicester to select the best 10 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW	b) Pycno	c) Dasy

Figure 5.27: Results of applying the MA model in Leicester to select the best 20 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW	b) Pycno	c) Dasy

Figure 5.28: Results of applying the MA model in Leicester to select the best 30 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

In terms of demand selection, the interaction results of the MA model with the three demand surfaces identified different results, depending upon the number of GP facilities to be chosen from the total of 66 and covering the demand points for each surface, within the distance of 800 metres. The weight of the demand selection from the Pycno surface achieved the best geographical coverage for the MA model, in terms of the weight of the demand, for the best 1 to 40 GP locations (see the blue points in Figure 5.29). The Dasy surface achieved the best performance in terms of geographical coverage for the best 50 to 66 GP locations, while the AW surface was deemed to be the worst (see the green and red points respectively in Figure 5.29). The results also reveal that there was substantial convergence between the weight of the demand selection between the Pycno and Dasy surfaces. As there was concentration on the process of determining the best locations for the MA model in the city centre with proximity to the majority of the demand, the study noted that the role of Dasy surface had less impact than the Pycno surface in terms of allocating the demand weight of the demand points (compare the results of sensitivity demand selection for the MI and MC models with those for the MA model). Also, the study noted that there was no saturation in the weight of the demand as had occurred when the MI and MC models were run to select the best 50, 60 and 66 GP locations for the three surfaces (compare Figure 5.29 to Figure 5.4).

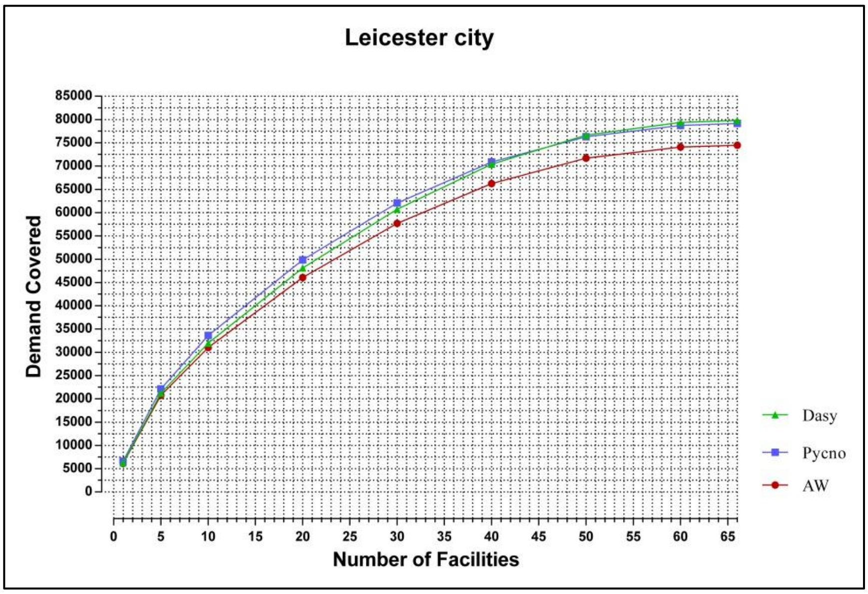
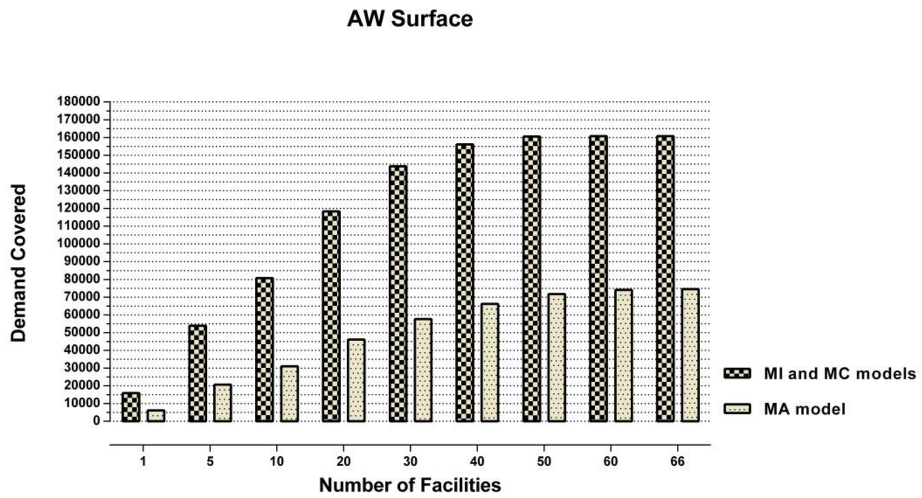
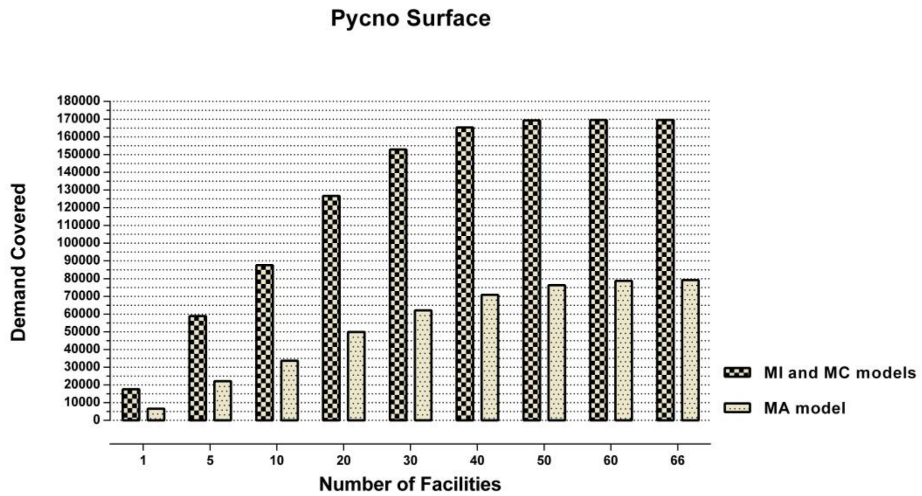


Figure 5.29: Results of the sensitivity demand selection from the MA model for the three demand surfaces in Leicester

However, the results show that the weight of the demand selection for the MA model was smaller than that for the MI and MC models when identifying the best 1 to 60 of the total 66 GP locations for the three surfaces within the distance specified (see Figure 5.30). This was due to using the MA model to allocate a ratio from the total demand weight for each demand point, as described previously, which subsequently decreased when the distance was increased between the GPs and the demand points. These results suggest that, of all the surfaces, the Dasy surface achieved the best geographical coverage in Leicester when using the MA model. This is similar to the MI, MC and MF models, in which the Dasy surface also provided a better performance in terms of geographical coverage of the demand.



a)



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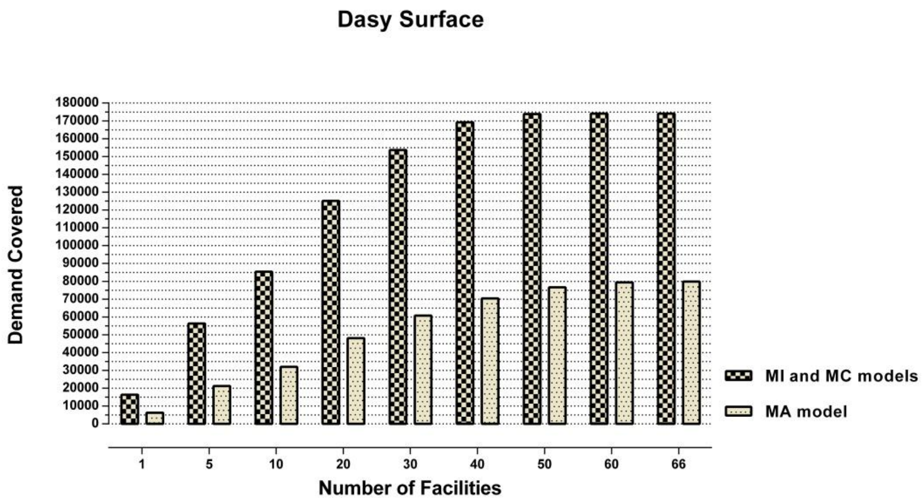


c)

Figure 5.30: Results of the sensitivity demand selection from the MI, MC and MA models for the three demand surfaces in Leicester: a) AW surface; b) Pycno surface; and c) Dasy surface.

The results of the Chi-square test for the results of sensitivity demand selections by the MA model were similar to those achieved by the test for the MF model (see Table 5.7). There were no statistically significant differences between the AW and Pycno surfaces. However, there were statistically significant differences between the AW surface when compared with Dasy and also the Pycno surface when compared with Dasy. It may be that the small area for the LSOAs in Leicester, along with the allocation of a ratio from the total demand weight for each demand point under the MA model, had an effect on the results of the sensitivity demand selection for the MA model on the AW and Pycno surfaces, because these two methods depend upon estimation of the population according to assumptions on all the areas inside LSOAs with different weights inside each point.

Table 5.7 Analysis the results of the sensitivity demand selection from the MA model in Leicester

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	12.11, 8	48.40, 8	99.85, 8
P value	0.1464	< 0.0001	< 0.0001
Statistically significant? (alpha<0.05)	No	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represent the sensitivity demand selection for the best 1, 5, 10, 20, 30, 40, 50, 60 and 66 GP locations. **The number of columns represents the two surfaces tested.

The results of applying the MA model on the three demand surfaces in this case study may be summarised as follows:

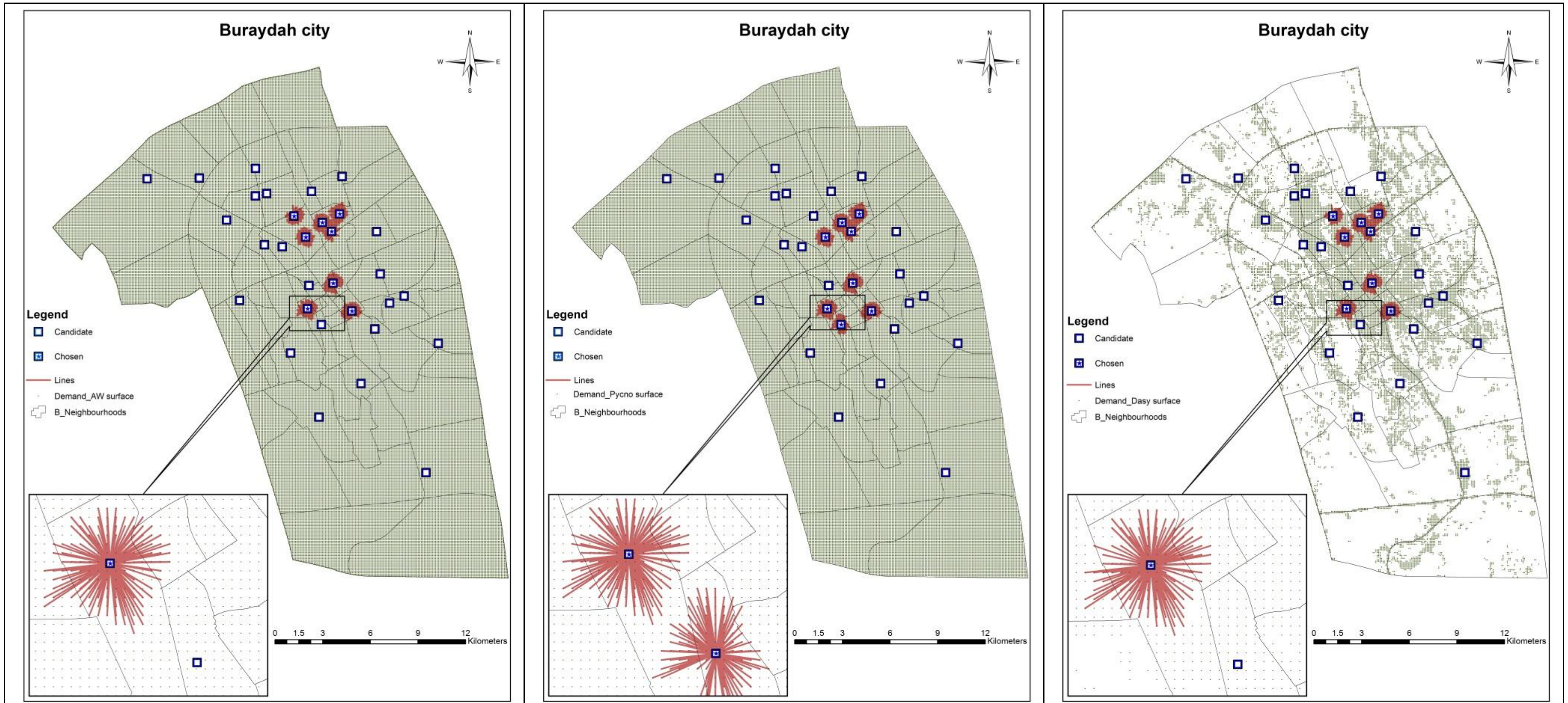
1. The results of interactions between the MA model and the three demand surfaces showed that the differences in facilities selections were less evident than for the MI and MC models when the MA model was used to select small numbers of facilities, such as the best single, 5 and 10 GP locations.
2. The MA model on the three demand surfaces produced some differences in facilities selection results; these demonstrate that the results of the population estimates obtained through the use of the AW, Pycno and Dasy methods affected the selection of the best GP locations in Leicester.

3. There was a form of concentration in determining the GP locations when the MA model was run on the three demand surfaces.
4. In some analyses, the Pycno surface provided a superior performance in terms of the weight of the demand selection; other analyses show that Dasy surface provided a better performance in terms of the weight of the demand selection.
5. The study noted that the role of the Dasy surface was less impactful than the Pycno surface in terms of allocating the demand weight of demand points because there was a form of concentration in the process of determining the best locations for the MA model in the city centre and proximity to the majority of the demand.
6. In terms of the demand selection, the weight of the demand selected by the MA model was smaller than that for the MI and MC models.

5.2.3.2 Results of the MA model for Buraydah

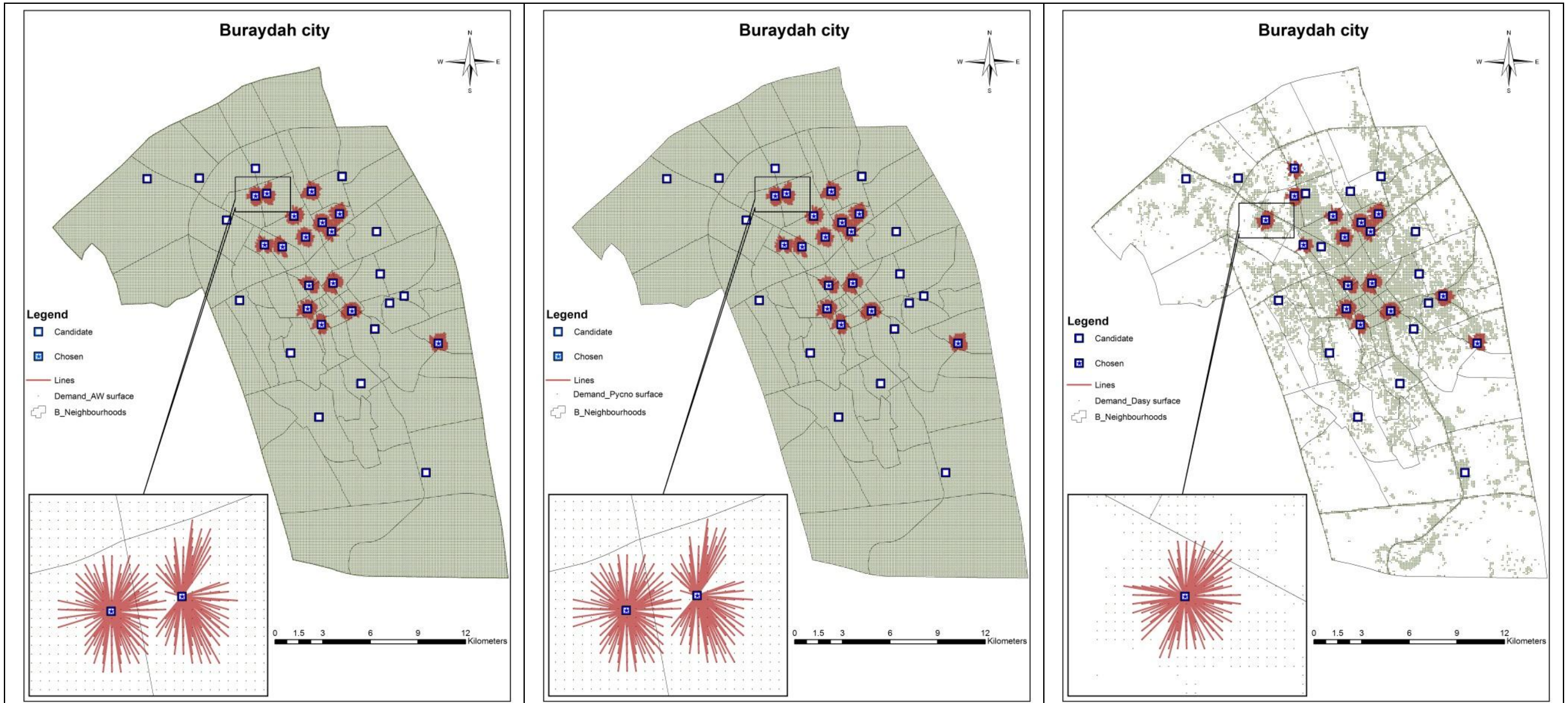
To serve each of the three demand surfaces within a distance of 800 metres, the MA model was run to select the best 1, 4, 8, 12, 16, 20, 24 and 28 of the 31 PHCC locations. The interaction results for the MA model showed that both similar and different facilities selections were made by using the three demand surfaces (see Figures 5.31 to 5.33 in the results and Figures 2.39 to 2.43 in Appendix 2). Figures 2.39 and 2.40 in Appendix 2 show the best single and 4 PHCC locations and the similar facility selection made by the three demand surfaces. Similar facilities selection results for the best 8 PHCC locations selected using the AW and Dasy surfaces are shown in Figures 5.31. In contrast, the Pycno surface produced different facilities selection results in the centre and east of Buraydah city. These eight locations are located in the middle and north of Buraydah, in neighbourhoods with a high population density. The MA model on the Dasy surface produced some new facilities selection results in the north-west and east areas of central Buraydah (see, for example, the best 16 PHCC locations in Figure 5.32; see also Figures 2.41 and 2.42 in the Appendix 2). Another example of the different facilities selection results for the three demand surfaces is shown in Figure 5.33 with regard to the best 20 PHCC locations. Different facilities selection results were also obtained from the three demand surfaces when selecting the best 28 PHCC locations (see Figure 2.43 in Appendix 2).

Differences in the facilities selection results for the MA model on the Dasy surface arose due to the assumptions made by the MA model when allocating the facilities close to the majority of demand weight. This was also due to the high demand previously noted at each point of the Dasy surface. In fact, the differences in facilities selections that arose when applying the MA model on the demand surfaces were clearer than the differences in facilities selections by the MI and MC models. Some of the PHCC selection results for the MA model also differed from the same results for the MI and MC models when these were run to select, for example, the best 8 PHCC locations selected by the MA model on Pycno surface and the best 8 and 16 PHCC locations selected by the MA model on the Dasy surface (see Figures 5.5 and 5.6). The operation of the MA model in selecting facilities close to the majority of the demand affected the results in selecting the best 12, 16 and 24 PHCC locations and resulted in similarity between the AW and Pycno surfaces. In some cases, the limited number of PHCCs and the large variation in population density in Buraydah had a clear impact on the similarity of the interaction results. The similarities in some results between the three demand surfaces are discussed in more detail in the discussion chapter.



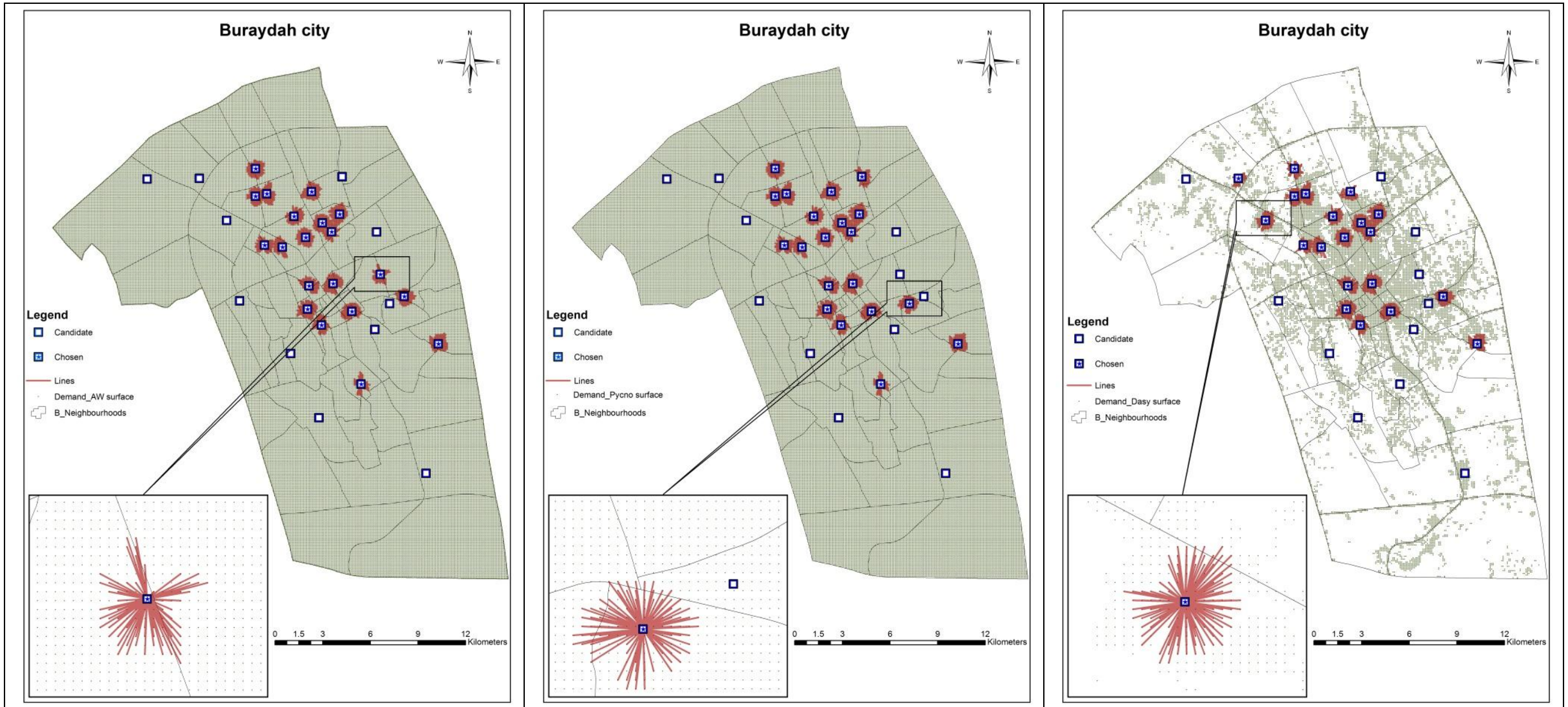
a) AW	b) Pycno	c) Dasy

Figure 5.31: Results of applying the MA model in Buraydah to select the best 8 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.32: Results of applying the MA model in Buraydah to select the best 16 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.33: Results of applying the MA model in Buraydah to select the best 20 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

The interaction results for the MA model with the three demand surfaces produced different outcomes in terms of demand selection. This depended upon choosing the number of PHCC facilities from the 31 available and covering the demand points for each surface within a distance of 800 metres. The interaction results showed that, of the three demand surfaces, the Dasy surface achieved the best geographical coverage for the weight of the demand when using the MA model (see the green colour in Figure 5.34). The Pycno surface was ranked second as it also achieved the best geographical coverage for the MA model when selecting the best 1, 4 and 8 PHCC locations (see the blue colour in Figure 5.34). In contrast, the AW surface was the worst in terms of geographical coverage (see the red colour in Figure 5.34).

The results of the demand selections for the MA model were also lower than the weight of the demand selections for the MI and MC models in the best 1, 4, 8, 12, 16, 20, 24, 28 and 31 PHCC locations (see Figure 5.35). From the results of the demand selections, it was noted that the Pycno surface achieved the best geographical coverage for the MA model when determining small numbers of PHCC locations in the centre of the Buraydah city. However, the Dasy surface was the best in terms of determining large numbers of PHCC locations and covering the demand points in the other parts of the city. The assumption of a smooth and gradual density function, under the Pycno method, helped this surface provide the best geographical coverage in the central Buraydah. In contrast, the Dasy surface proved its effectiveness in areas consisting of large neighbourhoods and small built up areas in which there was a wide variation in population density between neighbourhoods.

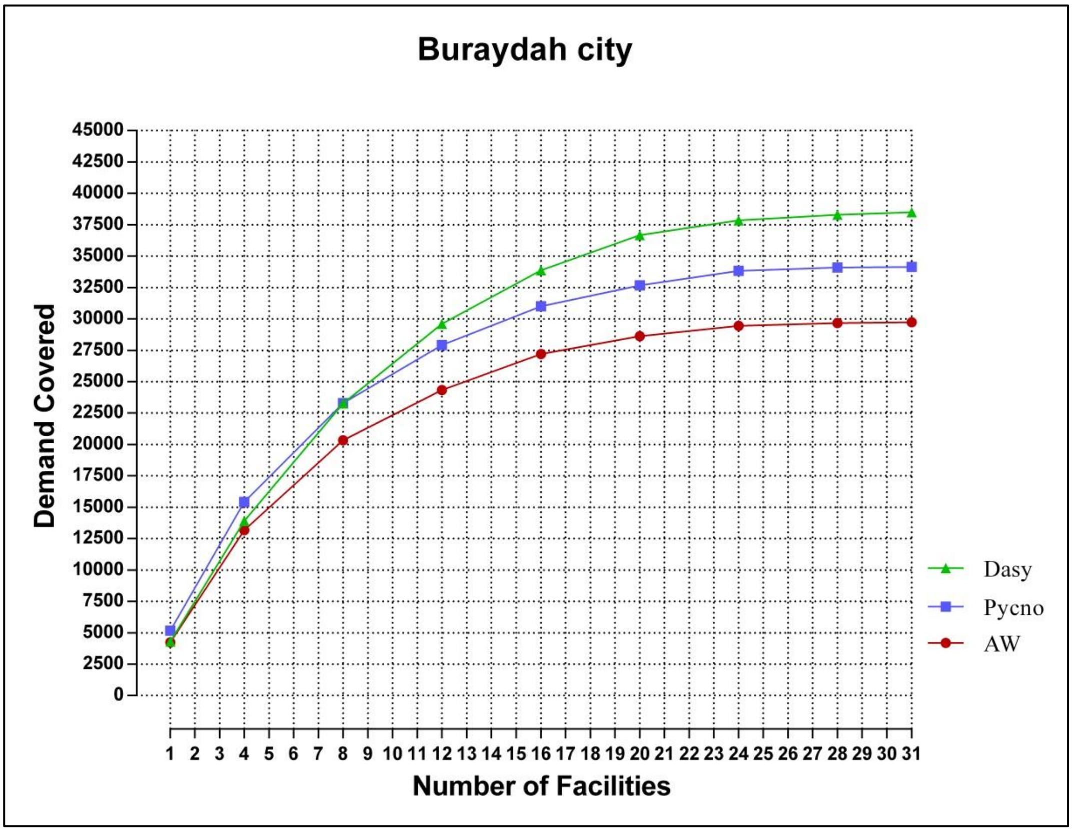
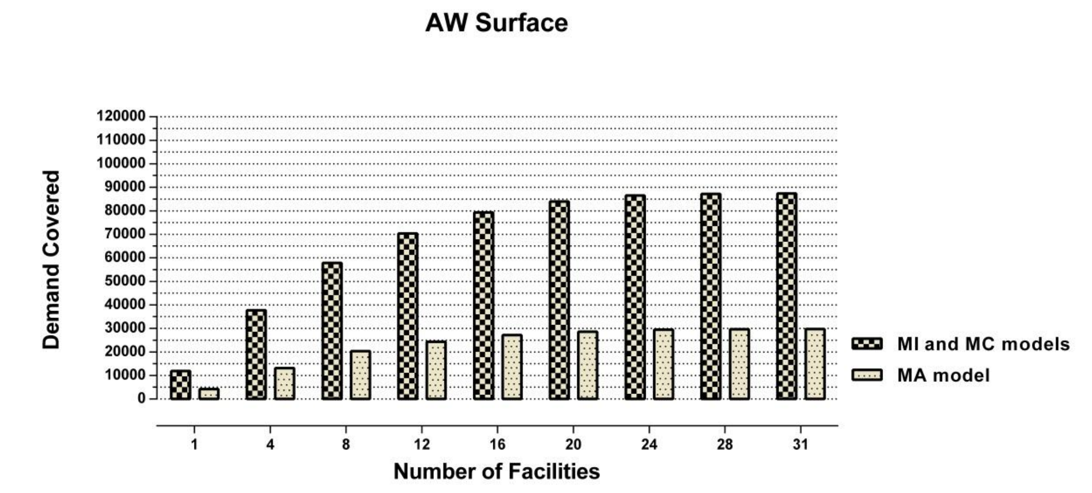


Figure 5.34: Results of the sensitivity demand selection from the MA model for the three demand surfaces in Buraydah.



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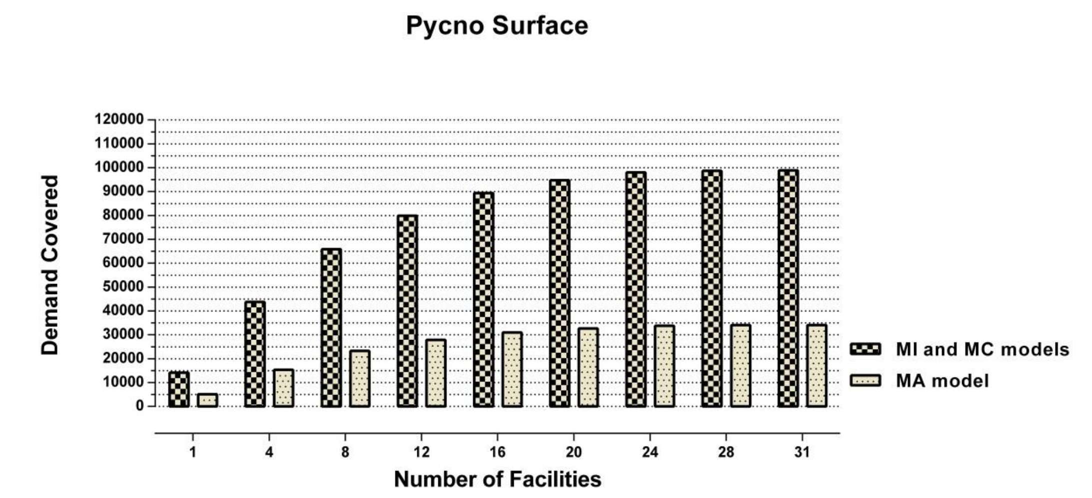

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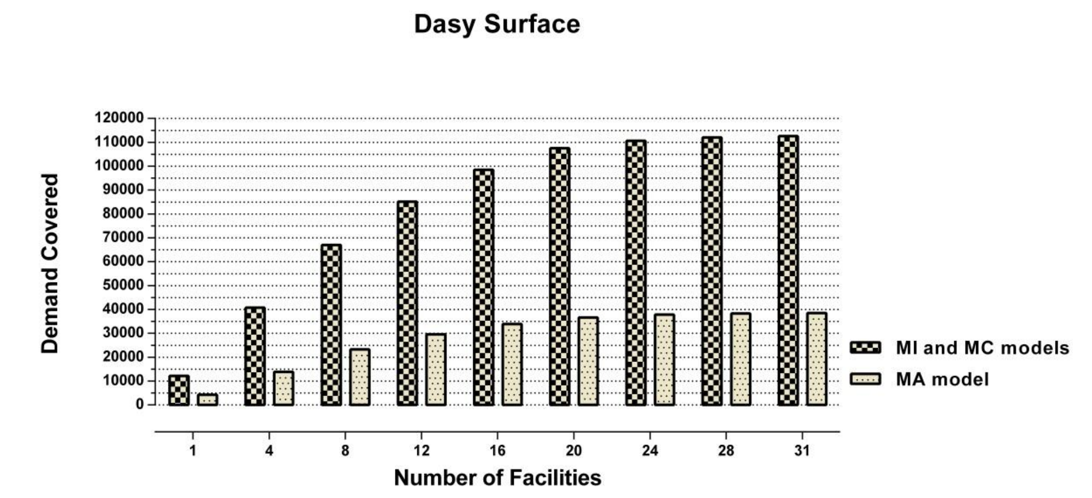


c)

Figure 5.35: Results of the sensitivity demand selection from the MI, MC and MA models for the three demand surfaces in Buraydah: a) AW surface; b) Pycno surface; and c) Dasy surface.

The Chi-square test was used to analyse the variation in demand selection size for the MA model between the three demand surfaces. The results of the test showed that there were statistically significant differences between the results of sensitivity demand selection for the AW surface when compared with Dasy and also for the Pycno surface when compared with Dasy (see the P value in Table 5.8). However, there were no statistically significant differences between the results of AW with Pycno surfaces. It seems that the demand selection results obtained from using the Dasy surface were different and had a clear impact on determining facilities.

Table 5.8 Analysis of the results of the sensitivity demand selection from the MA model in Buraydah

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	11.46, 8	437.1, 8	585.4, 8
P value	0.1772	< 0.0001	< 0.0001
Statistically significant? (alpha<0.05)	No	Yes	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represent the sensitivity demand selection for the best 1, 4, 8, 12, 16, 20, 24, 28 and 31 PHCC locations. **The number of columns represents the two surfaces tested.

The results of applying the MA model on the three demand surfaces in this case study may be summarised as follows:

1. In certain analyses for the MA model, similar facilities selection results between the AW and Pycno surfaces were obtained.
2. The MA model on the Dasy surface produced different facilities selection results in some parts of Buraydah city.
3. In terms of facilities selection, differences between the MA model and MI and MC models did not appear when the model was run on a small select number of facilities such as 1 to 4 PHCCs.
4. The differences in facilities selections that arose when applying the MA model on the demand surfaces were clearer than the differences in facilities selections noticed when using the MI and MC models.
5. The limited numbers of PHCCs and the large variation in population density in Buraydah had a clear impact on the similarity of the interaction results.

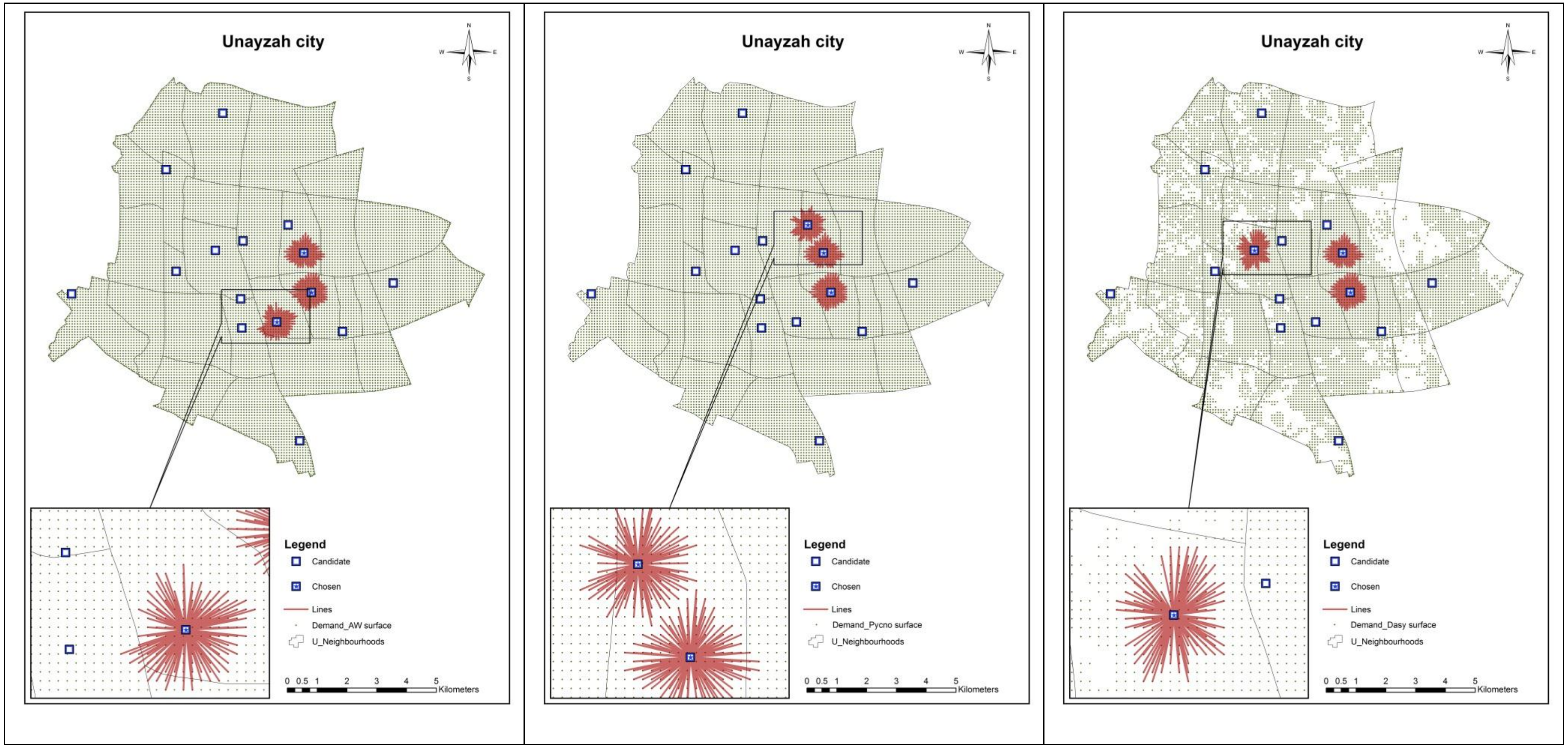
6. The MA model on the Dasy surface provided a better performance in terms of demand coverage.

5.2.3.3 The results of the MA model for Unayzah

The MA model was run to select the best 1, 3, 5, 7, 8, 9, 11 and 13 of the 15 PHCC locations to serve each of the three demand surfaces within a distance of 800 metres. In terms of facilities selection, some of the interaction results from the MA model showed that there were differences between the demand surfaces resulting from the three methods (see Figure 5.36 the different selections for the best 3PHCC locations between the demand surfaces). Two of these locations are located in a single neighbourhood which has a high population density when was run the MA model with the Pycno surface. In contrast, the AW and Dasy surfaces produced different facilities selection results for three neighbourhoods. There were also some differences between the demand surfaces when the MA model was run to select the best 9 PHCC locations (see Figure 5.37 and the different selection for the PHCC locations on the AW surface in the west of Unayzah, in the east for Pycno surface and in the south for Dasy surface). Similar PHCC selections between the AW and Pycno surfaces were apparent when the MA model was run to select the best 11 PHCC locations in the middle and east of Unayzah (see Figure 5.38). In contrast, the Dasy surface identified different selection for the PHCC locations in the south of the city. As in Buraydah city, this was due to the large size of the neighbourhood areas in the cities in the KSA and the assumptions used in the Dasy method to estimate the population of built up areas, which contributed to increase the weight of demand at each point on the Dasy surface.

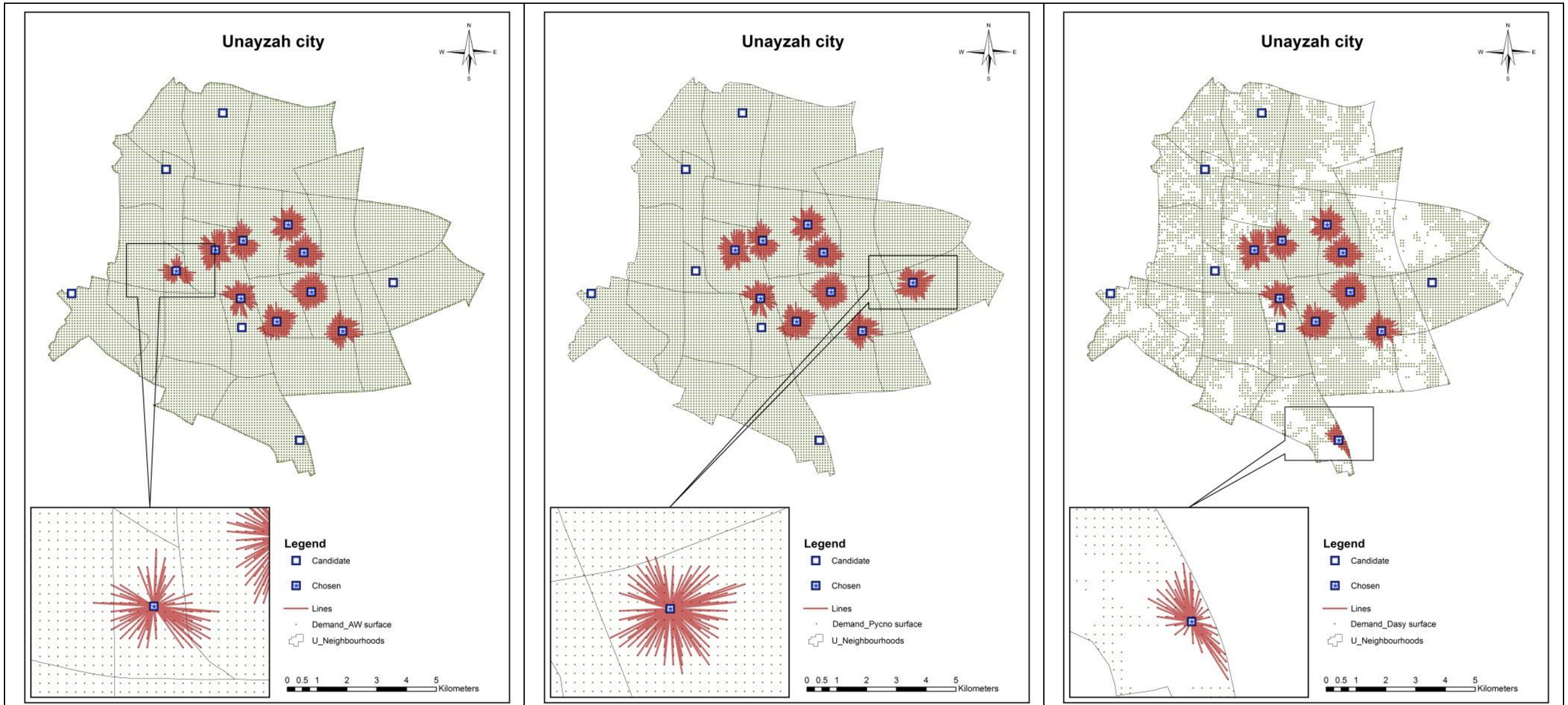
Other results for the MA model on the three demand surfaces identified some differences in the facilities selections, for example; MA model on the AW surface identified different facilities selection compared to the other two surfaces (see the best 7 PHCC locations in Figure 2.46 in the Appendix 2). Additionally, the MA model on the Pycno surface produced different facilities selection results for the best 13 PHCC locations when compared to the other two surfaces (see Figure 2.48 in the Appendix 2). The limited numbers of PHCCs in Unayzah city had a clear impact on the similarity of interaction results in some of the interaction analysis for MA model. For example, in some analyses there were similar PHCC selections between the three demand surfaces (see the best 1. 5 and 8 PHCC locations in Figures 4.44. 4.45 and 4.47 in the Appendix

2). However, with the small numbers of PHCCs in the city the study found that the assumptions used in the interpolation methods had an impact on the facilities selection results for the MA model for some facilities. There were therefore, some differences in the facilities selection results between the three demand surfaces. Additionally, there were some differences for the PHCC selection results from the MA model and those for the MI and MC models.



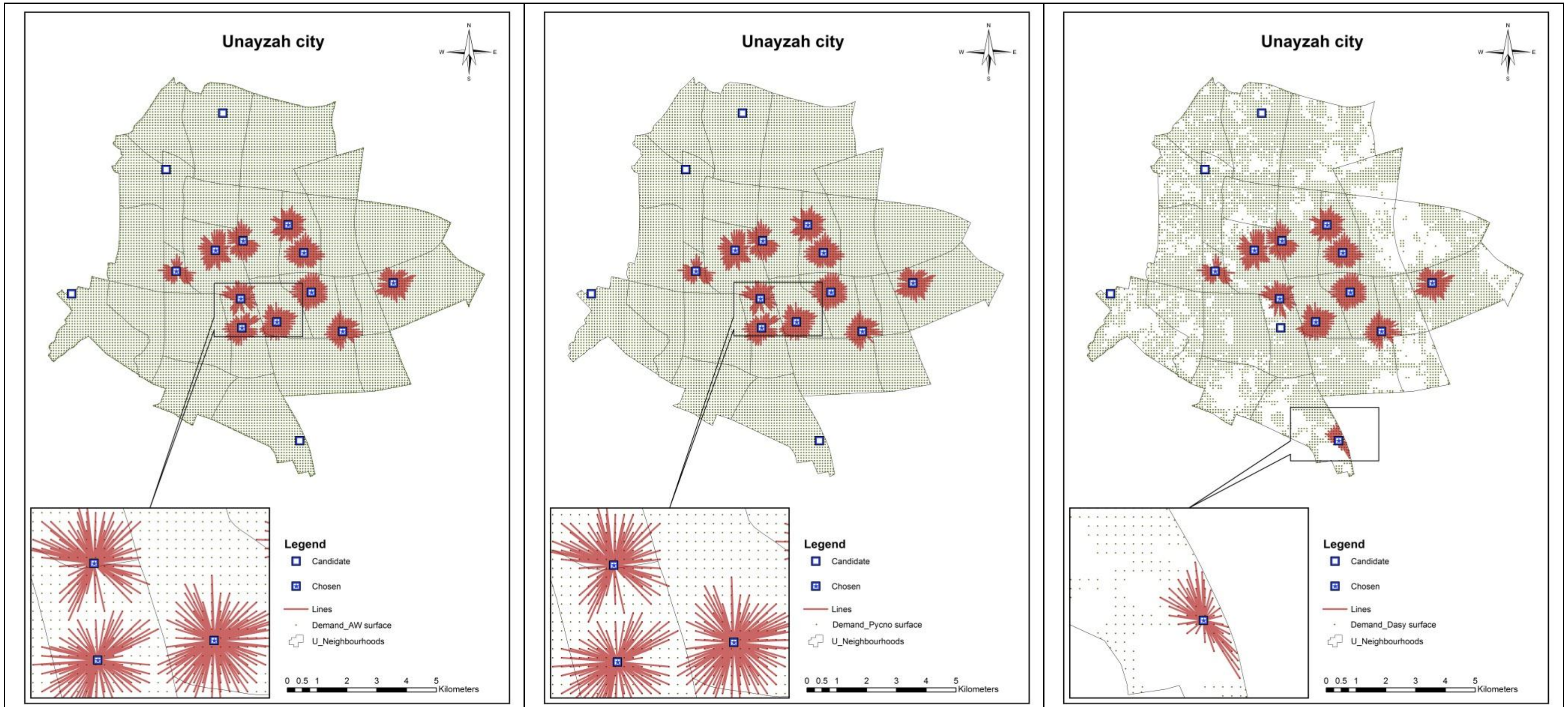
a) AW	b) Pycno	c) Dasy

Figure 5.36: Results of applying the MA model in Unayzah to select the best 3 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.37: Results of applying the MA model in Unayzah to select the best 9 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 5.38: Results of applying the MA model in Unayzah to select the best 11 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

For the three demand surfaces and at a distance of 800 metres, the MA model produced different results for the demand selection. These results depended upon the number of PHCC facilities selected from amongst the 15 locations. The results of the interaction showed that the Pycno surface provided the best geographical coverage for the demand weight from the best 1 and 3 PHCC locations (see the blue colour in Figure 5.39). The Dasy surface ranked second in the geographical coverage for the demand weight from the best 1 and 3 PHCC locations and ranked first among the best 5 PHCC locations (see the green colour in Figure 5.39). Of the three demand surfaces, the AW surface was deemed to be the worst in terms of geographical coverage (see the red line in Figure 5.39).

On the basis of the adoption of the MA model to allocate a ratio for the demand weight for each demand point, the results of the interaction for the MA model, in terms of demand selection, showed that the demand weights were also lower than the weight of the demand selections in the MI and MC models (see Figure 5.40). There was a substantial convergence in the weight of the geographical coverage between the Pycno and Dasy surfaces. In the case of the large areas, the Dasy surface produced the best geographical coverage for demand, as shown in Buraydah and Unayzah. However, it was noted that in the case of the concentration of the PHCC locations in some neighbourhoods, in the middle of a city with a high population density and a limited areas of non-built up areas as it was in Unayzah, the performance of the Pycno surface will be close to the Dasy surface in terms of the sensitivity demand selection.

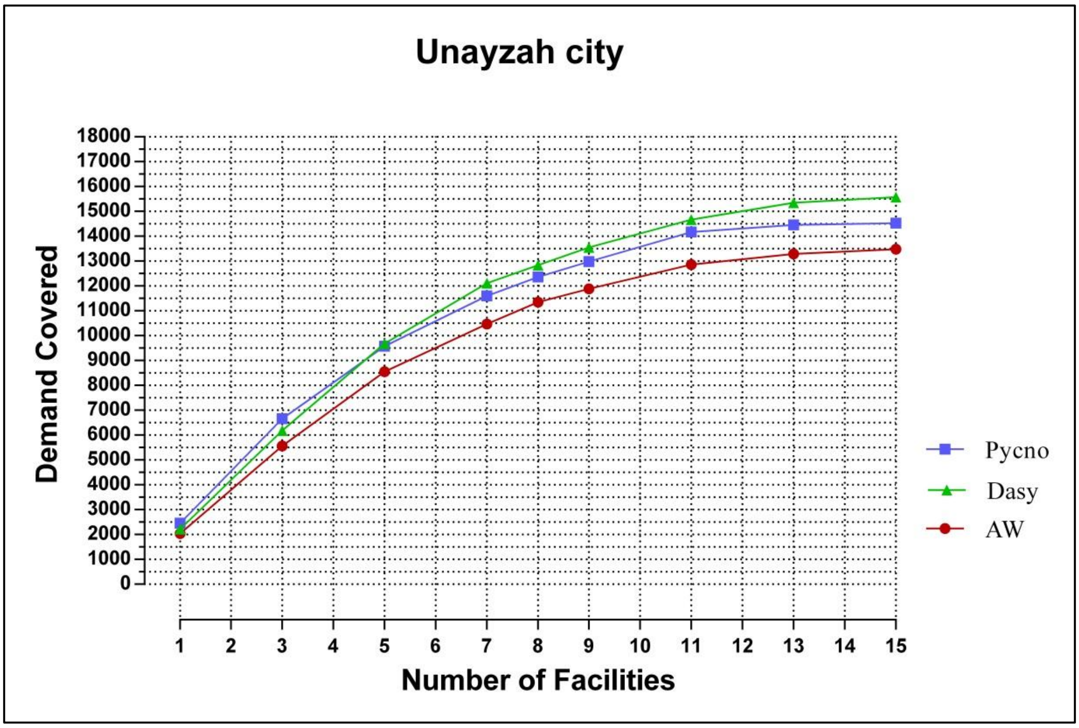


Figure 5.39: Results of the sensitivity demand selection from the MA model for the three demand surfaces in Unayzah

The Chi-square test was used to analyse the differences between the results for the three demand surfaces in terms of sensitivity and demand selection. The results in Unayzah showed that there were statistically significant differences between the results of AW with Pycno surfaces and Pycno with Dasy surfaces (see Table 5.9). In contrast, there were no statistically significant differences between the results for sensitivity and the demand selection for the AW and Dasy surfaces. It might be the case that the limited numbers for the PHCCs and the concentration of those facilities in some neighbourhoods in the middle of the city had an impact on results because there were statistically significant differences between the two surfaces in the other two case studies.

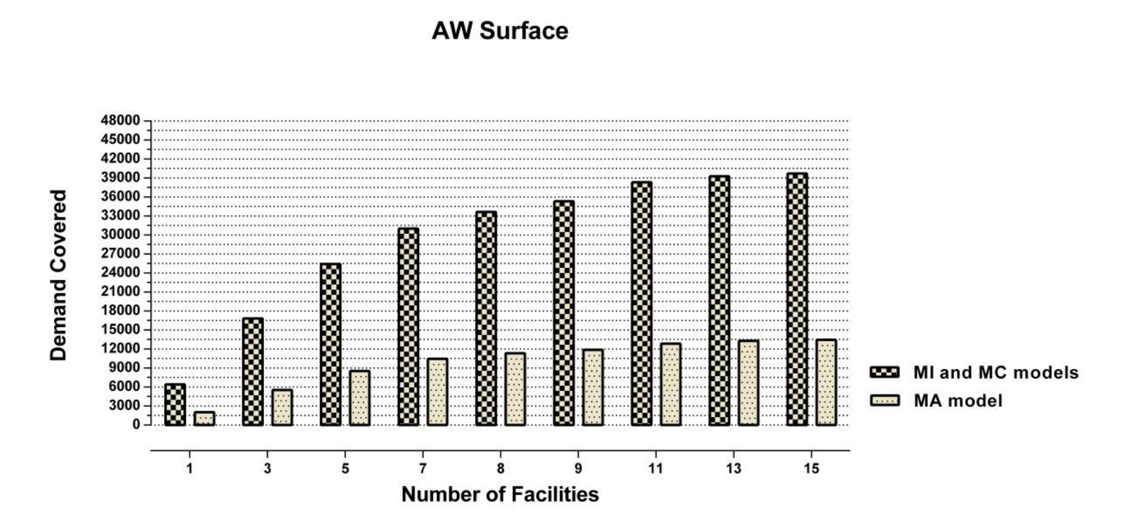
Table 5.9 Analysis of the results of the sensitivity demand selection from the MA model in Unayzah

Chi-square test	AW*Pycno	AW*Dasy	Pycno*Dasy
Chi-square, df	36.62, 8	8.347, 8	76.79, 8
P value	< 0.0001	0.4003	< 0.0001
Statistically significant? (alpha<0.05)	Yes	No	Yes
Data analysed			
Number of rows*	9	9	9
Number of columns**	2	2	2

*The numbers of rows represent the sensitivity demand selection for the best 1, 3, 5, 7, 8, 9, 11, 13 and 15 PHCC locations. **The number of columns represents the two surfaces tested.

The results when applying the MA model to the three demand surfaces in this case study may be summarised as follows:

1. In some analyses there were different PHCC selections between the three demand surfaces, and these were apparent at selected sites in the middle and other parts of Unayzah.
2. The AW, Dasy and Pycno surfaces produced some differences in facilities selection results when compared each surface results to the other surfaces results.
3. The limited numbers of PHCCs in Unayzah city had a clear impact on the similarity of the interaction results in some of the interactive analysis for the MA model.
4. It was noted that in the case of concentration of the PHCC locations in neighbourhoods with a high population density and limited areas of non-built up space, the performance of the Pycno surface will be close to the Dasy surface in terms of the sensitivity demand selection.
5. There were some differences in the PHCC selection results when derived from the MA model and the MI and MC models.



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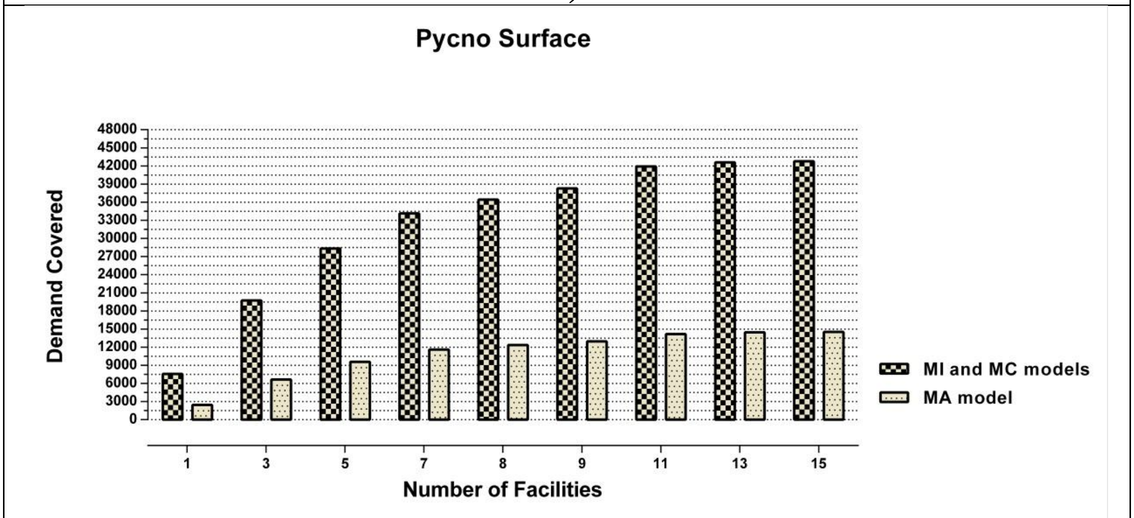

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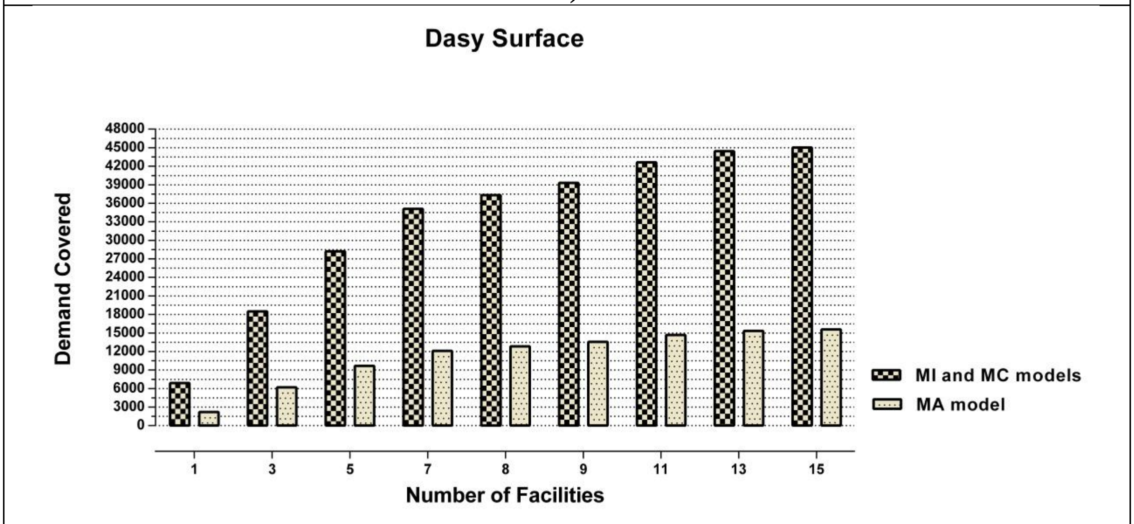


c)

Figure 5.40: Results of the sensitivity demand selection from the MI, MC and MA models for the three demand surfaces in Unayzah: a) AW surface; b) Pycno surface; and c) Dasy surface.

5.3 Summary of Results

The study applied four location-allocation models to three demand surfaces, resulting from the use of the AW, Pycno and Dasy methods for three contrasting case studies. Thus, each one of the location-allocation models was applied to the three demand surfaces in order to detect the interaction of the model with each of the different demand surfaces. The MI, MC and MA models were run for the three case studies by varying the number of facilities selected. Additionally, the MF model was also run, by varying the distances used from 600 to 1000 metres across the three case studies, using the distances and sensitivity for the facilities and the demand selection.

The results for the four models and the three demand surfaces showed interactions for three location-allocation models, resulting in some differences in terms of facilities and demand selection across the case studies. The most notable results, obtained through the interactions between the models and the demand surfaces, are outlined below:

1) The operations of the MI and MC were similar in terms of facilities and demand selection in the three case studies; this is because the MI model was applied with maximum distance constraints. The two models have different objectives. For example the MI model seeks to minimise the total weighted distances between the GPs or PHCCs and the demand. In contrast the MC model aims to maximise the coverage of the demand points within the distance used. Similarity in the results for the MC and MI models was due to how they handled demand, particularly when the MI model was applied with maximum distance constraints, as described at the beginning of this chapter. On this basis, the results of the interactions for the two models on the three demand surfaces were also similar in terms of facilities and sensitivity demand selection for all three case studies.
2) When the MI and MC models were run in Leicester to select, for example, small numbers of 10, 20, 30 and 40 of 66 GP locations, facilities selection differed between the three demand surfaces. The differences were due to the availability of a large number of GPs and the interaction between the two models, with the assumptions of three demand surfaces with regards to estimating population in the target areas. However, when the MI and MC models were run in KSA case studies, there were some similarities and differences observed between the three demand surfaces in terms of facilities selection in Buraydah, and some

similarities in Unayzah. The similarities in results associated with facilities selection arose due to the limited numbers of PHCCs and the high population density in some neighbourhoods, affecting the KSA case studies.

3) The assumptions concerning the three demand surfaces, when estimating population had an effect on the weight of the geographical coverage of demand when applied to the MI and MC models. For example, the Pycno surface, which depended on smoothly estimating the population within the target area, and the Dasy surface, which used remote sensing data, provided better performance than AW surface in terms of demand coverage in Leicester. Additionally, the performance of Pycno surface with the MI and MC models was close to Dasy surface in terms of demand coverage in Leicester and Unayzah, when there was a concentration of GPs and PHCCs in the middle of the city. In contrast, in the case of larger areas with a wide distributions and variation in the neighbourhood population density, the Dasy surface produced the best geographical coverage for demand, as shown in Buraydah city. This was due to the inherent assumptions in the Dasy method; particularly, that it only estimates population density in built up areas. The assumptions of the AW surface, which provided a homogeneous and unified distribution within the target area, led to it producing the worst surface for demand coverage.
4) The interaction results for the MF model in Leicester produced similar results to the numbers of facilities needed to cover the demand point, on the three demand surfaces and at all distances from 600 to 1000 metres. Additionally, the study noted that there was an increase in the number of facilities needed at 950 and 1000 metres, when compared to a distance of 900 metres in all three demand surfaces. In contrast, the interaction results for the MF model in the KSA case studies revealed no candidate facilities and that all of the PHCC locations were chosen to cover the whole of the three demand surfaces within the distances used. The facilities selection results for the MF model showed limited numbers of PHCCs in the KSA case studies.
5) Demand coverage results for the MF model in Leicester, Buraydah and Unayzah showed that within the distances used, the Dasy surface achieved the best geographical coverage for the demand weight; the AW surface achieved the worst results, and the Pycno surface was ranked in the middle. In Buraydah, there was a significant variation in terms of the sensitivity of demand selection

between the AW with Dasy surfaces and the Pycno with Dasy surfaces. These variations had no effect on the facilities selection results between the surfaces.

6) When the MA model was applied to the three demand surfaces in Leicester, the results of the interaction provided different GP selection results depending on the demand surfaces used. The GP selection results were also different from the results when using the MI and MC models. The results of the MA model depended on selecting GP locations close to the majority of the demand. However, there were some similarities and differences in facilities selection results when the MA model was run on some of the KSA case studies. In addition, some of the results from the MA model in Buraydah and Unayzah were generally similar to those from the MI and MC models, in terms of facilities selection. Only several of the analyses of the MA model differed from the results from the MI and MC models. As previously noted, the similarities in the results associated with facilities selection were due to the limited numbers of PHCCs in the KSA case studies.
7) Demand coverage for the demand weight from the MA model was lower than that for the MI and MC models in all case studies. This was due to the adoption of the MA model to allocate a ratio from the total demand weight for each demand point; this decreases when the distance is increased between the GPs or PHCCs and demand points. According to the resulting curves for the sensitivity demand selection from the MA model in Leicester, there was no saturation in the weight of the demand, such as that which occurred when the MI and MC models were run to select the best 50, 60 and 66 GP locations for the three surfaces. In terms of the rank in the geographical coverage for the three demand surfaces, that of the MA model was similar to the results from the MI, MC and MF models for Buraydah and Unayzah.
8) The Chi square test was used to analyse the differences in the results for the three demand surfaces in terms of sensitivity demand selection. The results showed significant differences when applying the MI and MC models, and between the three demand surfaces in Leicester, Buraydah and Unayzah. The significant differences in the results for the three demand surfaces, in terms of sensitivity demand selection for the MF and MA models, were lower than for the other models in Leicester, Buraydah and Unayzah, because there were no

significant differences in the sensitivity demand selection for the MF and MA models and between some of the three demand surfaces.

Four location-allocation models were used with the three demand surfaces to estimate the population inside the LSOAs and neighbourhoods, for the three case studies. The differences in the demand weights for the three demand surfaces were the main factors affecting the interactions of each model with different demand surfaces. When the demand weight was changed based on the assumptions for each areal interpolation technique, the MI, MC and MA models provided some differences in facilities selection between the three demand surfaces in regards to covering demand needs. Table 5.10 summarises the ranking of the geographical coverage according to demand, following the interactions between the four location-allocation models with the three demand surfaces in each case study. The reason for presenting this table is to summarise the effect of the assumptions for each demand surface on the facilities and the sensitivity demand selections for the results of each location-allocation model. For example, the AW surface produced the worst results in terms of sensitivity demand selection of the four models, resulting in some differences in the facilities selection results across the case studies. This was due to the operations of each location-allocation model, as previously described, and the homogeneous distribution of the population within weights of the demand points. In contrast, the differences in the assumptions of estimations for Pycno and Dasy surfaces in terms of the weights of the demand points meant that the two surfaces provided better results than the AW surface in terms of facilities and the sensitivity demand selections with MI, MC and MA models.

Table 5.10: Ranking of geographic coverage for demand after interactions between the four location-allocation models with the three demand surfaces for each case study

Case Studies	Best GP or PHCC locations	MI model			MC model			MF model			MA model		
		Interaction Results For The Three Demand Surfaces											
		AW	Pycno	Dasy	AW	Pycno	Dasy	AW	Pycno	Dasy	AW	Pycno	Dasy
Leicester	1	3	1	2	3	1	2	3	2	1	3	1	2
	5	3	1	2	3	1	2	3	2	1	3	1	2
	10	3	1	2	3	1	2	3	2	1	3	1	2
	20	3	1	2	3	1	2	3	2	1	3	1	2
	30	3	2	1	3	2	1	3	2	1	3	1	2
	40	3	2	1	3	2	1	3	2	1	3	1	2
	50	3	2	1	3	2	1	3	2	1	3	2	1
	60	3	2	1	3	2	1	3	2	1	3	2	1
	66	3	2	1	3	2	1	3	2	1	3	2	1
Buraydah	1	3	1	2	3	1	2	3	2	1	3	1	2
	4	3	1	2	3	1	2	3	2	1	3	1	2
	8	3	2	1	3	2	1	3	2	1	3	1	2
	12	3	2	1	3	2	1	3	2	1	3	2	1
	16	3	2	1	3	2	1	3	2	1	3	2	1
	20	3	2	1	3	2	1	3	2	1	3	2	1
	24	3	2	1	3	2	1	3	2	1	3	2	1
	28	3	2	1	3	2	1	3	2	1	3	2	1
	31	3	2	1	3	2	1	3	2	1	3	2	1
Unayzah	1	3	1	2	3	1	2	3	2	1	3	1	2
	3	3	1	2	3	1	2	3	2	1	3	1	2
	5	3	1	2	3	1	2	3	2	1	3	2	1
	7	3	2	1	3	2	1	3	2	1	3	2	1
	8	3	2	1	3	2	1	3	2	1	3	2	1
	9	3	2	1	3	2	1	3	2	1	3	2	1
	11	3	2	1	3	2	1	3	2	1	3	2	1
	13	3	2	1	3	2	1	3	2	1	3	2	1
	15	3	2	1	3	2	1	3	2	1	3	2	1

1 represents the highest sensitivity demand selection (the geographic coverage for the demand weights), 2 represents the second rank in the geographic coverage and 3 represents the worst rank in the geographic coverage.

5.4 Generalisations

This section seeks to generalise details describing the results of the interactions between the four location-allocation models, across the three demand surfaces as follows:

1) It was anticipated that the differences between the three demand surfaces when the MI, MC, MF and MA models were run to determine the best facility locations would not always be very clear in some case studies. For example, in the situation of homogeneous distribution for the population within source zones and within small areas for those zones, this is due to the differences in the population estimations for each surface, which were solely within the boundaries of the source zones. Secondly, it is due to the relatively smaller areas for the source zones compared with those for other case studies and thirdly, it is due to the operations of the models in terms of minimising the distances or facilities and maximising the coverage or attendance for the demand based on demand weights, within the areas of high population density for source zones. High population densities were the same for all three demand surfaces, although there were differences between the demand weights for each point inside the source zone, as presented in chapter four.
2) In the situation of heterogeneous distribution of the population within the source zones, and if there are limited numbers of facilities and those facilities were concentrated in some of source zones with high population densities, the results of interactions between the four models and demand surfaces will be similar.
3) Minimising distances and identifying the optimal facility locations depends on selecting those facilities that serve the largest possible of demand needs. As is evident in the three case studies in terms of the sensitivity demand selection for the four models. Were some of the source zones suffer from a significant increase in population density in the middle of the city (and there were a few non-built up areas), the Pycno surface performed better in terms of the sensitivity demand selection. However, the Dasy surface will provide better performance in situations where there are large numbers of facilities distributed in all of the target areas of the case study.
4) The use of MI, MC and MA models with the Pycno surface will identify unacceptable results as regards the best facilities. This is due to the assumptions

of the Pycno method in situations of homogeneous distribution for the population within source zones; some case studies produced zero value for the weight of population estimation across some of the target areas.

5) The interactions for the MF model with the three demand surfaces produced negative results in terms of the differences in the facilities selection across three case studies compared to the other three location-allocation models.
6) There were relatively large variations between the WA and Dasy surfaces in terms of the weight of the demand selection when the four models were applied to the three surfaces in the KSA case studies. This implies that in situations of heterogeneous distribution for the population within source zones, the large size of the source zones and the small areas for the built-up areas, the assumptions of two methods will produce significant differences between the weights of demand for the two surfaces. This, in turn, will have an impact on the facilities and sensitivity demand selections, as shown in the results.
7) There was saturation in terms of demand selection results for the MI, MC and MA models that appeared in the three case studies. However, this was most clear when the MI and MC models were run on three surfaces to select the best 50 GPs and more in Leicester, in Buraydah to select the best 24 PHCCs and more, and in Unayzah to select the best 11 PHCCs and more.
8) The use of MI, MC and MA models with the AW surface will have an impact on optimal facility selection results for those facilities located within larger source zones. This was due to low weights for the demand points within the estimated areas based on the assumptions of AW method.
9) The study found that in the situations of heterogeneous or homogeneous distribution of the population within source zones, the performance of the AW surface was the worst one in terms of allocating the demand weights for the four models in all three case studies.
10) The MA model depends on allocating a ratio from the total demand weight for each demand point; this decreases when distance is increased between the facility and demand points. However, the study noted that with the large number of demand points for each facility, the model allocated very low weightings for those demand points within the distance used compared to other study which applied the MA model with the centroid points for the census area (see Algharib, 2011).

11) It can be argued that in situations of heterogeneous or homogeneous distribution for the population of the source zones, the four models with the Dasy surface will produce the best results for optimal facilities selection. This was due to a number of reasons; firstly, the weights for the demand points for this surface only represent the populated areas; all other areas are excluded. Secondly, the weights for the demand points for the Dasy surface will be greater in areas that are closer to the road network than the other two surfaces. Finally, where the operations of the four models depend on allocating the highest weights for the demand points (in order to identify the optimal facilities), the results of the Dasy surface will be the best for the representation of the population's real situation.

The results of this study, particularly in reference to the above points, are discussed in more detail in the following chapter. These were also discussed in the light of the results from other studies, in order to provide a better understanding for the techniques and models used.

Chapter Six: Discussion

6.1 Introduction

Many studies have considered different areal interpolation techniques for the estimation of population size over areas that are not described by census data (see for example; Tobler, 1979; Goodchild and Lam, 1980; Lam, 1983; Martin, 1989; Fisher and Langford, 1995; Langford, 2006; Comber et al., 2008 and Kim and Yao, 2010). Many other studies have also discussed and compared the use of different location-allocation models (see for example; Hakimi, 1964; Teitz and Bart, 1968; Toregas et al., 1971; Holmes et al., 1972; Church and ReVelle, 1974; Rahman and Smith, 1991; Schilling et al., 1993; Serra and Marianov 1999; Cromley and McLafferty, 2002; Spaulding and Cromley, 2007 and Church and Murray, 2009). However, to date, minimal research has considered the interaction of different locational-allocation models with different interpolation techniques. This study has focused on the effects of three areal interpolation techniques – the Areal Weighting (AW), Pycnophylactic (Pycno) and Dasymetric (Dasy) methods – with four location-allocation models; Minimise Impedance p-median (MI), Maximise Coverage (MC), Minimise Facilities (MF) and the Maximise Attendance (MA) models. It sought to explore the impact of inherent assumptions for the three areal interpolation techniques and the spatial characteristics of each case study on the results of population estimations for the surfaces and the results of optimal facilities selection for each location-allocation model over the three demand surfaces. An additional objective was to provide a deeper understanding and to advance scientific knowledge regarding the objective function and the operations embedded in each of the four location-allocation models when applied to case studies with different spatial characteristics and where demand was estimated using different areal interpolation techniques. The study of these interactions between the models and different demand surfaces provides scientific support to assist facility locations issues in this field, and is particularly relevant in countries lacking spatially detailed census data.

The results of this study have shown that the demand weight surfaces were the main cause of variation in the outputs of the analyses, although the results were also affected by the objective function underpinning each location-allocation model. Additional important factors that have affected the results relate to the case study population density, the area over which the aggregated census data is reported, and the concentration and number of facilities. These issues are discussed in more detail throughout this chapter.

This chapter is structured as follows: Section 6.2 discusses the results of the areal interpolation techniques. Section 6.2.1 discusses the findings after employing the three areal interpolation techniques, in terms of their methods and assumptions, and the spatial characteristics of the case studies, with particular consideration of the effects of census area size for some LSOAs and neighbourhoods, populated areas and the large spatial disparities in population densities. It then outlines the advantages and disadvantages of each method and offers some generic recommendations. Section 6.2.2 discusses the results of mapping the differences between the three surfaces across the case studies. Section 6.3 discusses the results of the interaction between the location-allocation models and the areal interpolation techniques, in terms of the effect of the operations associated with each of the four models and the assumptions of population estimations for each surface. It then outlines the specific effects of high population density in some neighbourhoods, the large area sizes for some LSOAs and neighbourhoods, the effects of limited numbers of facility locations and their concentrations. Section 6.4 presents some reflections on the methods and results. Finally, Section 6.5 provides a summary of the points raised in this chapter.

6.2 Discussion of the results of the areal interpolation techniques

This section discusses the results of applying three areal interpolation techniques to estimate populations over target areas, and the results of mapping the differences between the three surfaces.

6.2.1 Discussion the results of the population estimations for the target areas

This study applied the AW, Pycno and Dasy methods to three case studies in cities covering different areas with different population densities. The source zones were the LSOAs in Leicester and neighbourhoods within Buraydah and Unayzah. The target areas were based on a grid cell size of 90 metres, which was applied to each case study. Before discussing these techniques in detail, it is important to take into account the large disparities between the population densities for the neighbourhoods in some of the KSA cities and the LSOAs within the city of Leicester. For example, in Buraydah city, the population size varied from 31,792 people in one neighbourhood to just 87 in another (Ministry of Economy and Planning, 2004); whereas, Leicester had more consistent population sizes across LSOAs due to their design (Martin, 2010). For example, the largest population size was 1,842, and the smallest was 1,220.

This study has shown that when AW is used to estimate population size over large areas with low population densities, it will frequently underestimate the actual population. For example, this was the case with neighbourhoods with large areas and low population densities in the north, east and south of Buraydah and Unayzah (see Figure 4.1 in Chapter Four). This was due to the small size of the target areas and the assumptions made in the AW method, in terms of providing a homogeneous estimate of the population within the target area and its neglect of the spatial aspects of population distribution.

A number of authors have demonstrated that the AW method produces less accurate results when compared to other methods (see for example; Hawley, 2005; Brinegar and Popick, 2010 and Kim and Yao, 2010). Brinegar and Popick (2010) argued that the AW method had errors in those areas with heterogeneous distributions of population. This was due to the simplicity of population estimations for this method and the lack of ancillary data that would help to provide more information about the spatial aspects of population distribution within the source zones. Thus, it can be argued that the performance of this technique would be expected to be acceptable in studies with smaller source zone areas and homogeneity in the populations, as in Leicester city.

The Pycno method proposed by Tobler (1979) produced heterogeneous estimation results of the population in the target areas in all three case studies. The Pycno method may have provided a more accurate representation of the population than the AW method because it is unreasonable to assume that the population will be distributed homogeneously across any geographic area, as is the assumption made with the AW method. The assumptions of heterogeneous distribution for the population from the Pycno method, based on the smooth density function, helped to produce both gradual and smooth population estimations within the target areas. The method was able to overcome the weaknesses of some of the spatial aspects of the AW method in terms of homogeneous population estimation within the target areas.

This study has shown that with the large source zone area the Pycno method underestimated the population within the target areas when contrasted with the Dasy method results (see Figures 4.2 and 4.3 in Chapter four). This was especially evident in the results for Buraydah, because in the centre of the city and other area there are some neighbourhoods with high population densities. The disadvantage of this method is that, when used in quite heterogeneous census areas such as Buraydah, it can homogenise the population in order to smooth the densities. Additionally, the smooth density function for the Pycno method has an effect on the heterogeneous surfaces with high population densities, which are dispersed in different parts of the city such as the Unayzah. This is because the smooth distribution for the population estimations of this method may differ from the actual distribution of the population. However, the literature review discusses areal interpolation techniques without ancillary data, revealing that the Pycno method provided more accurate results when compared to AW method results (see for example; Hay et al., 2005; Hawley, 2005 and Kim and Yao, 2010). Therefore, it has been combined with the Dasy method to provide a heterogeneous estimation for the population in the target areas and to simulate the reality of the spatial population distribution in the case study (Comber et al., 2008 and Kim and Yao, 2010).

The study has noted that when the Dasy method was applied, there were significant differences in the population estimation densities in the target areas compared to the other methods; this was particularly the case for Buraydah city (see Figures 4.1, 4.2 and 4.3 in Chapter four). The reason for this was the large areas with high population densities in some of the neighbourhoods and the small built-up areas within these neighbourhoods. In contrast, with the small areas for the LSOAs and the homogeneity in the population densities within Leicester, the significant differences in population estimation densities for the target areas between this method and AW method were minimal. The Dasy method was the only one of the three techniques that incorporated the use of ancillary data in the form of satellite images. This represents an important step towards obtaining a more realistic estimate of the spatial structure to describe population distribution (Comber et al., 2008).

Some studies have demonstrated the accuracy of the estimation results for the Dasy method when compared to the AW or Pycno methods in case studies (see for example; Hawley, 2005 and Kim and Yao, 2010). According to Kim and Yao (2010: 5659) "many researchers find that Dasy mapping gives the best estimation result among those by all other popular methods tested". However, there are some points worth noting regarding this method. The literature review demonstrated the Dasy method as one of the techniques proposed for overcoming some of the disadvantages associated with the AW and Pycno methods. In contrast, in terms of actual analysis, the Dasy technique lacks a uniform methodology, leading to differences in terms of the selection of ancillary data (Langford and Higgs, 2006). The Dasy method did not work well in areas with smoothly varying neighbourhoods, only in situations where a 'staircase' effect was present. Mennis (2003) argued that industrial complexes are one of the important factors that should be considered when using the Dasy method, because they contain wide roads and open spaces that are similar, to a certain extent, to residential and commercial areas.

This study has shown that despite the observations regarding the Dasy method, it tends to perform well in situations with clear land use classifications (parks, lakes, arid lands and residential areas) as in Buraydah and Unayzah; and therefore diversity and variation of residential land use should perhaps be used consistently with the Dasy method.

6.2.2 Discussion the results of mapping the differences between the three surfaces

The aim of mapping the differences between the results of the three surfaces was to illustrate the differences between the weights of population estimation for each target area (see Figures 4.5 to 4.7 in chapter four). The differences in the assumptions of each areal interpolation technique as described in the previous section played an important role in producing different weights for the population estimation results for the target areas. Additionally, there were other factors that contributed to producing the differences in the weights of the population estimation results; these related to the characteristics of the case study areas in terms of the degree of population density, the effect of large or small area sizes for some of the source zones and the size of the populated areas within the source zones.

The differences between AW and Pycno surfaces, in terms of the weights of population estimation for each target area in the three case studies, were less than the differences between the AW surface when compared to the Dasy surface, or the Pycno surface when compared to Dasy surface. However, in the case of small area size for the source zones with a homogenous population, such as Leicester, the differences between the AW and Pycno surfaces were greater than those in Buraydah and Unayzah. This was due to the differences in the assumptions made in the two methods in terms of the homogeneous estimations for AW method, the heterogeneous estimations for Pycno method and the small area size for the source zones in Leicester. In contrast, with the large area size for the source zones, such as in Buraydah and Unayzah, the assumptions of the two methods were less effective for generating significant differences between the two surface areas. Therefore, it can be argued that because the AW and Pycno methods are preserving volume for the source zones, the differences between them in the population estimation results will be fewer than those arising from comparisons of the AW to Dasy surfaces or the Pycno to Dasy surfaces, if the areas of the source zones are large with low population densities.

This study has shown that the differences in the population estimations between the AW and Dasy surfaces were very clear in all three case studies (see Figures 4.5 to 4.7 in chapter four). The use of the ancillary data to identify the populated areas for the Dasy method led to the production of different population estimations results for the target areas. Additionally, these ancillary data become more effective in situations with clear land use classifications and large source zones, as in Buraydah and Unayzah. However, it becomes less effective where there are small non-populated areas, such as in the middle of Leicester. The study noted that the population estimation results for the Dasy method will produce high estimation weights for the target areas, especially in the larger areas of the source zones that have high population densities and smaller populated areas (see for example the east and north of Buraydah in Figure 4.5 b in chapter four). Thus, it can be argued that the Dasy method is the most appropriate method to estimate the population in situations with clear land use classifications between the populated and non-populated areas in the case study.

Moreover, the differences between the Pycno and Dasy surfaces were very clear in the three case studies (see Figures 4.5 to 4.7 in chapter four). The two surfaces produced different weights in the population estimation results for each target area within the source zones. Additionally, the study noted that there were significant differences between the two surfaces in situations of heterogeneous population distribution, as in Buraydah and Unayzah. This was due to the assumptions of heterogeneous estimations for the Pycno method, which could make the quite heterogeneous densities for the population in the source zones appear less heterogeneous, in order to achieve a smooth density function between the target areas. Another reason for the significant differences between the two surfaces was related to the different assumptions of the two methods in terms of the population estimations applied to the populated areas for the Dasy method and estimates of the population in all the areas within the target areas for the Pycno method.

The differences in the weights of the population estimation results in the targeted areas, which originated from the use of three areal interpolation techniques, were the main factors contributing to the identification of different facility selection results within the four location-allocation models. Therefore, the assumptions of the methods, the objective function and operations for each location-allocation model, the characteristics of the case study in terms of degree of population density, the effect of the large or small area sizes for some of the source zones, the size of the populated areas within the source zones, the effects of the limited number of facilities' locations and the concentrations of those facilities in some of the source zones with high population densities are discussed in the next section.

6.3 Discussion of the results of interaction between the location-allocation models and areal interpolation techniques

This study has demonstrated that the interactions of the different location-allocation models with the three demand surfaces resulted in differences in the facilities selection results across the three case studies. There were also some similarities in the facility selection results regarding the three demand surfaces. The main objective of this study was to explore the interactions between the four location-allocation models, MI, MC, MF and MA, when applied across the three demand surfaces, AW, Pycno and Dasy, in order to support optimal facility selections. A road network and the location of facilities were the common factors specified in all the interactions between the models and surfaces. In contrast, the demand weights were the main differentiating factors for those interactions. The location-allocation models depended on processing the demand weights in order to select the best locations; and these weights had an impact on the selection of the best facility locations between the three demand surfaces.

This section provides an extensive discussion of the interaction results for the MI and MC models, MF model and MA model, because of a number of factors relating to the following points:

1) The effect of the objective function and the operations for each location-allocation model;

2) The effect of the assumptions for each areal interpolation surface;

3) The effect of the large or small area sizes for some of the source zones;

4) The effects of the population pattern for the source zones in terms of the degree of heterogeneity or homogeneity in the demand surface; and

5) The effects of the limited number of facility locations and the concentrations of those facilities in source zones with high population densities.

6.3.1 Discussion of the interactions of the MI and MC models

In terms of facility and demand selection within the distance used, the results have demonstrated that the MI and MC models provided similar selection results between the two models concerning the three demand surfaces when the study applied the MI model with maximum distance constraints. Algharib (2011) compared different location-allocation models in the context of spatial planning for fire station locations in Kuwait, and the study found that within the timeframe allocated, the MI and MC models identified similar results for facility and demand selection. This was due to the similarities between the MI and MC models in terms of the operation and handling of the demand if the MI model was applied with maximum distance constraints. The operation of the two models depends on the interchange or substitution between the locations chosen as candidate locations (Church and Sorensen, 1994). This was the main factor for minimising the weighted distance between the facility and demand locations for the MI model, and when maximising the coverage for the demand in the MC model (Church and Sorensen, 1994). Therefore, the two models identified some different facility and demand selections for the three demand surfaces across the three case studies (see the results of the MI and MC models in Chapter five).

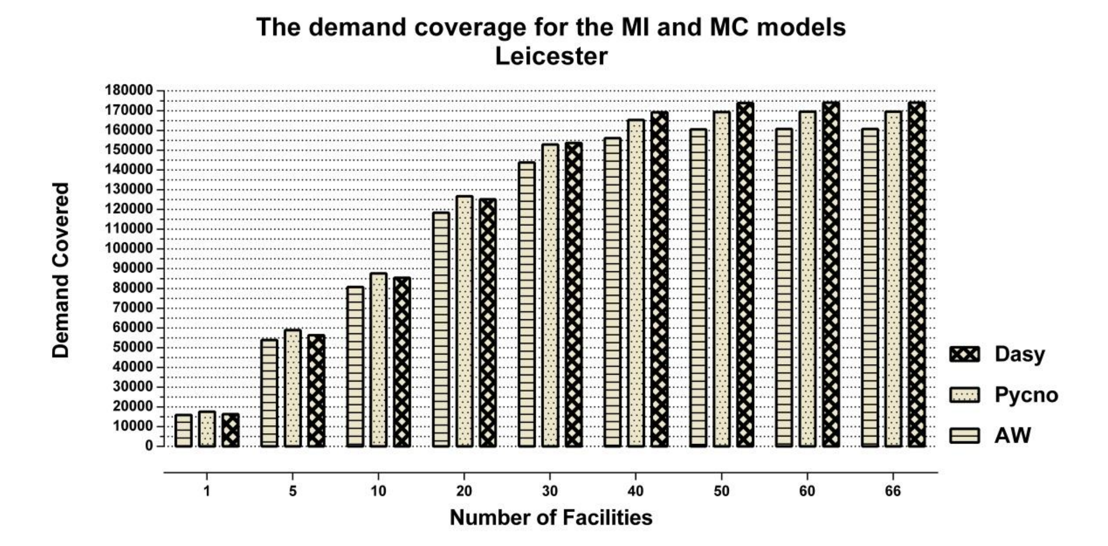
The different assumptions associated with each areal interpolation method were the main factors contributing to the differences in the facilities' selection. However, the degree of influence of these assumptions differed from one case study to another, due to a number of considerations, as follows:

1) The study noted that the sensitivity demand selection for the weight of the demand from the MI and MC models on the AW surface was lower than that for the other two surfaces in the three case studies (see Figure 6.1). This was due to the assumption of homogeneous estimation for the demand weight in most of the target areas, the small grid cell size for those areas and the large area size for the source zones. These have had an effect on determining the best facilities and achieving the best geographical coverage by the two models, especially where the area of the source zone was large. However, the AW surface may produce a better performance in cases where the source zones are very small and there are no unpopulated areas.

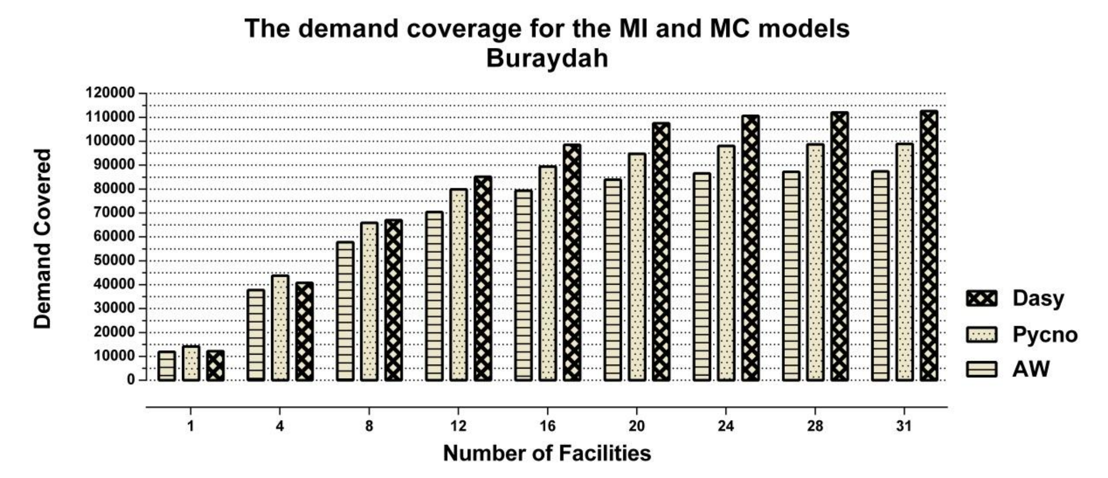
2) This study has shown that in the case of a small area size for the source zones and homogeneous distribution of the population within those zones, such as in Leicester, the Pycno method produced estimates delivering a zero value for the weight of some of the demand points close to some of the facilities in central Leicester. The presence of the zero value in those targeted areas represented a potential to increase greatly in other target areas. The Pycno surface provided a heterogeneous estimate of the target area based on the smooth density function, in order to determine the volume-preserving property (Lam, 1983 and Kim and Yao, 2010). In light of these results the MI and MC models on the Pycno surface identified some differences in the facility and demand selection results when compared to the other two demand surfaces, especially when the two models were run to select the best 1, 10 and 20 GP locations.

3) The heterogeneous estimation for the Pycno method may produce an increase for the weight of the estimated population in some of the targeted areas when compared to the other two methods, especially in some of the source zones at the centre of each case study which have high population density. The MI and MC models depend on minimising the distances and selecting the facilities which can serve the largest possible area for the demand needs. Thus, the study noted that when the MI and MC models were run on the Pycno surface to select the small numbers, such as the best 1, 10 and 20 GP locations in Leicester, there were some differences in the facility selection results;

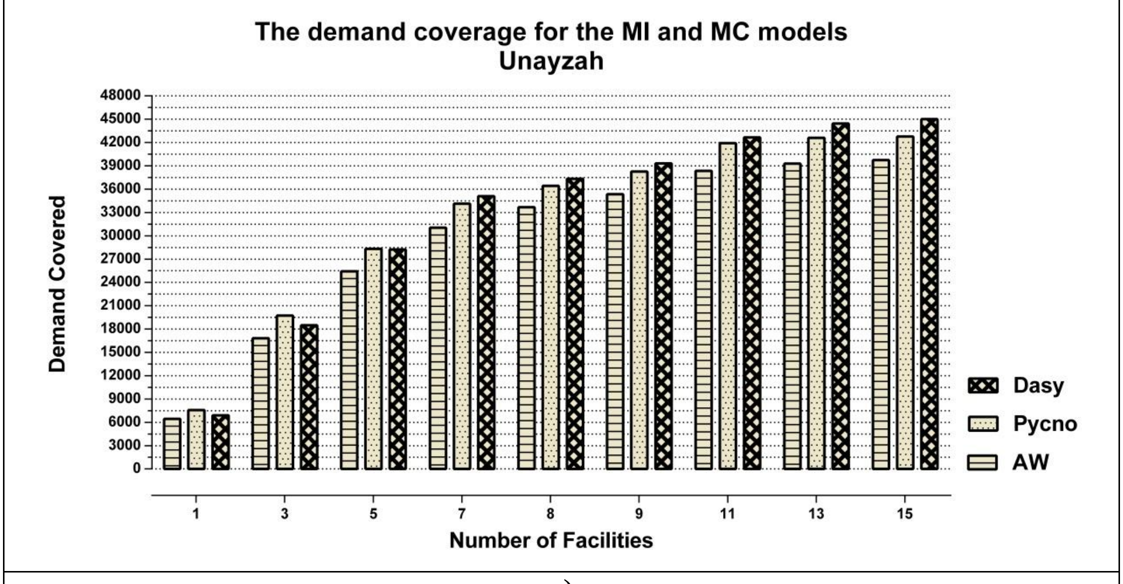
in addition, the sensitivity demand selection for the weight of demand from the Pycno surface was higher than with the AW and the Dasy surface. However, there were no differences in the facility selection results when the two models were run on the three demand surfaces in Unayzah and Buraydah. The best 1 and 4 PHCCs were selected in Buraydah, and the best 1 PHCC was selected in Unayzah. This was due to the impact of the limited number of facilities and the quite heterogeneous surfaces, such as Buraydah in the results of the MI and MC and the optimal facilities selections. In contrast, the sensitivity demand selection for the weight of demand from the Pycno surface was higher than the AW and Dasy surface in the best 1 and 4 PHCCs in Buraydah and the best 1 to 5 PHCCs in Unayzah (see Figure 6.1). However, if there were more than two facilities in some of the source zones in the centre of Buraydah and Unayzah, the Pycno surface could potentially produce some differences in the facility selection results.



a)



b)



c)

Figure 6.1: Results of the sensitivity demand selection from the MI and MC models for the three demand surfaces: a) Leicester, b) Buraydah, and c) Unayzah.

4) This study has shown that the MI and MC models on the Dasy surface identified some differences in the facility selection results, especially in Buraydah and, subsequently, in Leicester and Unayzah. This was due to the large areas for the source zones and the small built-up areas within those zones, especially in some of those zones located far from the centre of each case study. Additionally, as normally road networks are distributed close to built-up areas, the location-allocation models will work better on the Dasy surface than the other two surfaces. Thus, there were increases in the demand weight for the Dasy surface, which helped the MI and MC models to select some different facilities within the distance used in this study. The use of ancillary data, such as satellite images, helped this method to provide a relatively heterogeneous demand weight within the target areas. Therefore, the demand weights were distributed close to the actual places for the populations within each source zone. However, the performance of the Dasy surface will be less than for the other two surfaces if the case study area has few un-built up areas, parks, lakes and arid land within the source zones.

5) The study has noted that the interactions of the MI and MC models on the three demand surfaces provided evidence that the Dasy surface performed better in terms of demand coverage when the two models were run to select the best 30 GPs and more in Leicester, 8 PHCCs and more in Buraydah, and 7 PHCCs and more in Unayzah (see Figure 6.1). In contrast, when the two models were run to select a small number of facilities, the Dasy surface performed less well in terms of the demand coverage. This was due to the lack of un-built up areas and the concentrations of most of the selected facilities, either in the city centres or in the zones with high population densities close to the centre of the case study. It can be argued that if the facilities were distributed randomly and covered most of the source zones in the case study, the MI and MC on the Dasy surface would perform better than the AW and Pycno surfaces in terms of their facility and demand selection.

In general the MI p-median model and all the extensions of this model, are founded on the assumption that optimal accessibility to locations can be achieved by minimising the total distance between supply and demand. However, there are cases in which the use of the MI p-median model may be less appropriate, because the model does not in general realistically suit those health systems with a hierarchical nature (Hodgson, 1988). This issue was addressed in the present study by using the MI p-median model to determine the best facility locations from a set of locations with no differences between them.

Rahman and Smith (2000: p.440) argued that "it has frequently been observed that the usage of service facilities may decline rapidly when the travel time exceeds some critical value". In this case, the MI p-median model may result in unacceptable solutions from the standpoint of service provision. The MC model provides solutions to cover the largest possible areas of demand according to specified distance requirements or the time lapse between supply and demand. The model is more appropriate than any others when resources are limited (Church and Murray, 2009). However, in practice it may maximise the coverage to a set of demand points which may exceed the capacity of the facility.

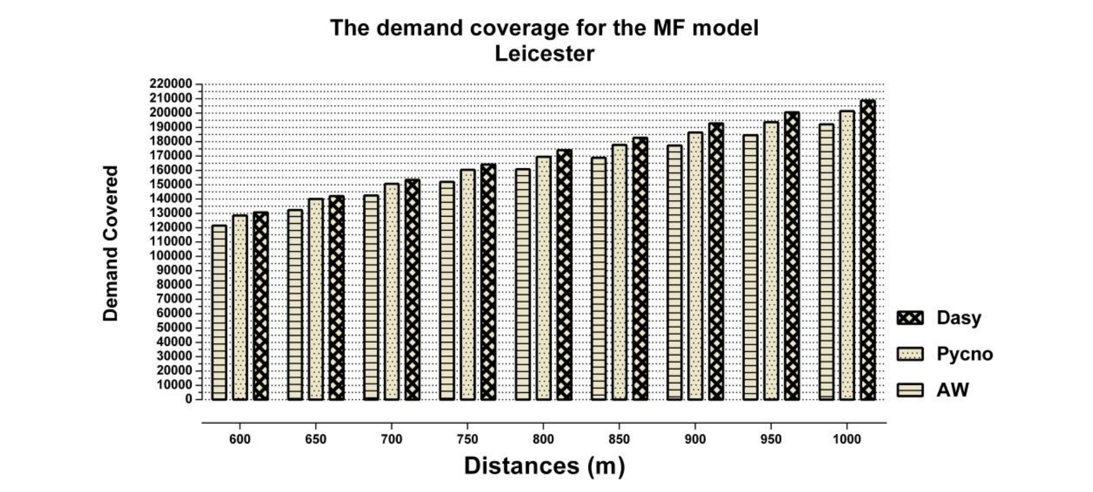
6.3.2 Discussion of the interactions of the MF model

This study has shown that the MF model identified a number of chosen and candidate facilities for the three demand surfaces at 50 metre intervals from 600 to 1000 metre distances in Leicester (see the results of MF model in Chapter five). However, the limited number of PHCCs, and large spacing between these in Buraydah and Unayzah had an effect on the results of the MF model and the selection of the candidate facilities for the three demand surfaces. The operations of the MF model differ from those of the MI, MC and MA models which seek to fit a set number of facilities optimally to a demand surface. The MF model seeks to minimise distances and determine the minimum number of facilities needed to serve the demand within a certain distance or travel time (Toregas et al., 1971; ReVelle and Hogan, 1989a; Schilling et al., 1993; Church and Murray, 2009). The availability of the appropriate number of facilities and the close spatial concentrations of those facilities are important factors that can assist the MF model to produce optimal results. The results of the MF model reveal that the model is similar to the MC and MC models in terms of handling or allocating demand points, as described in the methodology chapter, but it differed in terms of the number of facilities allocated.

The interactions of the MF model on the AW, Pycno and Dasy surfaces in Leicester produced similar numbers for the chosen and candidate facilities that were identified to cover the demand needs. The assumptions of the three areal interpolation techniques in Leicester had less impact on the objective function and operations of the MF model in order to provide different numbers of chosen and candidate facilities at the three demand surfaces when compared to the MI, MC and MA models. It can be argued that the homogeneous distribution of the population, the small area sizes assigned as source zones and the concentration of facilities in some of the zones had an impact on the lack of significant differences between the weight of demand within each source zone and the results of the interaction for the MF model. However, if there were some concentrations of facilities in some of the larger source zones in the east and north of Leicester, the MF model for the Dasy may provide different numbers of facilities required to cover demand needs. Additionally, if there were more than two facilities in some of the source zones in Buraydah and Unayzah, and they were spatially concentrated, particularly in the centre of the city, the MF model (within a 1000 metre distance) and over the three demand surfaces could identify some candidate facilities in those areas.

The significant differences in the sensitivity demand selection from the MF model on the three demand surfaces in some case studies will not necessarily produce differences in the chosen and candidate facility selection results for the three demand surfaces, as with the MI, MC and MA models (see Figure 6.2). This is because the MF was considered to be more comprehensive than the other models and sought to minimise the facilities and cover all demand needs in all the areas within the case study, (while not minimising the distances or maximising the coverage for attendance, in order to optimally fit a set number of facilities to a demand surface) (Church and Murray, 2009).

The spatial distribution of the facilities, the concentrations of those facilities and the distances used are important factors that affect the results of the MF model. Therefore, it can be argued that the MF model was suitable for use in some of the case study locations; for example, Leicester, because there were high concentrations of facilities in some areas with small spacing between them. However, the MF model was not suitable for use in those case study areas that suffer from heterogeneous distribution of the population and large spacing between the facilities, such as Buraydah and Unayzah. In some cases the use of the MF model without restrictions on the current status of the facilities' distribution may marginalise those facilities that were found to relieve pressure in areas with high demand. This was evident in the results of the MF model across the three demand surfaces in concentrations for the GP locations in certain areas of Leicester.



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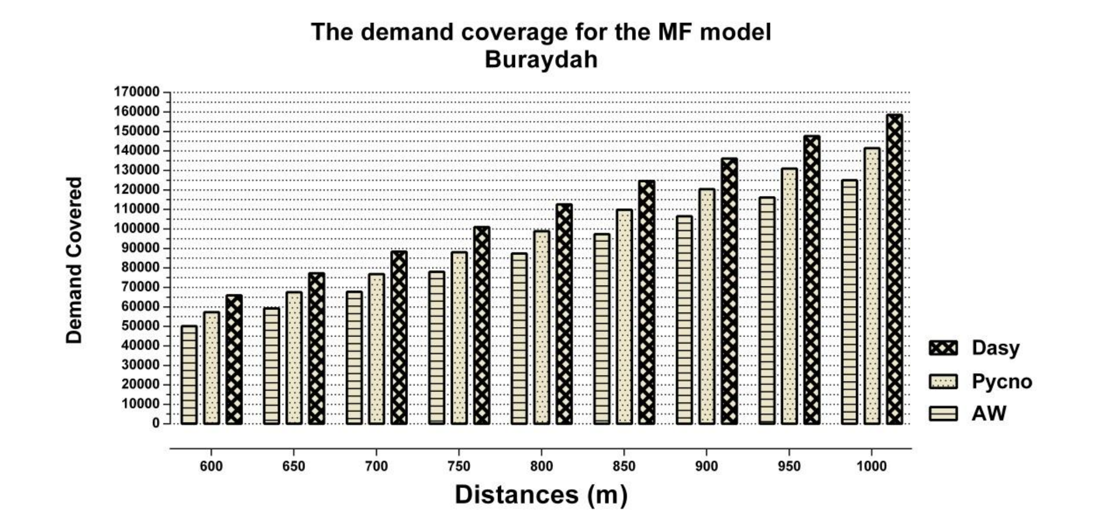

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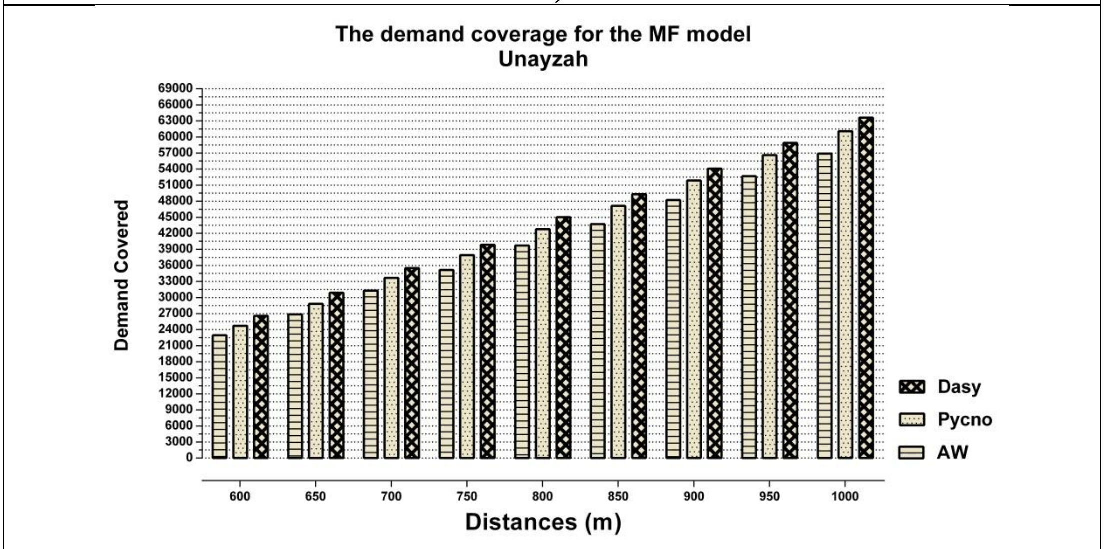


c)

Figure 6.2: Results of the sensitivity demand selection from the MF model for the three demand surfaces: a) Leicester, b) Buraydah, and c) Unayzah.

6.3.3 Discussion of the interactions of the MA model

This study has shown that the MA model for the three case studies identified a number of different facility selections from the MI, MC and MF models across the three demand surfaces. The objective function of the MA model sought to maximise the attendance of demand by aggregate-weighted distances of demand in areas close to the majority of the demand (Holmes et al., 1972; Algharib, 2011). Identifying the facilities close to the majority of the demand depended on allocating a ratio of the total demand weight on the basis of the distance between the demand and the facility. Distance was a critical factor regarding the ratio of total demand weight, which subsequently decreased when the distance was increased between the facilities and the demand points.

The different weights of demand which resulted from the different assumptions for the three areal interpolation techniques played a role in providing different facility and demand selection results with the MA model. As previously mentioned in the discussion of the results in the MI and MC models, the degree of influence exerted by these assumptions varied from one case study to another. However, the study noted that there was some effect caused by the operation of this model on the results of the interactions (as follows):

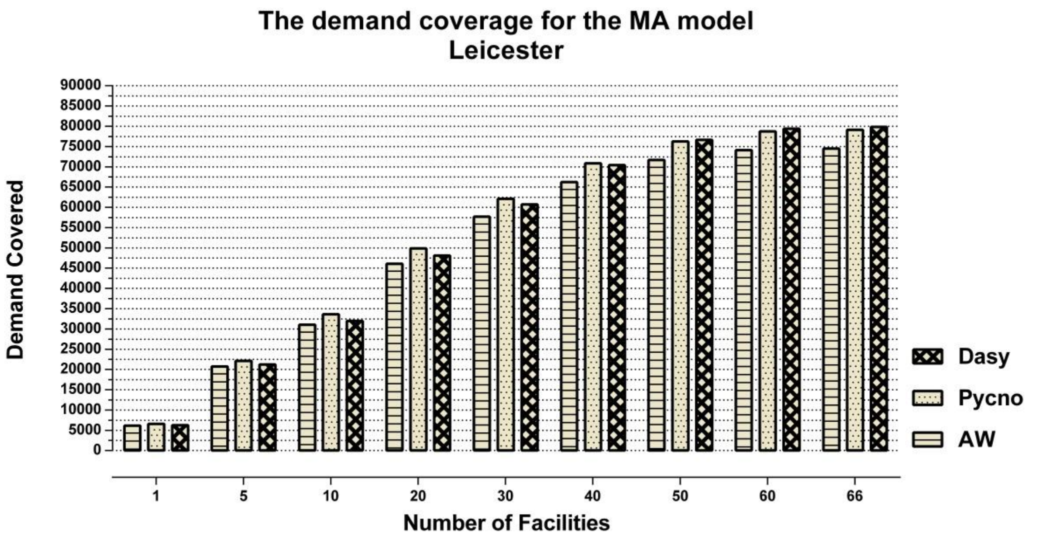
1) Due to the adoption of the MA model for allocating a ratio of the total demand weights for each demand point, this study has noted that there was a form of concentration in determining the optimal 5, 10 and 20 GP locations for the MA model on the AW, Pycno and Dasy surfaces when results were compared to those from the MI and MC models (see the results of MA model in Leicester in Chapter five). These were clear in central Leicester and some of the areas with high population densities. The MA model on the three demand surfaces was allocated a heterogeneous demand weight based on the distance. Thus, the demand needs, which were distributed across large source zones in the east, north and west of Leicester, affected the facilities' selection for those areas. This is because the ratio of demand weight, based on distance within the small source zones in the central and other parts of Leicester were greater than the other areas.

2) The concentrations in the selection of facilities for the MA model on the three demand surfaces when compared to the results of the MI and MC models was unclear

for Buraydah and Unayzah. This was due to the heterogeneous distribution of the population within the source zones and the limited numbers of facilities in both case studies. It can be argued that if there was a homogeneous distribution of the population in the source zones and variations in the sizes of the source zones, the MA model over the three demand surfaces would generate a concentration of the optimal facilities for the benefit of the demand weight located in the small source zones, as in the case of Leicester.

3) The demand weight in each target area, and the operations of the MA model as described above, were important factors affecting the determination of the best facilities over the three demand surfaces. The effects of the assumptions made in each areal interpolation technique for each case study in terms of the homogeneous distribution for the AW method, heterogeneous distribution for the Pycno method and the use of the ancillary data for the Dasy method, as described in the discussion of MI and MC models played a role in the facility selection results between the surfaces. However, the differences between the interactions of the MI and MC models and the interactions of the MA model were the effect of the ratio of the demand weight allocated from each demand weight and the concentrations in the selection of the optimal facilities over the surfaces. The performance of the MA model in terms of the geographical coverage for the demand weight was less than for the MI and MC models (compare Figure 6.3 to Figure 6.1). Additionally, the study noted that the degree of saturation in the weight of demand was less than that which occurred when the MI and MC models were run to select the best 50 GP locations and more in Leicester.

In general, this study has shown how the use of the MA model with a large number of demand points would produce a very low performance in terms of the demand coverage, when compared to the MI and MC models. This was due to the adoption of this model to allocate the ratio of the demand weight for each of the selected facilities. Algharib (2011) used the MA model with centroid points for the districts in Kuwait in the context of spatial planning for fire station locations. The study found that the demand coverage for the MA model was lower than that for the MI and MC models, but it remained within acceptable rates.



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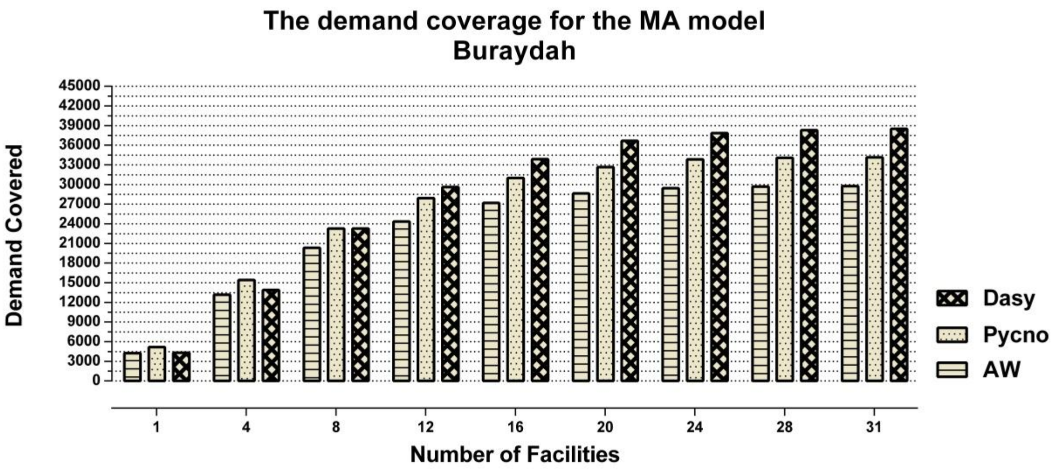

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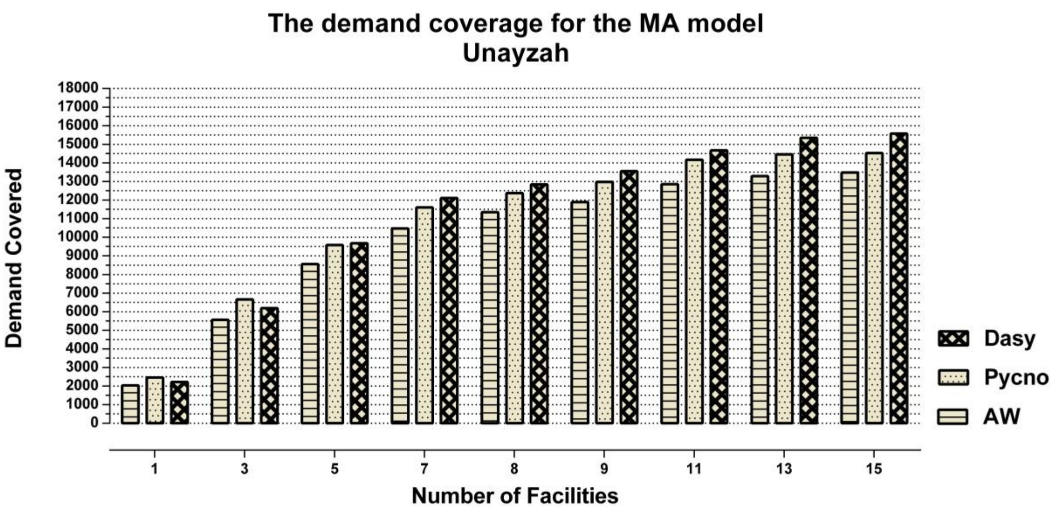


c)

Figure 6.3: Results of the sensitivity demand selection from the MA model for the three demand surfaces: a) Leicester, b) Buraydah, and c) Unayzah.

6.4 Reflections on the methods and results

This section provides some philosophical reflections on the performance of the areal interpolation techniques and the location-allocation models, as well as the results of the study. As was presented in the background and literature review, a number of studies exist that have discussed the use of different areal interpolation techniques and location-allocation models. However, exploring the interactions of these techniques with the models could help to provide scientific support regarding the impact of the use of the results of the areal interpolation techniques with the location-allocation models. Therefore, the reflections regarding the impact of the results of the AW, Pycno and Dasy methods on the location-allocation models can be described as follows:

The study has provided evidence of clear differences between the three demand surfaces in terms of the weights of the population estimations for each of the target areas. Demand weights are important data and represent one of the three triangle vertices (demand, facilities and road network) necessary for the application of location-allocation models. The differences in the weights of demand based on the assumptions of the AW, Pycno and Dasy methods have had a direct impact on facility selection results with the objectives, functions and operations of the four location-allocation models used in this study. There were some other important factors related to the spatial characteristics of each case study which, in turn, contribute (with the inherent assumptions for the AW, Pycno and Dasy methods) to producing differences in demand weights in the target areas. For example, the nature of the distribution of the population in the census area, the area of the source zones and the built-up areas in each case study. These factors should be taken into account by the researcher before using the areal interpolation technique results, as these results will have an effect on the results of the location-allocation models in terms of the optimal facility locations.

The Dasy method is considered appropriate for use in those case studies that have a heterogeneous distribution of the population, a large or small area of source zones and limited built-up areas: for example in Buraydah and Unayzah. It was also appropriate for the homogeneous distribution of the population in the same situations for the source zones as mentioned above. The adoption of the Dasy method on the use of the satellite imagery and the function of the spatial overlay for land use helped to select built-up areas and then to estimate the population for those areas. Thus, the study noted that the interactions of the MI, MC and MA models on the Dasy surface identified some clear differences in the facility selection results and the sensitivity of demand selection, particularly in Buraydah. This was firstly due to the objectives functions and the operations of the three models which seek to minimise the distances for the MI model, maximise the coverage for the MC model and maximise attendance for the MA model based on the weights of demand in the target areas. Secondly, the high demand weights in the target areas for the Dasy surface were larger than for the AW and Pycno surfaces. Finally, due to the high demand weights and the concentrations of these weights in populated areas close to the road networks. Therefore, the use of MI, MC and MA models with Dasy surface will produce the best results when selecting the optimal number of facilities or minimising the distance between demand and facilities. However, researchers should understand that in some cases the Dasy method would perform less well in the central area of a case study due to the limited quantity of undeveloped areas such as parks, lakes, and arid lands, even where the source zones are large.

The study has noted that with the highest concentrations of population density in some of the source zones in the centre of the KSA case studies, and the homogeneous distribution of the population in Leicester in terms of sensitivity demand selections, some of the interactions results for the MI, MC and MA models on the Pycno surface identified a higher weight of demand than the other two surfaces. Thus, the higher weights of the demand from the Pycno surface contributed to producing different selections for optimal facility distribution compared to the other surfaces. Depending on the spatial characteristics of the population of the census area, the inherent assumptions for the Pycno method could make the population of the target areas in some of the source zones look more or less homogeneous than they are in reality. This was due to the smooth density function between the neighbours borders for the source zones and the volume-preserving in these zones. This was clear in the results of the sensitivity demand selections for the small numbers of subsets of the best locations (best 1 to 20 GP locations in Leicester, best 1 and 4 PHCC locations in Buraydah and best 1 to 5 PHCC locations in Unayzah). Therefore, it can be argued that the results of the use of MI, MC and MA models with Pycno surface could not be trusted, especially in situations where there is heterogeneous distribution of the population in source zones.

There was a clear reduction in the results of the sensitivity demand selections for the four location-allocation models on the AW surface, especially in Buraydah and Unayzah. The AW method which assumes that the population is evenly distributed across the source zone is considered inappropriate for use with small grid target areas over large source zones with low population densities. It results in an under-estimation of the population in the target areas. Therefore, the optimal facilities selection results for the MI, MC and MA models with the AW surface will generate the worst results when compared to those from the Dasy and Pycno surfaces.

The MF model was less well-suited in situations where a small number of facility locations were sought with significant spacing between them (such as in Buraydah and Unayzah). This provides evidence that different location-allocation models are more or less suited to specific facility location optimisation and demand depending on the spatial distribution of the facilities and the number of those facilities in the case study.

This study has also shown that differences for the sensitivity demand selection from the MF model on the three demand surfaces in Leicester will not necessarily identify differences in the chosen and candidate facility selection for the three demand surfaces, as occurred with the MI, MC and MA models. This is because the MF is considered more comprehensive than the other models in terms of handling the demand points in all the areas within the case study (Church and Murray, 2009).

One of the reflections that should be taken into account by researchers relates to the distribution of the facilities and the availability of the road network near these facilities. These factors could affect the results provided by the location-allocation models. In some cases, siting the facilities in areas far from the different classifications of the road networks could have an effect on the results of the location-allocation models, even if there are high weightings for demand.

There are many tests that can be used to validate the accuracy of the results of areal interpolation techniques; for example, the Root Mean Square Error and R squared. These tests can provide information about the error rates between the variables to be tested, such as comparing the actual population with the estimated population (see for example; Hawley, 2005; Comber et al., 2008; Brinegar and Popick, 2010 and Kim and Yao, 2010). Therefore, these tests could provide scientific support for the accuracy of results for the techniques and the differences in the facilities' selection results between the three demand surfaces used in this study. However, the tests were not used in the study due to the use of the 90-metre grid cell size, and because in all three case studies there was no actual population data for these grids. Thus, to achieve the objective of this research it was necessary to use grid cells to represent the demand points for the facilities, and in order to explore the interaction between the models and techniques, the validation of the accuracy of the results had to be sacrificed.

The application of these interactions between the four location-allocation models and the three demand surfaces with larger distance thresholds may identify more significant differences in terms of facilities' selection. This is because the large distance thresholds will assist in the allocation of different demand weights from the different source zones, especially with the large area source zones.

The use of high image resolution such as 1 metre or less with the Dasy method could provide more accurate information about land use classification, particularly relating to the small areas around the source zones. Additionally, the use of other ancillary data such as street segments could assist the Dasy surface to provide more accurate results about the target areas and the demand weights for the four location-allocation models.

The availability of a large number of facilities in any case study can prompt significant differences to arise between the three demand surfaces, especially when there are more than three facilities within each source zone. This will allow for the operations of each location-allocation model to be more effective when allocating demand weights based on the different assumptions about the three demand surfaces.

Future work or further investigations are planned to extend this work and will be applied to the interactions of different location-allocation models over different demand surfaces resulting from the use of different areal interpolation techniques on different source zones with varying grid cell size as target areas in one case study. For example, in Leicester city different source zones could be used with the areal interpolation techniques, such as a census of the Output Areas, Layer Super Output Areas and Wards or Neighbourhoods with different grid cell sizes such as 30 and 60 metres. The results of different surfaces from different source zones and different target sizes will be used with the location-allocation models to determine the best subsets for determining facility locations over the demand surfaces. The differences, which the source zones and grid cell sizes make to the case study, will provide a deeper understanding of the effect of inherent assumptions about each interpolation method for the different area of source zones and different target sizes. It will also help to provide scientific support for the decisions of the optimal facility locations in terms of the interactions when using different results for the demand surfaces obtained from each interpolation method with the location-allocation models.

6.5 Summary

Three areal interpolation techniques were applied in each case study in order to estimate the population of the source zones in a grid cell size of 90-metres. Different estimation densities for the population, based on the assumptions of each method, were obtained in the target areas within the source zones. The lack of availability of actual population data in all three case studies for these grids was an obstacle to validating the accuracy of the results for the three areal interpolation techniques and to comparing the results with other studies. The study discussed the impact of the spatial characteristics of each case study on the population estimations for the target areas, in terms of the degree of population densities, size of the source zones, the different spatial characteristics of the land use classification (parks, lakes, arid lands, industrial areas and residential areas); also presenting the advantages and disadvantages of each method with some recommendations.

Exploring the interactions of the MI, MC, MF and MA models on the AW, Pycno and Dasy surfaces was the main aim of this study. Several factors played a role in influencing the differences in facility and demand selection results between the three demand surfaces. These factors have been discussed with regards to the operation of each model, the inherent assumptions for each areal interpolation surface, the effect of area size and the characteristics of land uses for some of the source zones, the effects of the population pattern for those source zones and the effects of the limited number of facilities and the concentrations of those facilities in specific areas. However, the degrees of influence of these factors varied from one case study to another, leading to varying results when determining the best facilities' locations.

The interactions of the four location-allocation models with the three demand surfaces provided some important philosophical reflections and a deeper understanding of the impacts of the demand surfaces, resulting from the use of different areal interpolation techniques on the location-allocation models and the decision of the optimal facility locations. This in turn will contribute to providing scientific support for the best surface, to be used with any of the four models based on the case study and the factors discussed in this study. Finally, some important rubrics about the lessons learned from the interactions of the four location-allocation models with the three demand surfaces are presented in the concluding chapter.

Chapter Seven: Conclusions

7.1 Introduction

The purpose of this study has been to explore the interactions between different location-allocation models and different interpolation techniques, in order to support the decisions made about optimal facility locations. Three case studies were conducted, using four location-allocation models; each model was applied to three demand surfaces derived using a range of standard interpolation techniques. The differences in the demand weights for each surface, which were based on the assumptions underpinning each method, played a prominent role in the facilities selection results from each model when run for the three demand surfaces. This, in turn, contributed to the identification of some differences in the decisions made as to optimal facility locations. However, the degree of influence of the assumptions to each areal interpolation method varied from one case study to another, leading to different decisions being made to determine the optimal facility locations for each of the three case studies.

By exploring the interactions between the models and techniques, the results demonstrated that the spatial characteristics of the problem could be potentially more or less suited to generating the demand surfaces, based on the assumptions of the areal interpolation methods and using those surfaces with location-allocation models. Additionally, based on the objective functions and the operations embedded in each location-allocation model, the results also demonstrated that the spatial distribution for the facilities and the demand weights and the distances used influenced the decisions made by the models for the optimal facility locations. Therefore, this study has provided some important rubrics based on the lessons learned from the interactions of the four location-allocation models with the three demand surfaces. These rubrics include some recommendations about the interpolation methods and location-allocation models which can help future researchers to determine optimal facility locations. Additionally, this study has provided an example of applying the MI model on the Dasy surface to select the best distribution for the facility locations across the three case studies.

7.2 Rubrics

This section provides some important rubrics and recommendations about the lessons learned from the interactions of the four location-allocation models with the three demand surfaces. The different spatial characteristics of the three case study areas, in terms of the size of the source zones, the pattern and the distribution of the population densities, and the distribution of the facilities, were important factors. These variations provided information regarding the effects of those factors on the assumptions made about the demand surfaces and the interactions of the four location-allocation models with the three demand surfaces. Demand was appropriate for any kind of public and private sector facility: for example health facilities, schools, libraries, retail opportunities and so on. Thus, the rubrics and recommendations were able to contribute towards providing scientific support for planning decisions, decision-makers and academic researchers in terms of the use of location-allocation models and also the best surface to use to represent demand needs in those areas that lack census data. The following points describe the important lessons learned from the interactions:

1) In situations with large source zone areas, this study has shown that the assumption of a homogeneous population distribution for the AW method will produce an under-estimate for the demand weight in different regions of the study areas. This would impact on determining optimal facility locations and achieving the best geographical coverage with the MI and MC models. The impact of large source zone areas on AW surface in some cases was greater with the MA model, due to the way that the model makes allocations based on the ratio of the demand weights.
2) The impacts of homogeneous surface estimations using the AW method were less where the source zones were small and the non-built up areas few, such as in the centre of each case study area.
3) The use of the Pycno method in those case study areas with a homogeneous population distribution, such as Leicester, produced an under-estimate of the demand weight in some of the target areas in the central area of the city. This had an impact on the selection of optimal facilities locations when using the MI, MC and MA models.
4) The study noted that in some circumstances, such as the quite heterogeneous distribution of the population in the source zones, the smooth density function

for the Pycno method could make the population of the target areas in some of the source zones appear more or less heterogeneous than they actually were (see Figures 4.1, 4.2 and 4.3 in chapter four). Thus, the use of the location allocation models on the Pycno surface will identify different facility locations than the other surfaces.

5) The results of applying four models on the three demand surfaces provided evidence that the Dasy surface gave better performance in terms of the sensitivity of demand selections. In contrast, the AW surface was the worst surface in terms of the sensitivity of demand selections.
6) The study also noted that if the case study has large source zoned areas with small populated areas and a heterogeneous population distribution within those zones, then the Dasy surface should be used with the location-allocation models. This applies as long as the case study area contains large non-built up areas, such as parks, lakes, and arid lands, even when the source zones are small.
7) The interactions of the MF model on the three demand surfaces were negative when compared to the MI, MC and MA models, in terms of the differences in the number and facilities selections that required to cover the demand points. This is because the objective function of MF seeks to cover all of the demand needs and is considered more comprehensive than the other models (Church and Murray, 2009).
8) The MF model was less suited to situations where a small number of facility locations were sought, with significant spacing between them (such as in Buraydah and Unayzah). Thus, different location-allocation models are more or less well-suited to specific facility location optimisation and demand, depending on the spatial distribution of the facilities, the number of those facilities and the distances used in the case study.
9) The study has shown that in cases where the population is distributed homogeneously within different size source zones, such as Leicester, the MA model will identify facility locations that support the majority of the demand weight and which are located in the small source zones in the central of the case study.
10) The differences in the facilities selection identified through the interactions of the four location-allocation models on the three demand surfaces were applied to the current facilities locations based on the case studies. However, if these

interactions apply to the examination of the planning facilities for a network of potential sites, with at least three or more facilities within each source zone, differences in the facilities selection will be bigger.

11) The use of some areal interpolation methods such as AW and Pycno methods that lack spatial aspects or ancillary data for the population distribution within the target areas will have an impact on the decisions made for location-allocation models when determining the optimal facility locations. However, the Dasy method, or intelligent interpolation methods, which used spatial aspects or the ancillary data for the population distribution within the target areas will provide better performance with the location-allocation models.

12) Supporting optimal facility locations necessitates clear spatial data on the geographical distribution of demand. On this basis, the hybrid models that depend on combining the Dasy method with the Pycno method, or road network interpolation methods, can improve upon the results of the location allocation models. This is because the assumptions of the hybrid methods may contribute to estimates of the population effectively in terms of spatial aspects, and the ability to create heterogeneous variables in the target areas.

13) The use of ancillary data, in terms of the use of the remote sensing techniques, can be applied to combine this data with the length and class of street segments to provide spatial information about the actual distribution of demand. This is another possibility when applying hybrid methods that can improve the results of location allocation models.

14) It is appropriate to use grid cells to represent the target areas and determine the spatial distribution for the demand with location-allocation models. However, in situations where the source zone areas are large, the rationing for the target areas based on the distribution of the road network within the source zones (for those interpolation methods that lack spatial aspects or the ancillary data for the distribution of the population) will contribute to improving the results of location-allocation models on the interpolation surfaces.

15) Based on the assumptions of the areal interpolation methods, the spatial characteristics of the case study have also played an important role in generating the differences in the demand surfaces. Therefore, the spatial characteristics of the case study should be taken into account by researchers when using areal

interpolation methods, because it will have an impact on the results of location-allocation models in terms of the optimal facility locations.

Different lessons were learned in order to support the decisions of optimal facility locations and to fill a gap in the literature regarding the suitability of a range of location-allocation models to interpolation surfaces and the characteristics of the problems.

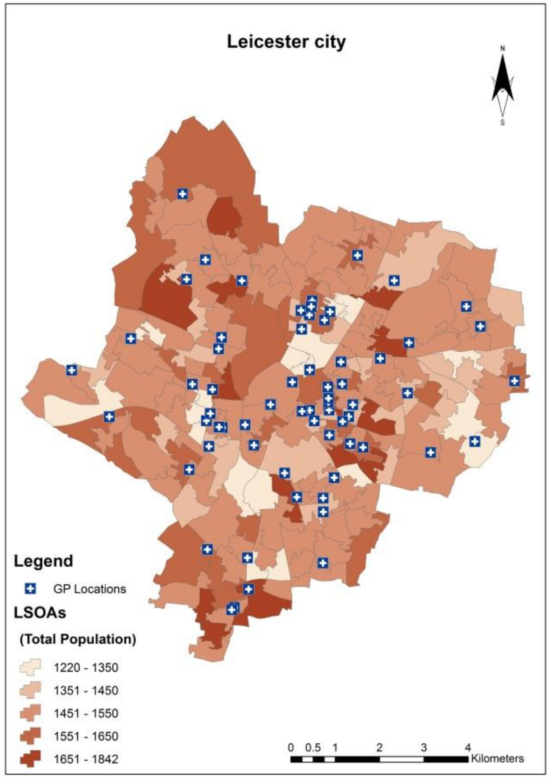
7.3 An example of applying the MI model on the Dasy surface to select the best distribution for the facility locations across the three case studies

This section provides exemplifies the application of the MI model to the Dasy surface to select the optimal distribution for facility locations across each case study area. The aim was to redistribute the current number of facilities for each case study, to provide greater coverage to the demand points and to compare existing provisions against so-called 'best' provision. In addition, to determine where the location allocation model would place health facilities, in order to clarify the potential of the methods to site new facilities, or for strategic planning.

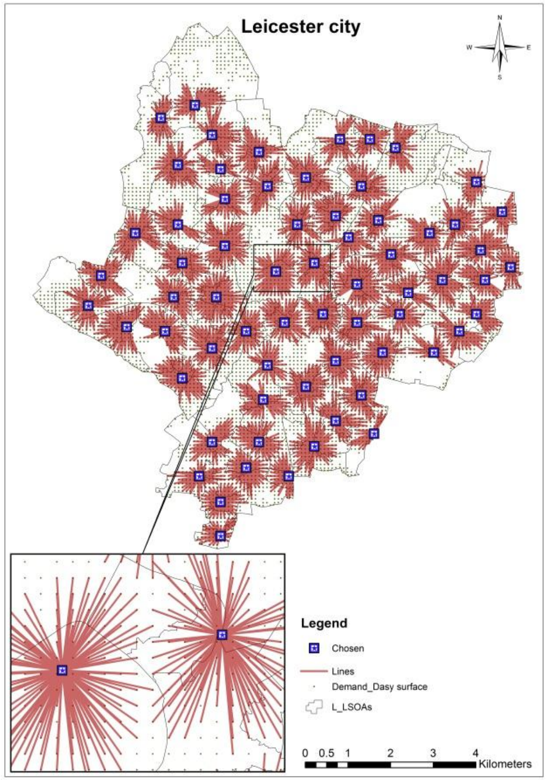
The MI model is one of the best location allocation models for siting new facilities or strategic planning. This model seeks to minimise the aggregated demand weighted distance between supply and demand. In contrast, the assumptions of the Dasy method, as described previously, produces more realistic data about the actual distribution of the population within the source zone; this is especially the case with a larger source zone area size. For these reasons, the study chose the MI model and the Dasy surface in this section.

To select the optimal distribution for the facility locations the researcher created grid points measuring 100 metres across to define each case study area. These points represented the potential locations for the optimal distribution of the current number of facilities for each case study. Figures 7.1, 7.2 and 7.3 show the results for the MI model when applied to select the best provision and to redistribute the current number of facilities serving the demand points within 800 metres of each case study. Figure 7.1 compares the existing provision against what the 'best' provision in Leicester. The results of the best provision for Leicester distribute GP locations evenly in order to cover all the demand points. The large number of GP locations and the homogeneous distribution of the source zone population in Leicester plays a role in the wider distribution of GP locations. However, with the heterogeneous distribution of the source zone population and the small number of PHCC locations in the KSA case studies, the results when comparing existing provision against 'best' provision in Buraydah and Unayzah showed the concentrations for the optimal distribution in the middle of the two case studies (see Figures 7.2 and 7.3).

The results of the sensitivity demand selection from the MI model for the best provision or optimal distribution of facilities across the three case studies showed that the best provision produced better coverage for demand than the existing health locations in each case study. Figure 7.4 compares the results of the sensitivity demand selection from the MI model on the Dasy surface, for the existing provision against the 'best' provision in each case study. The results demonstrated that the new geographical distribution of health facilities in each case study area was better than the existing health locations, in terms of minimising the aggregated demand weighted distance between supply and demand and demand coverage. This reflects the role, or the advantage of using location allocation models for siting new facilities and strategic planning.

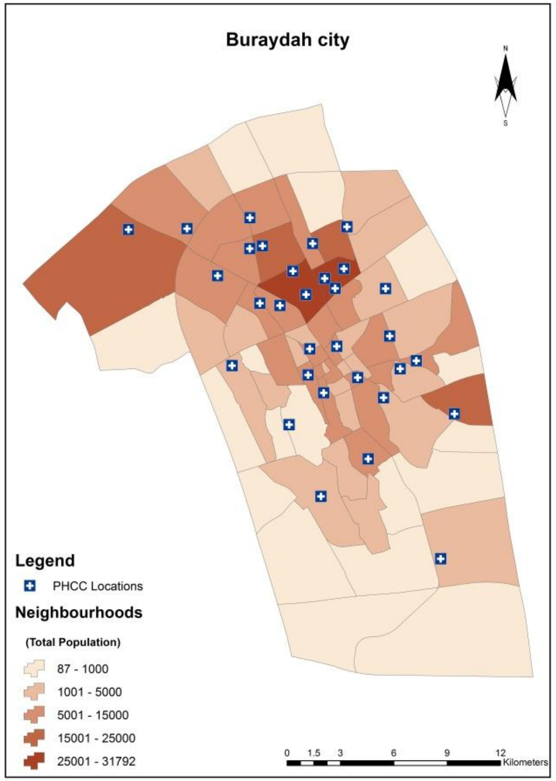


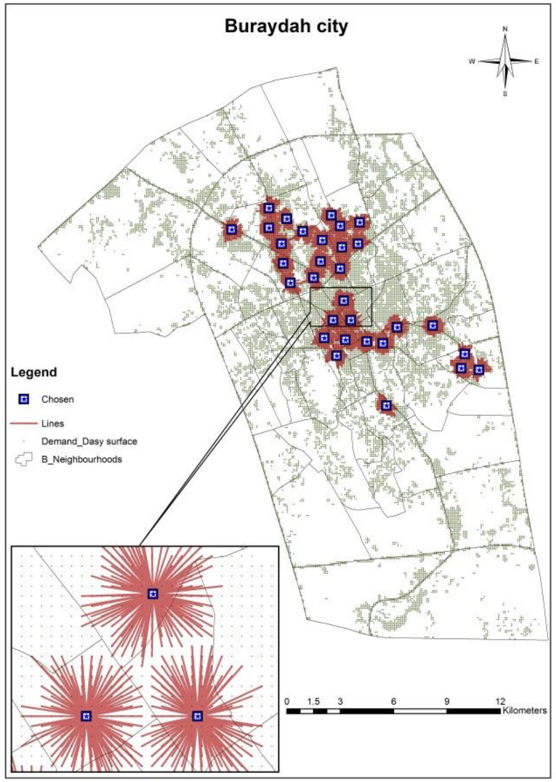
a) Existing GP locations in Leicester



b) The results of the MI model when applied to select the best provision and to redistribute the current number of GP locations to serve the demand points within 800 metres of Leicester

Figure 7.1: Comparing the existing provision against the potential 'best' provision in Leicester. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.





a) Existing PHCC locations in Buraydah

b) The results of the MI model when applied to select the best provision and to redistribute the current number of PHCC locations to serve the demand points within 800 metres of Buraydah

Figure 7.2: Comparing the existing provision against the potential 'best' provision in Buraydah.

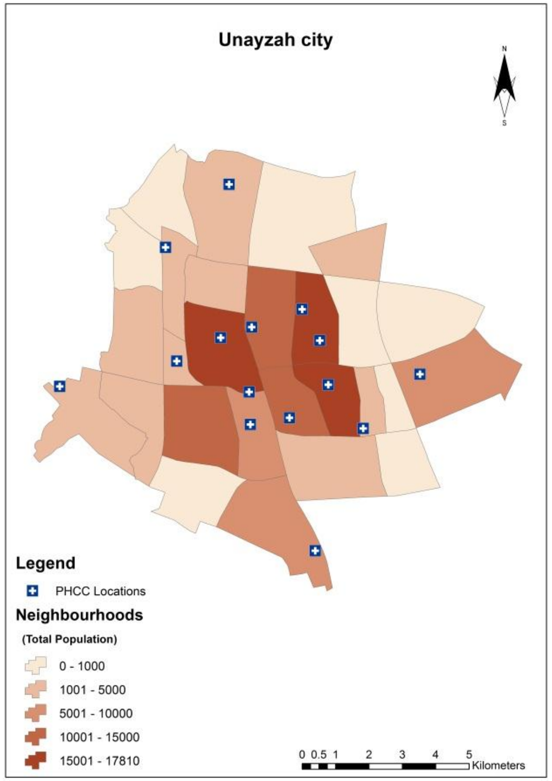
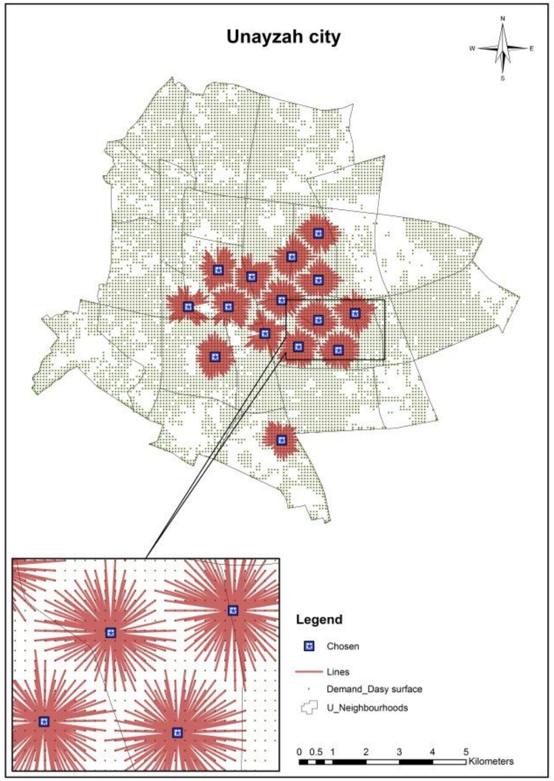
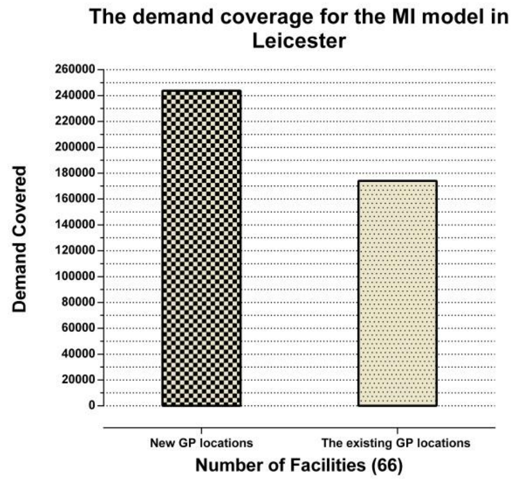
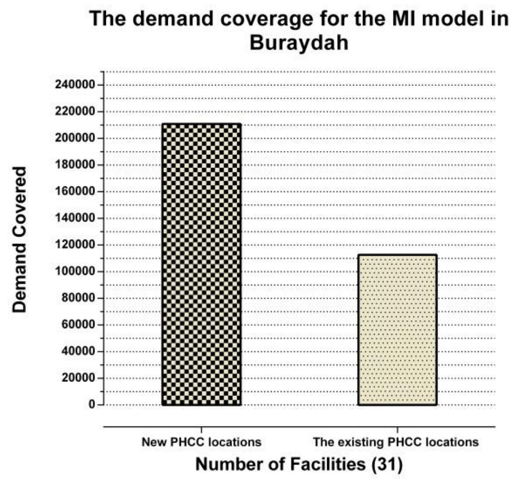
	
a) Existing PHCC locations in Unayzah	b) The results of the MI model when applied to select the best provision and to redistribute the current number of PHCC locations to serve the demand points within 800 metres of Unayzah

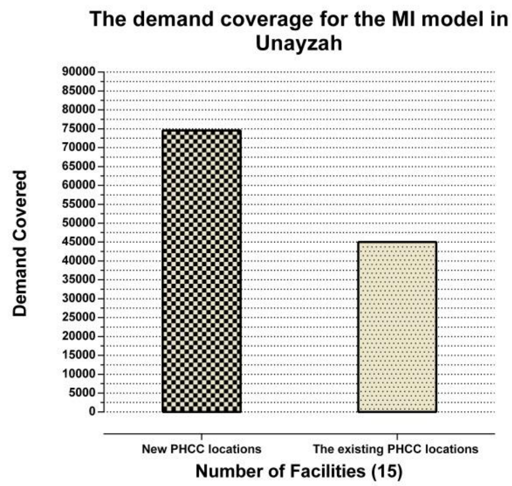
Figure 7.3: Comparing the existing provision against the potential 'best' provision in Unayzah.



a) Leicester



b) Buraydah



c) Unayzah

Figure 7.4: Comparing the results of sensitivity demand selection from the MI model on Dasy surface for the existing provision against the 'best' provision in each case study.

7.4 Summary

This study has shown that there was an impact caused by inherent assumptions for the use of the results of areal interpolation techniques with some of the location-allocation models, on the results of the optimal facility locations. The spatial characteristics of the case study area, in terms of the population densities, the size of the source zones and built up areas also played an important role in generating differences between the population estimation results for each target area and between the three demand surfaces for each case study. Therefore, based on objective functions, the operations embedded in the location-allocation models and the results of the population estimation for the areal interpolation methods, the results of the optimal facility locations for the MI, MC and MA models over each case study produced differences in the facility selections results across the three demand surfaces. It is hoped that the results of this study will provide scientific support to the decisions about optimal facility locations, facilitating exploration of different areal interpolation methods based on the spatial characteristics of problems and demonstrating how the different demand surfaces could potentially be more or less suited to different location allocation models.

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Appendix 1

- **Results of the supervised classification for the three case studies**

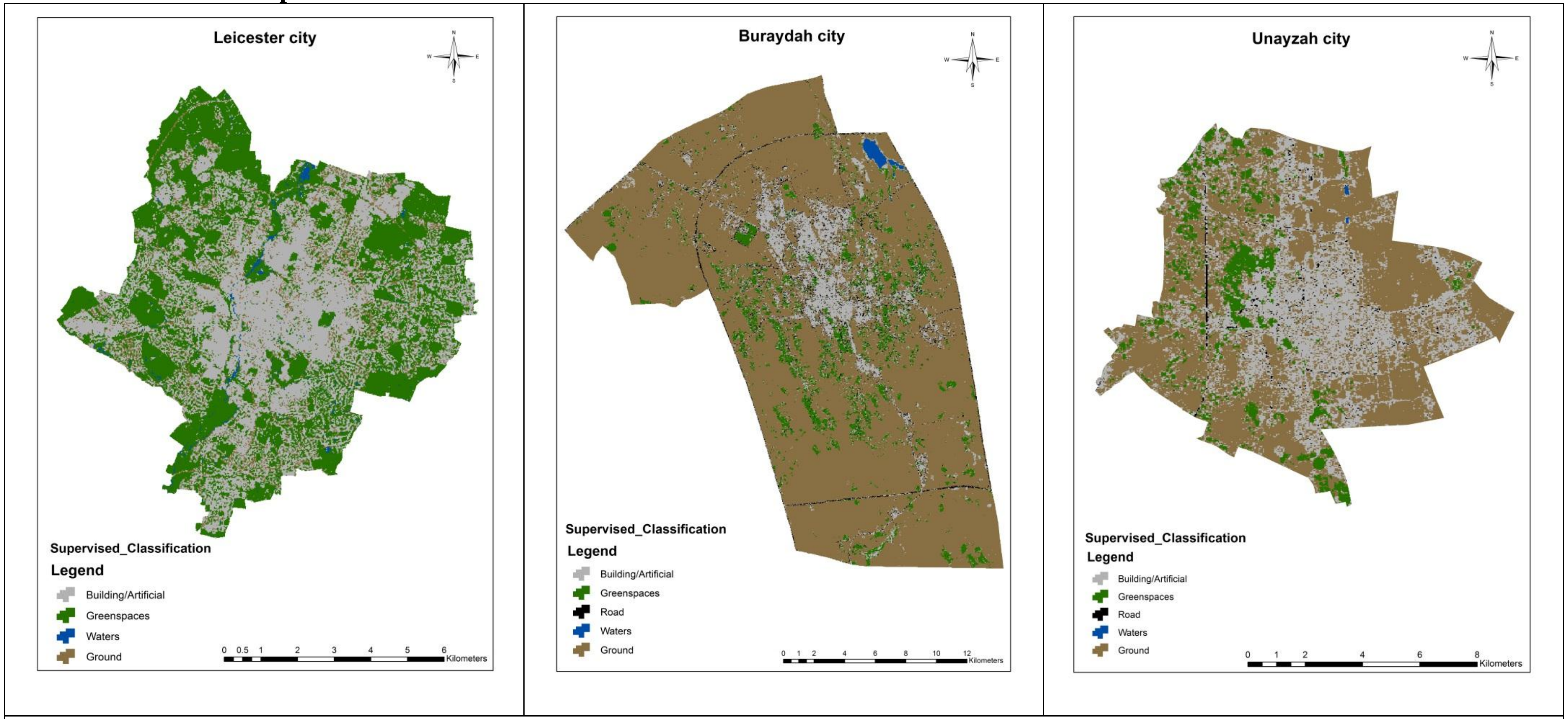
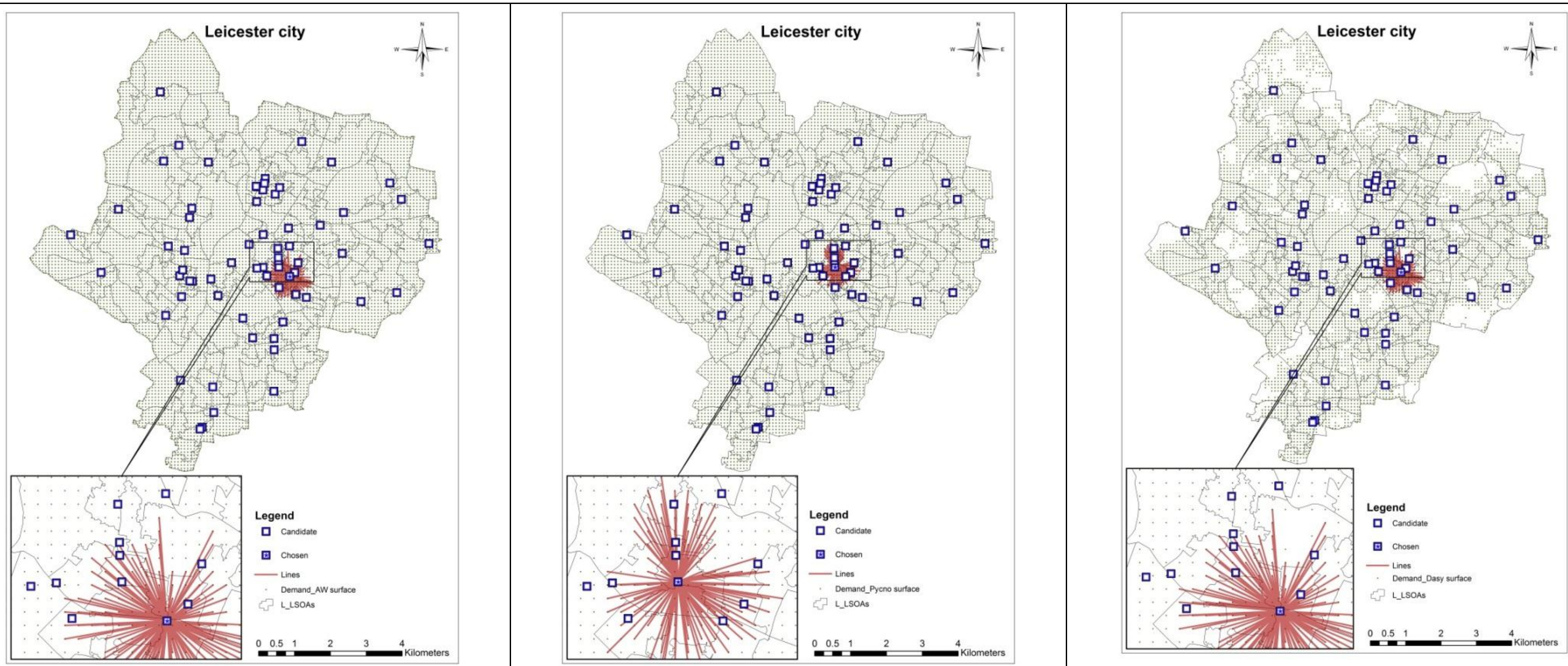


Figure 1.1 Results of the supervised classification for the three case studies. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

Appendix 2

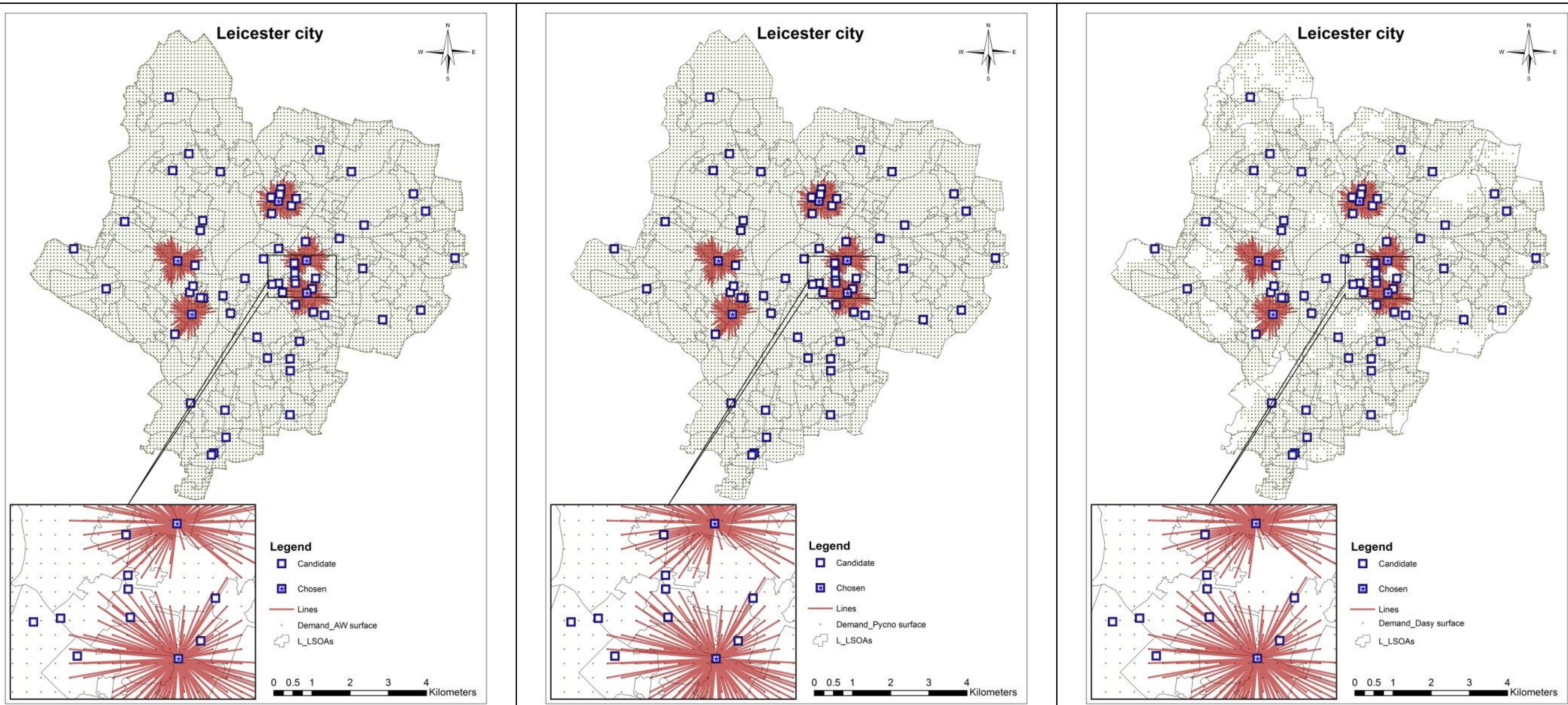
2.1 Results of the MI and MC models

2.1.1 Results of the MI and MC models for Leicester



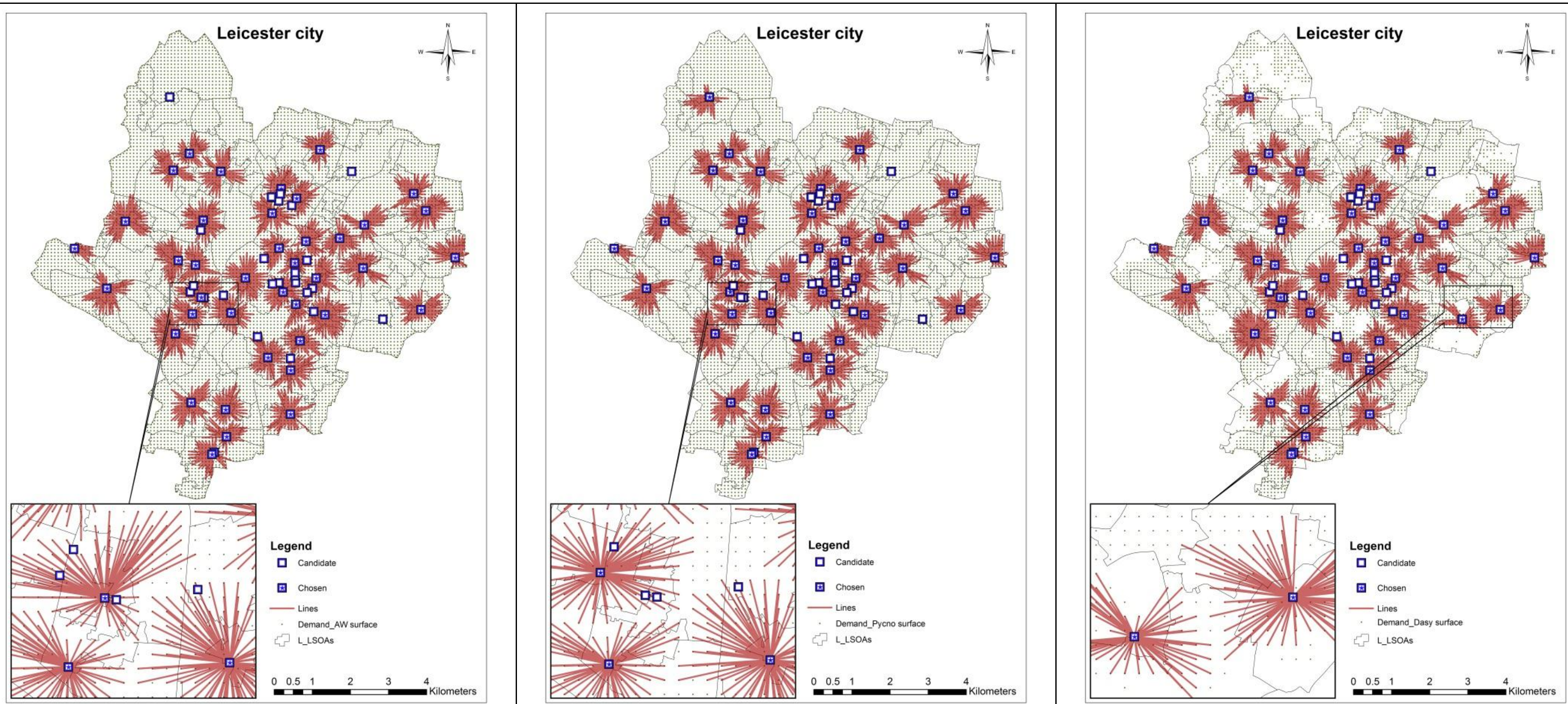
a) AW	b) Pycno	c) Dasy

Figure 2.1: Results of applying the MI and MC models in Leicester to select the best 1 GP location within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



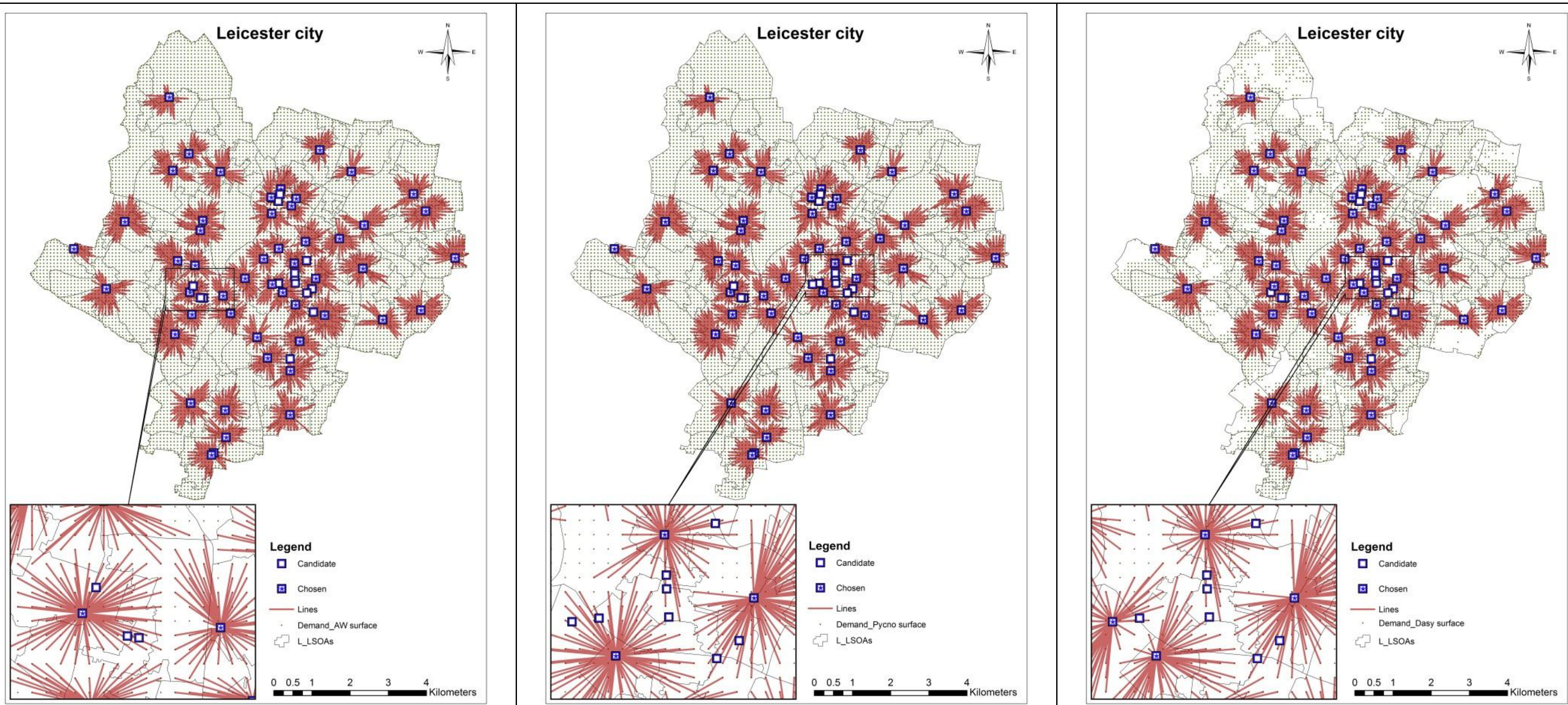
a) AW	b) Pycno	c) Dasy

Figure 2.2: Results of applying the MI and MC models in Leicester to select the best 5 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



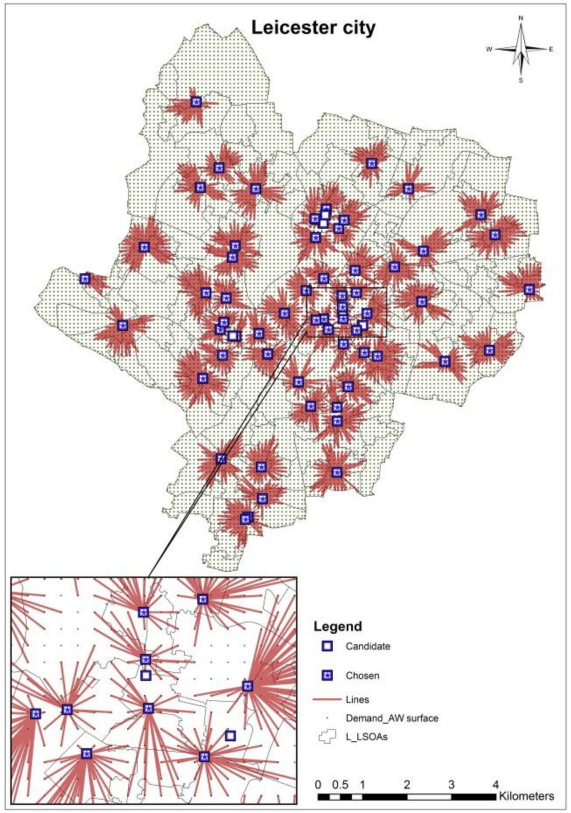
a) AW	b) Pycno	c) Dasy

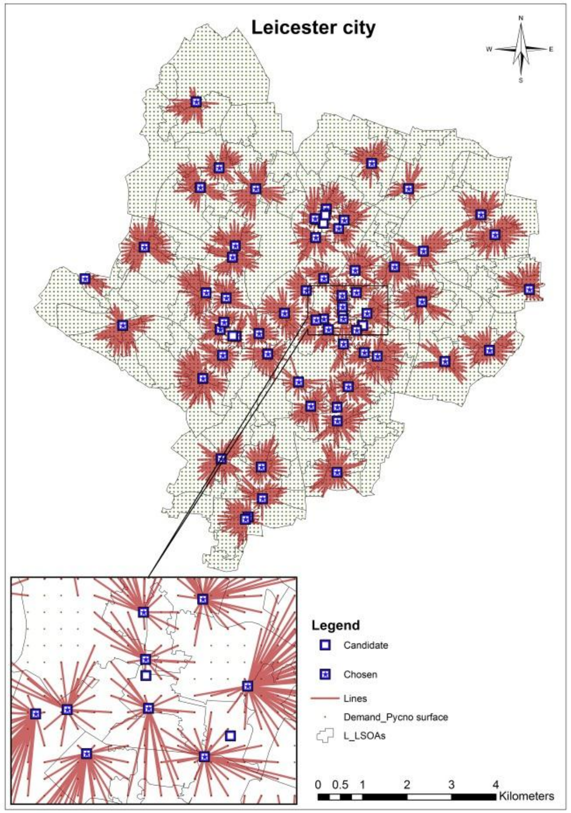
Figure 2.3: Results of applying the MI and MC models in Leicester to select the best 40 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

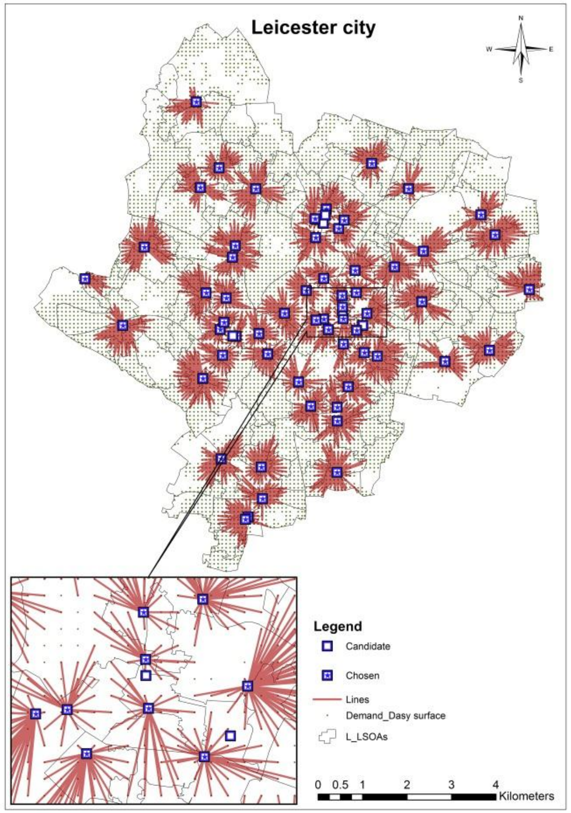


a) AW | b) Pycno | c) Dasy

Figure 2.4: Results of applying the MI and MC models in Leicester to select the best 50 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



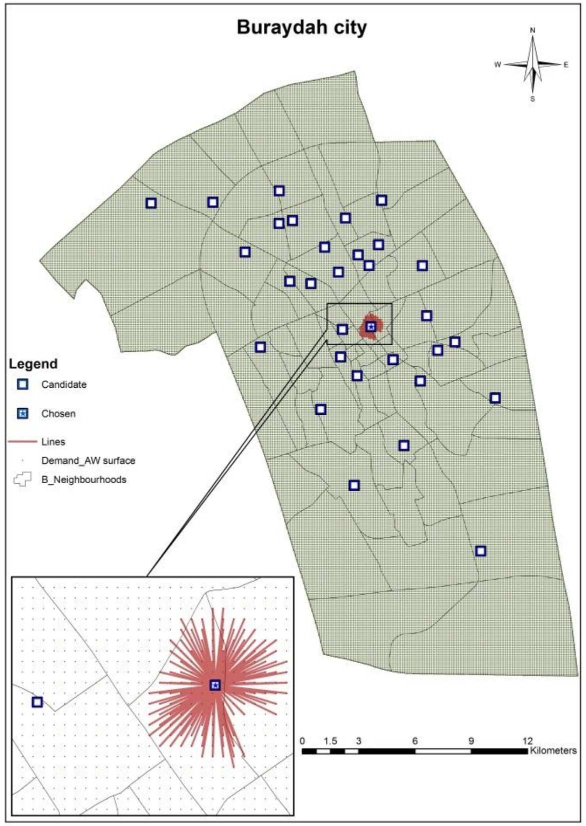


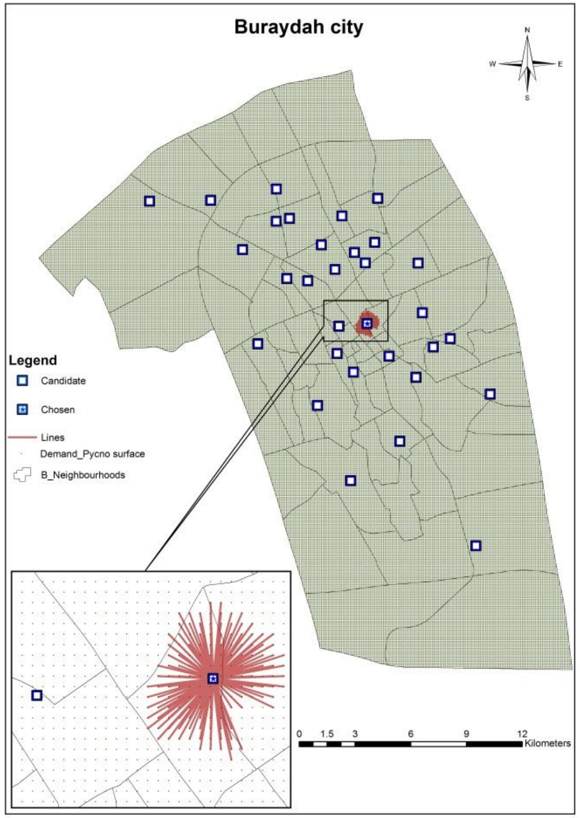


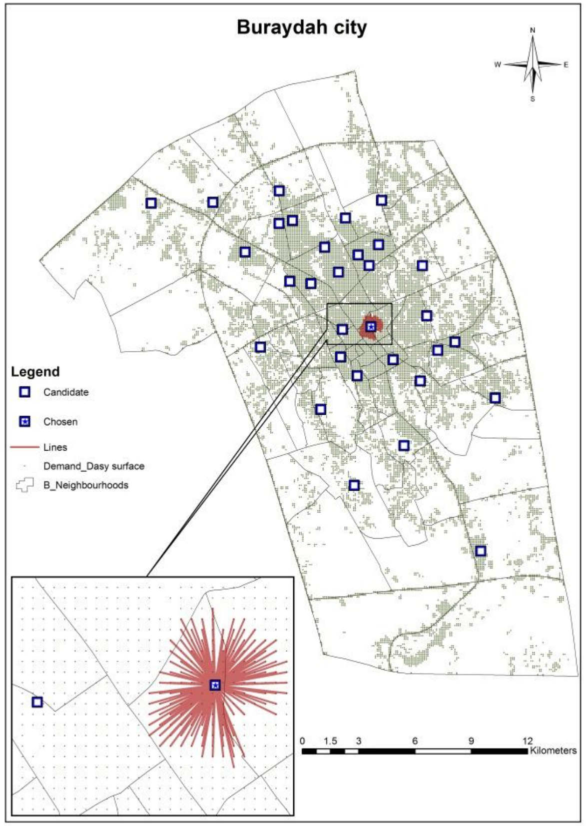
a) AW	b) Pycno	c) Dasy

Figure 2.5: Results of applying the MI and MC models in Leicester to select the best 60 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

2.1.2 Results of the MI and MC models for Buraydah

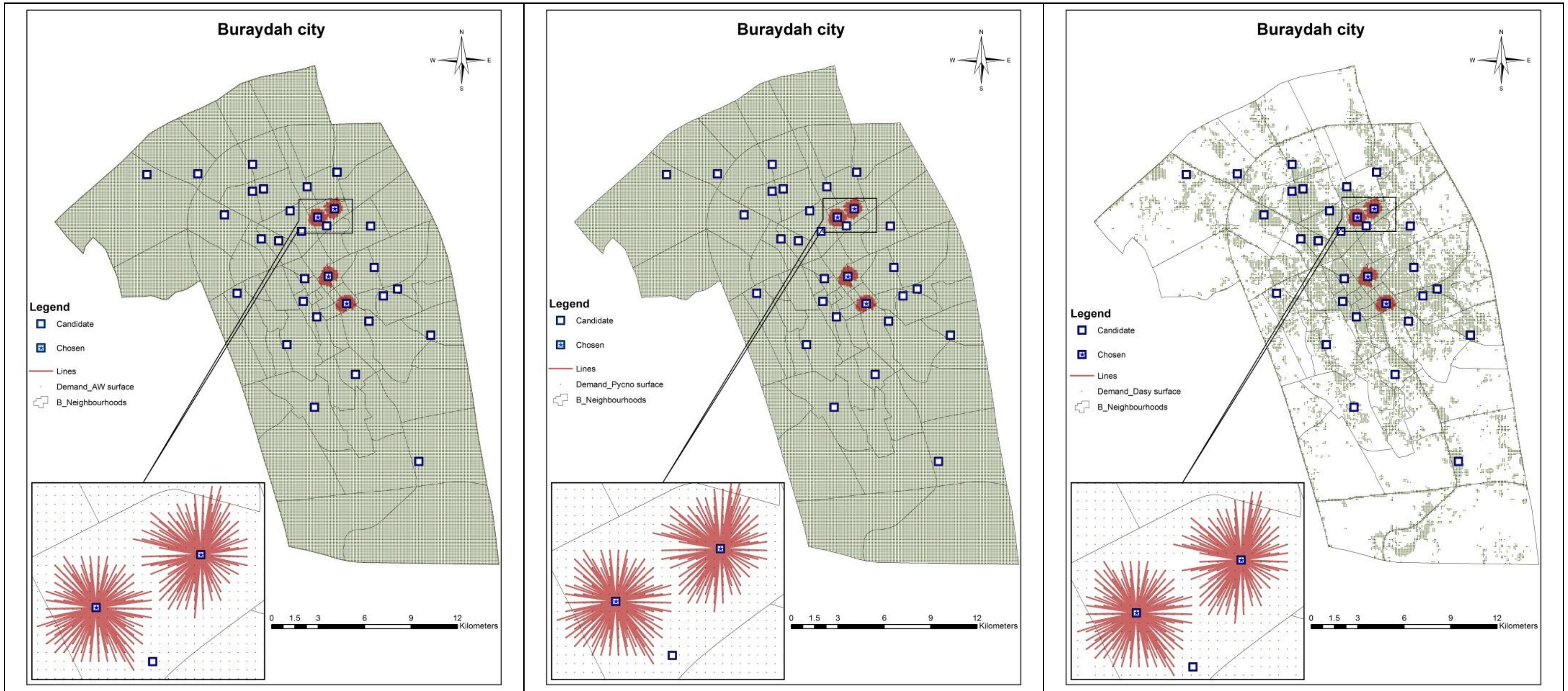






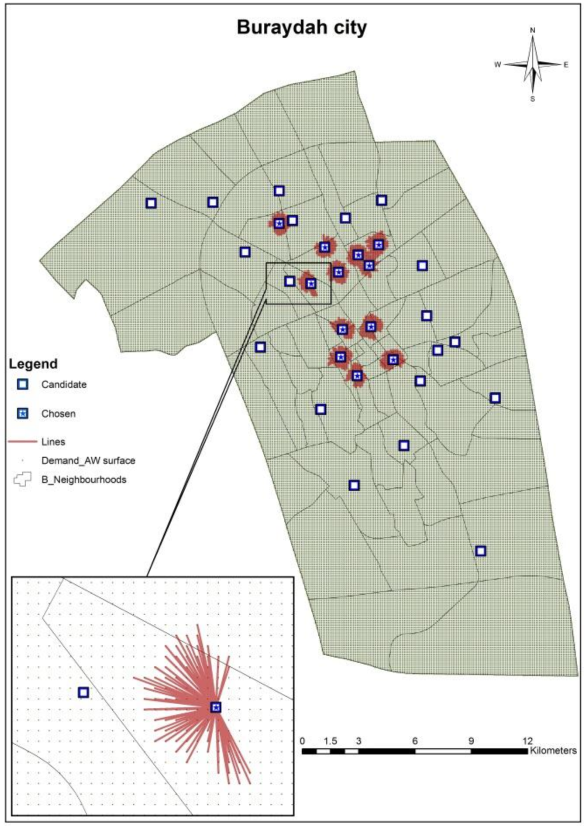
a) AW	b) Pycno	c) Dasy

Figure 2.6: Results of applying the MI and MC models in Buraydah to select the best 1 PHCC location within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

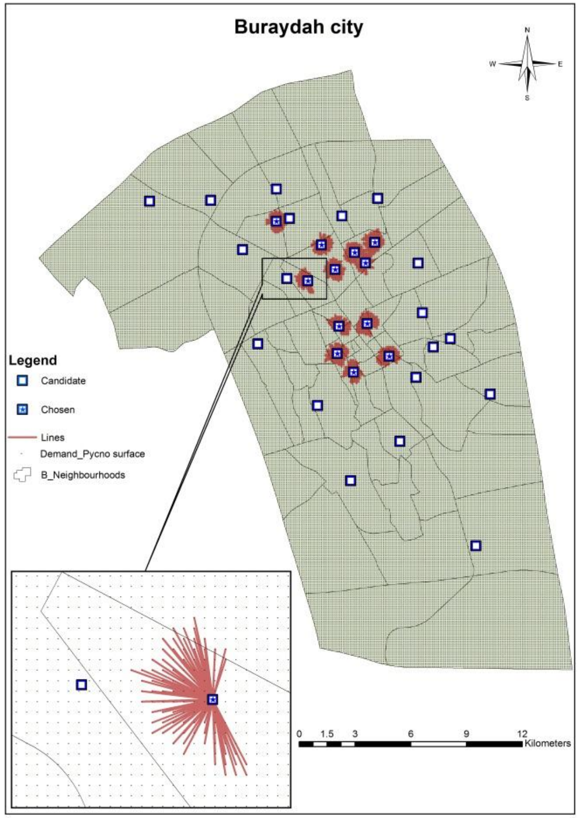


a) AW	b) Pycno	c) Dasy

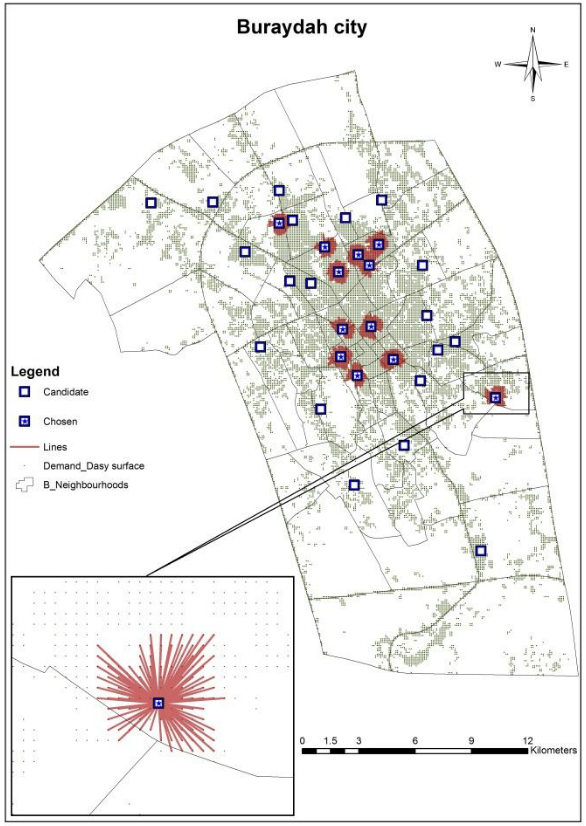
Figure 2.7: Results of applying the MI and MC models in Buraydah to select the best 4 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW

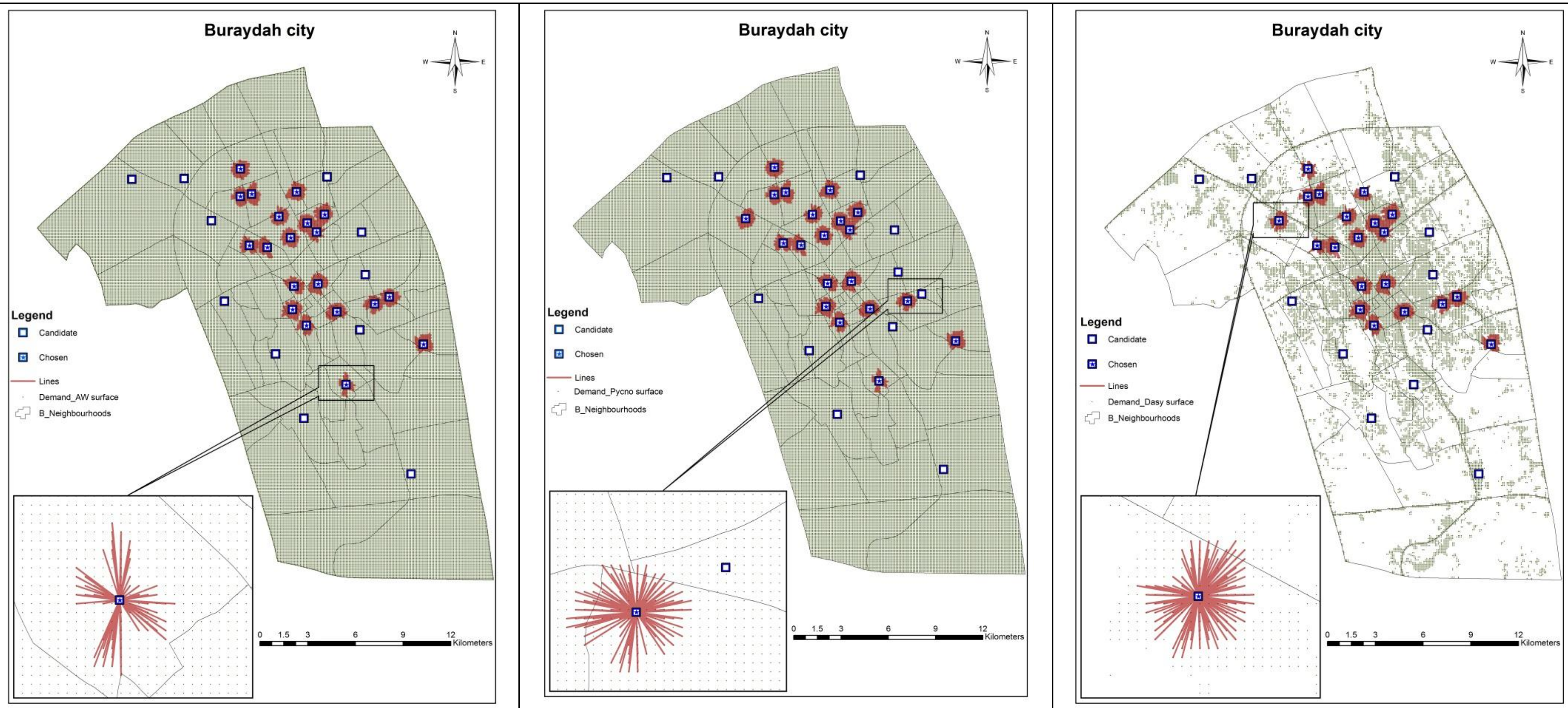


b) Pycno



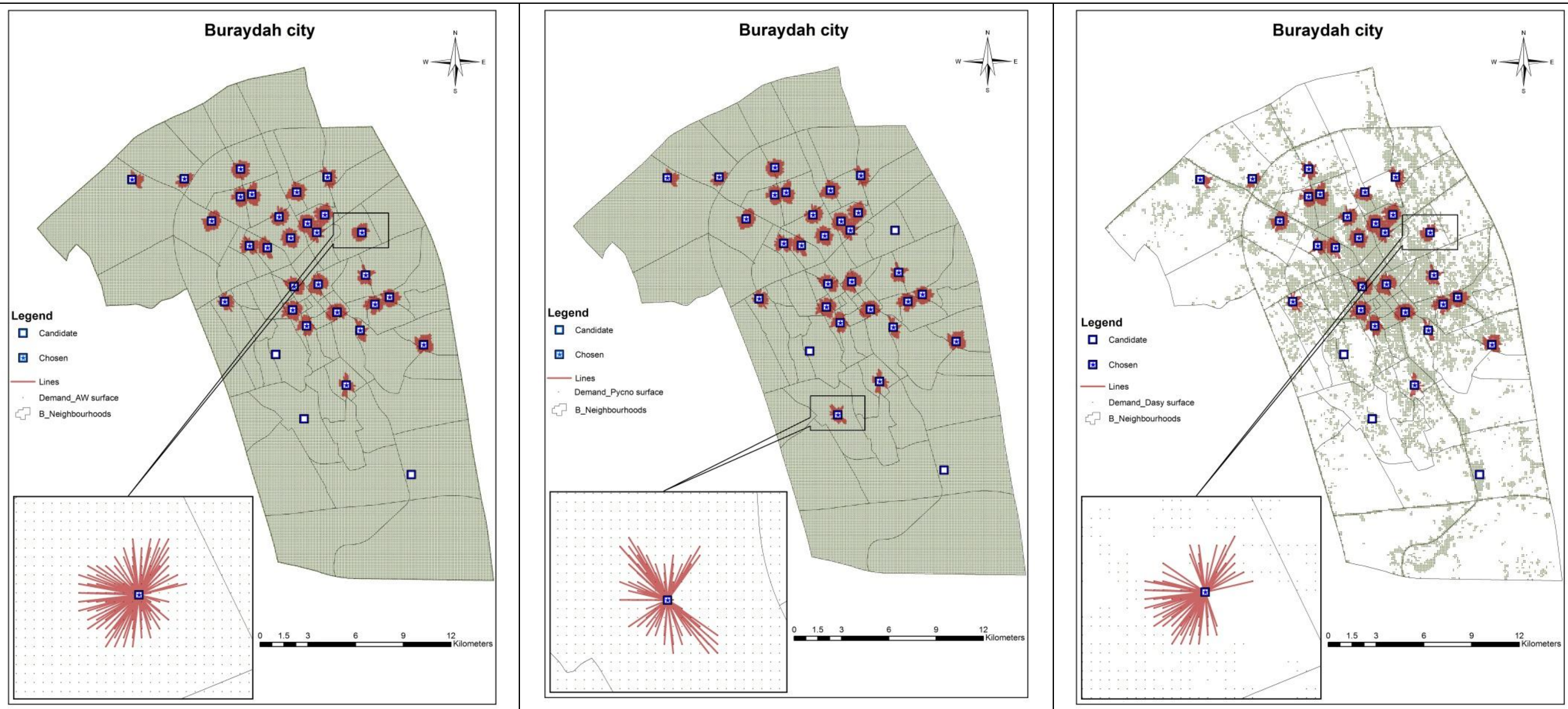
c) Dasy

Figure 2.8: Results of applying the MI and MC models in Buraydah to select the best 12 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

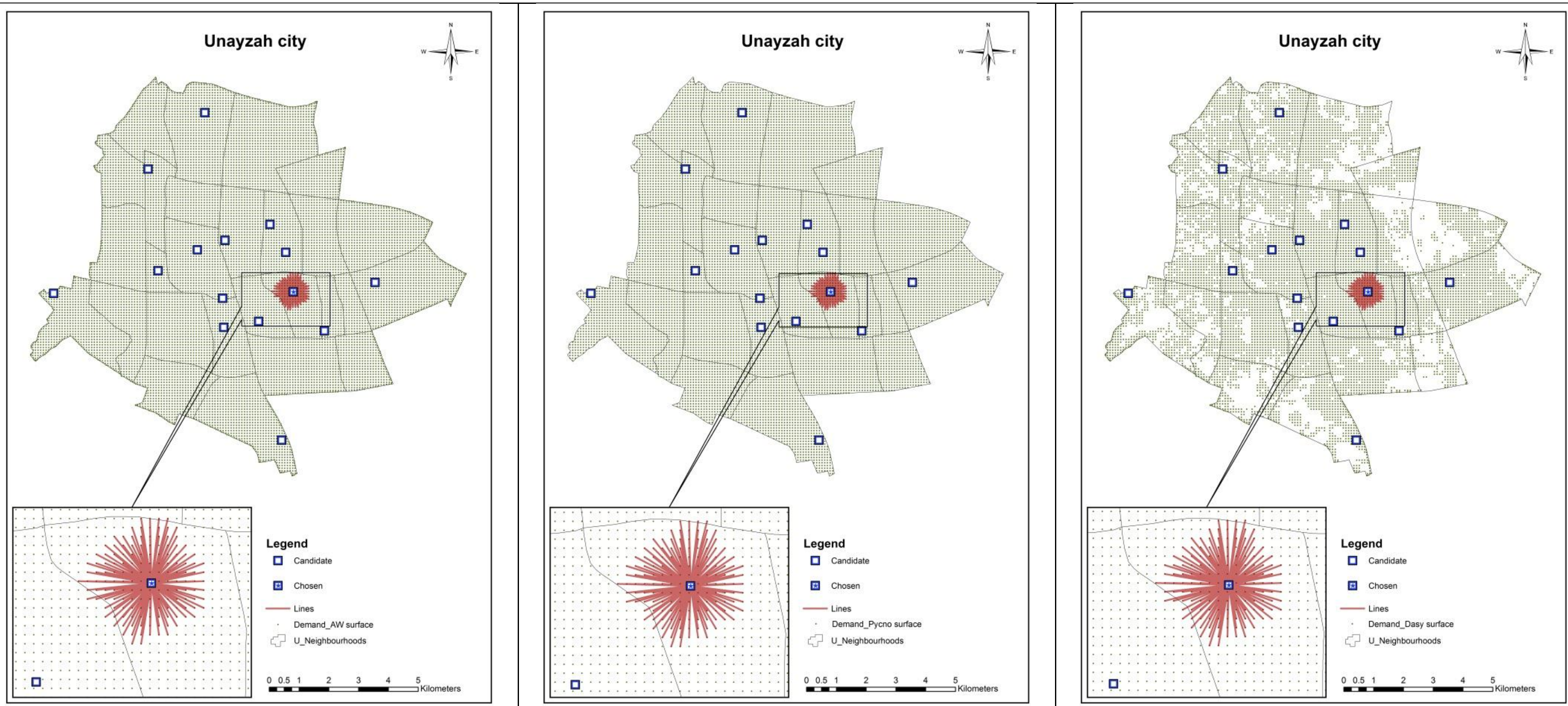
Figure 2.9: Results of applying the MI and MC models in Buraydah to select the best 20 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

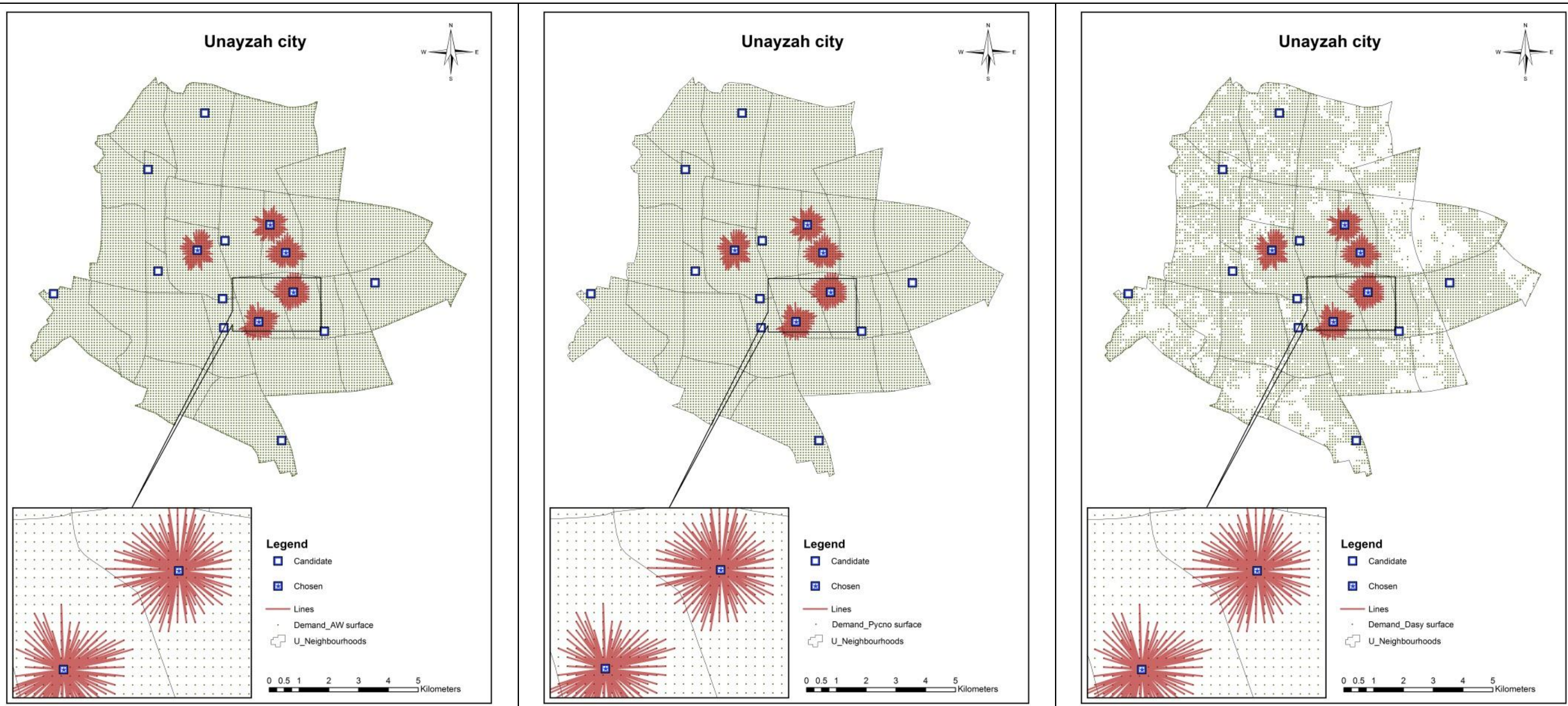
Figure 2.10: Results of applying the MI and MC models in Buraydah to select the best 28 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

2.1.3 Results of the MI and MC models for Unayzah



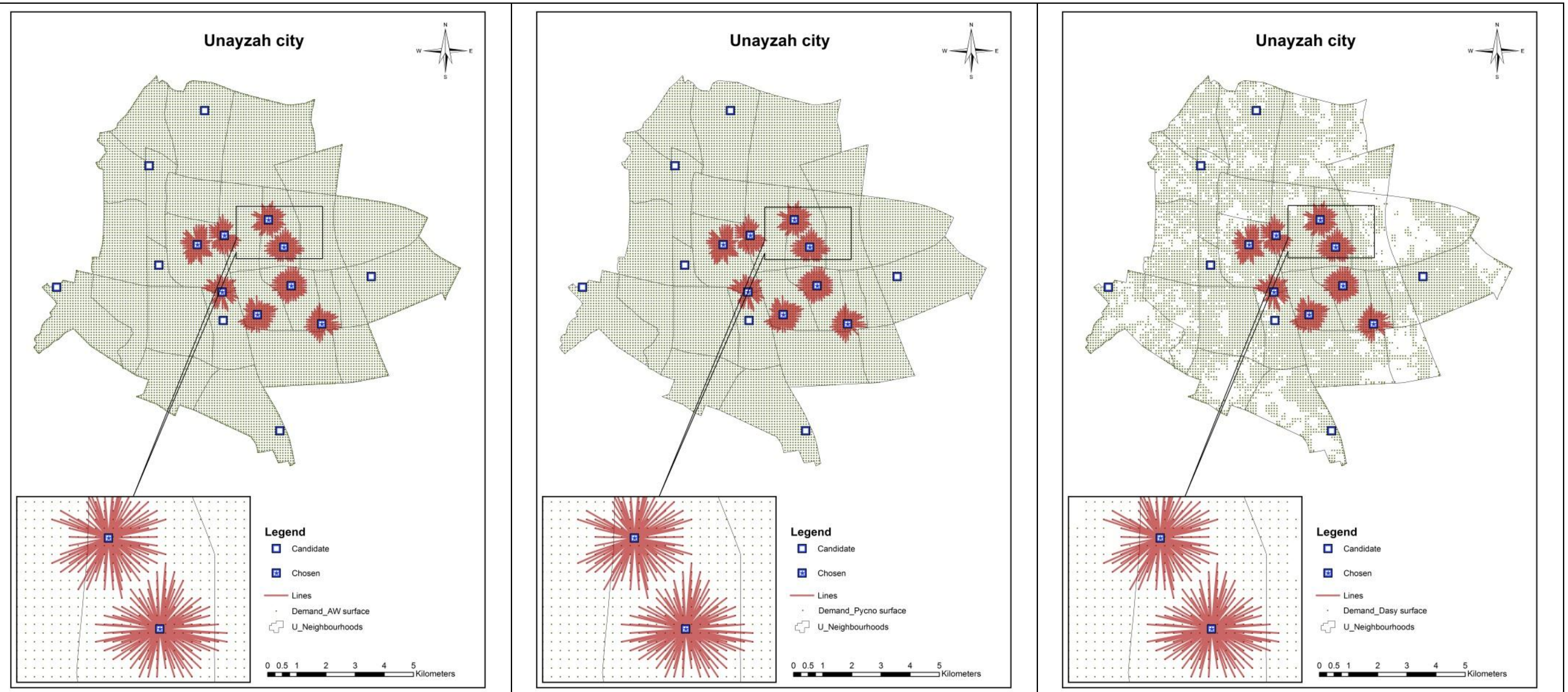
a) AW b) Pycno c) Dasy

Figure 2.11: Results of applying the MI and MC models in Unayzah to select the best 1 PHCC location within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



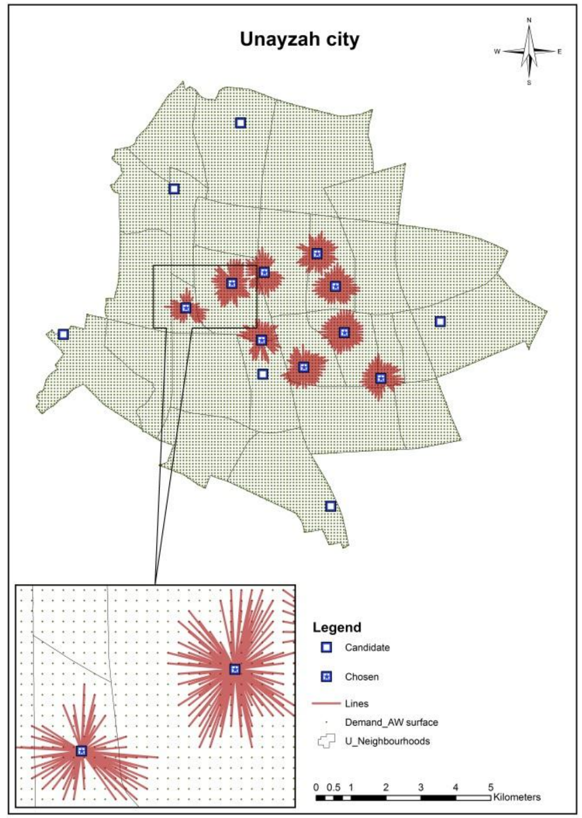
a) AW	b) Pycno	c) Dasy

Figure 2.12: Results of applying the MI and MC models in Unayzah to select the best 5 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



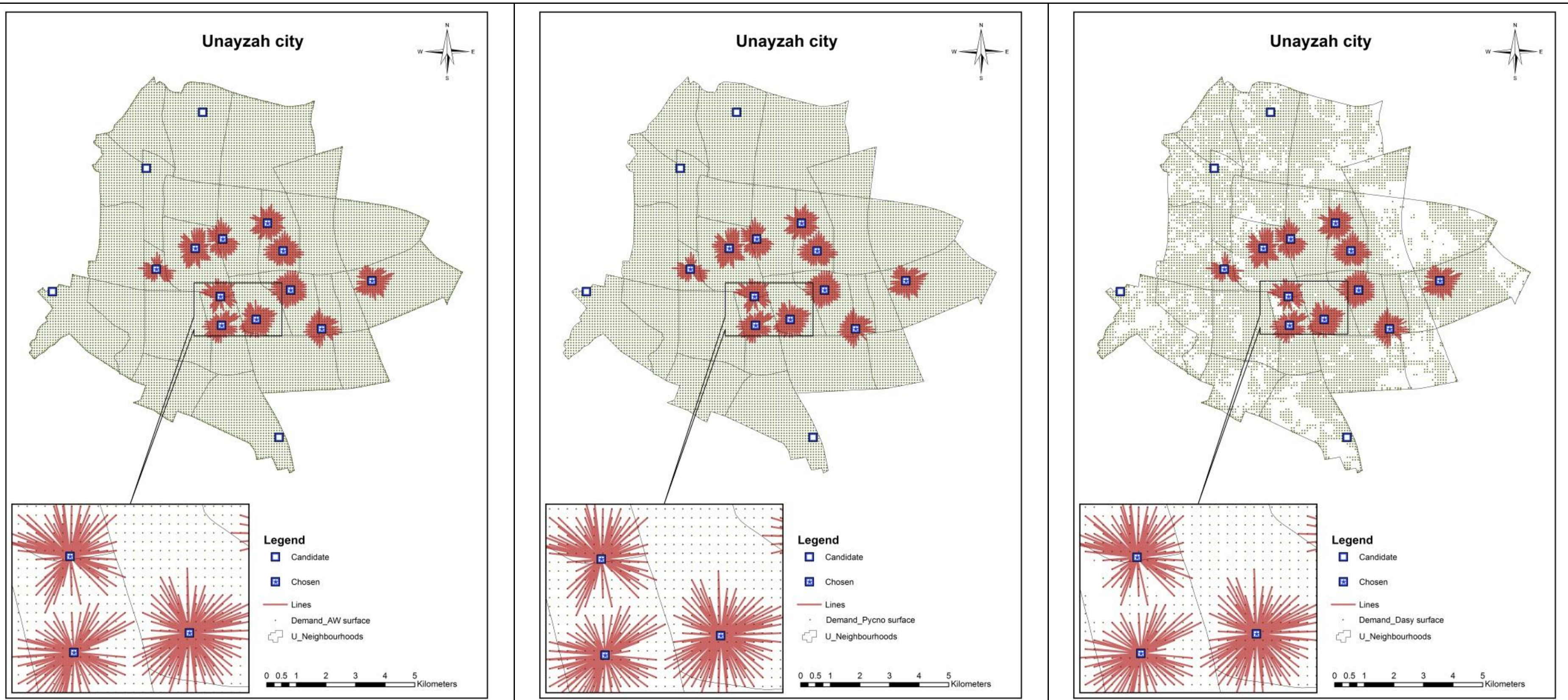
a) AW	b) Pycno	c) Dasy

Figure 2.13: Results of applying the MI and MC models in Unayzah to select the best 8 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 2.14: Results of applying the MI and MC models in Unayzah to select the best 9 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

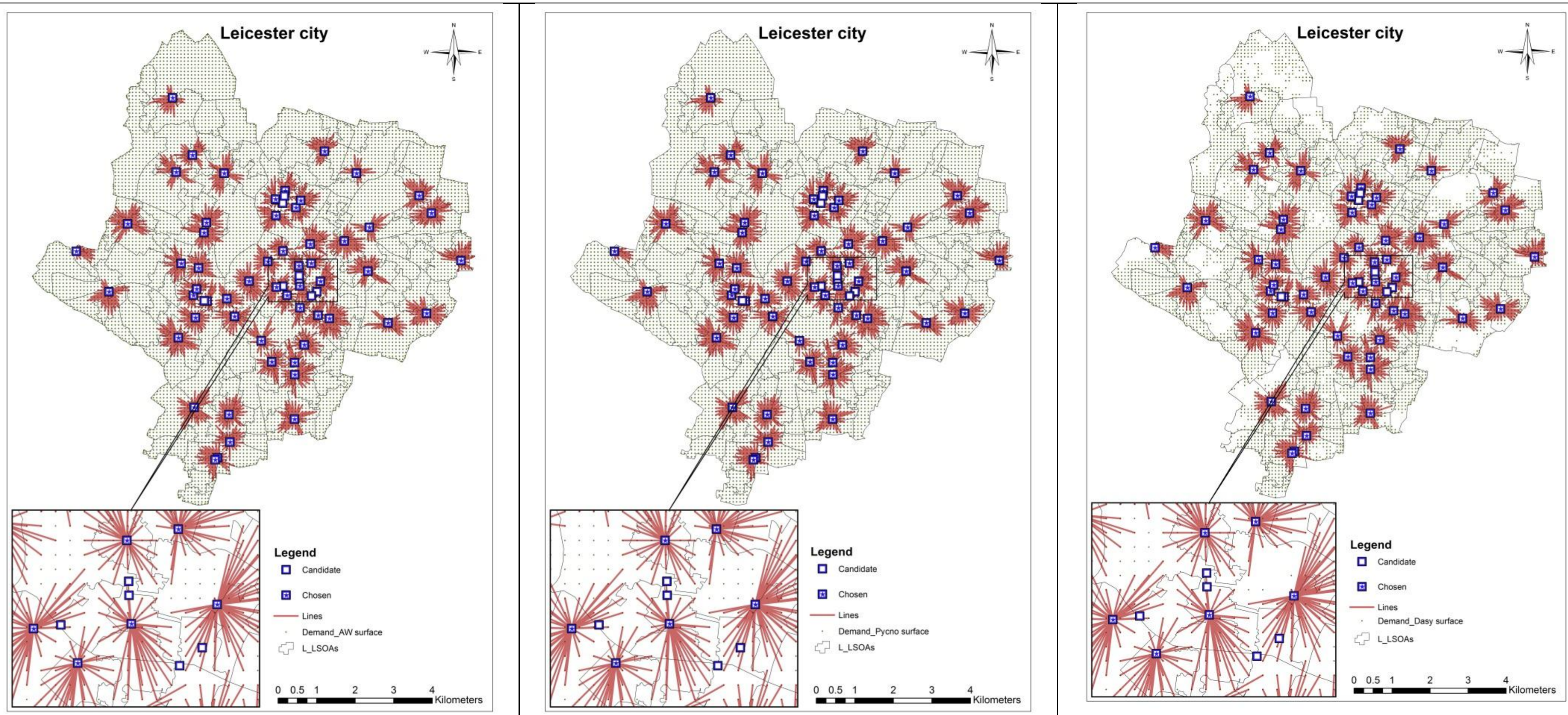


a) AW	b) Pycno	c) Dasy

Figure 2.15: Results of applying the MI and MC models in Unayzah to select the best 11 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

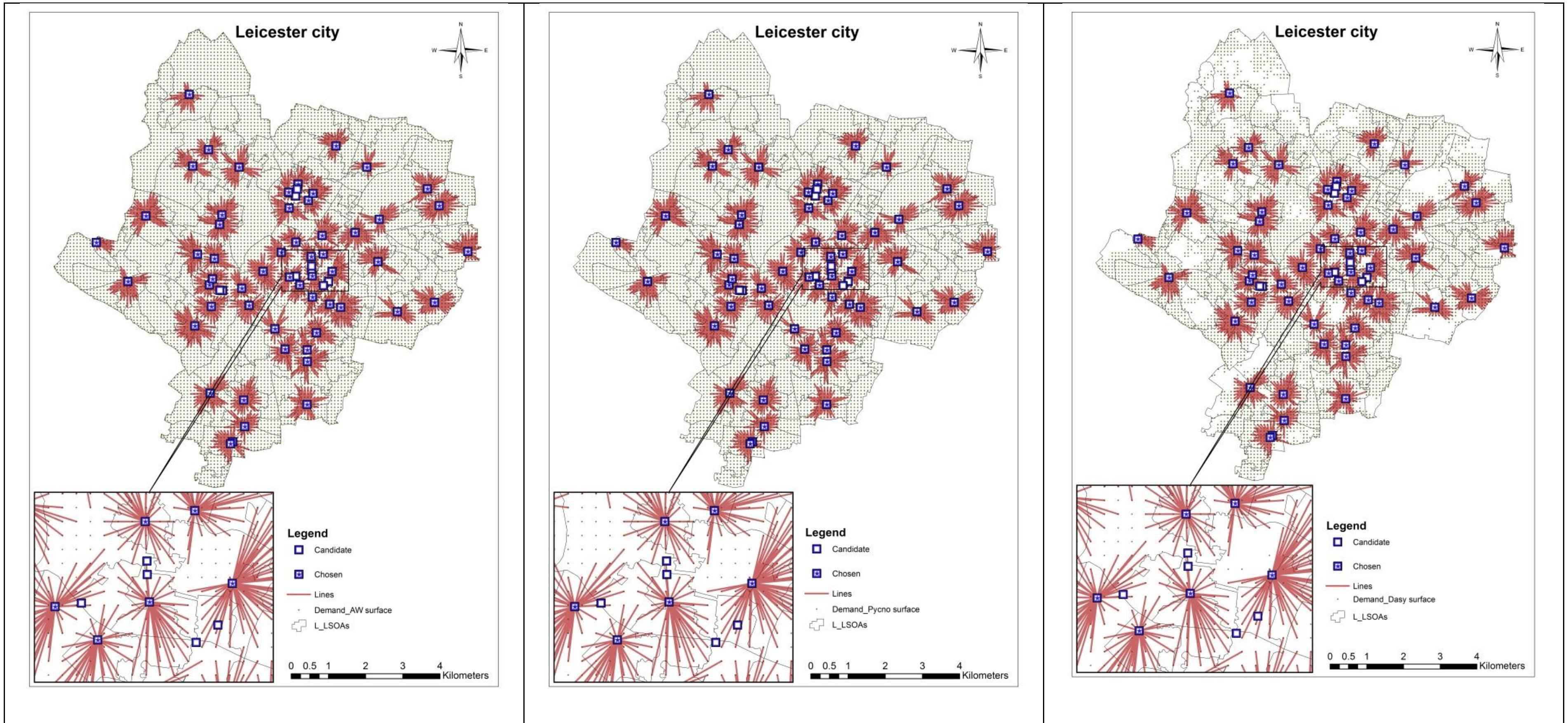
2.2 Results of the MF model

2.2.1 Results of the MF model for Leicester



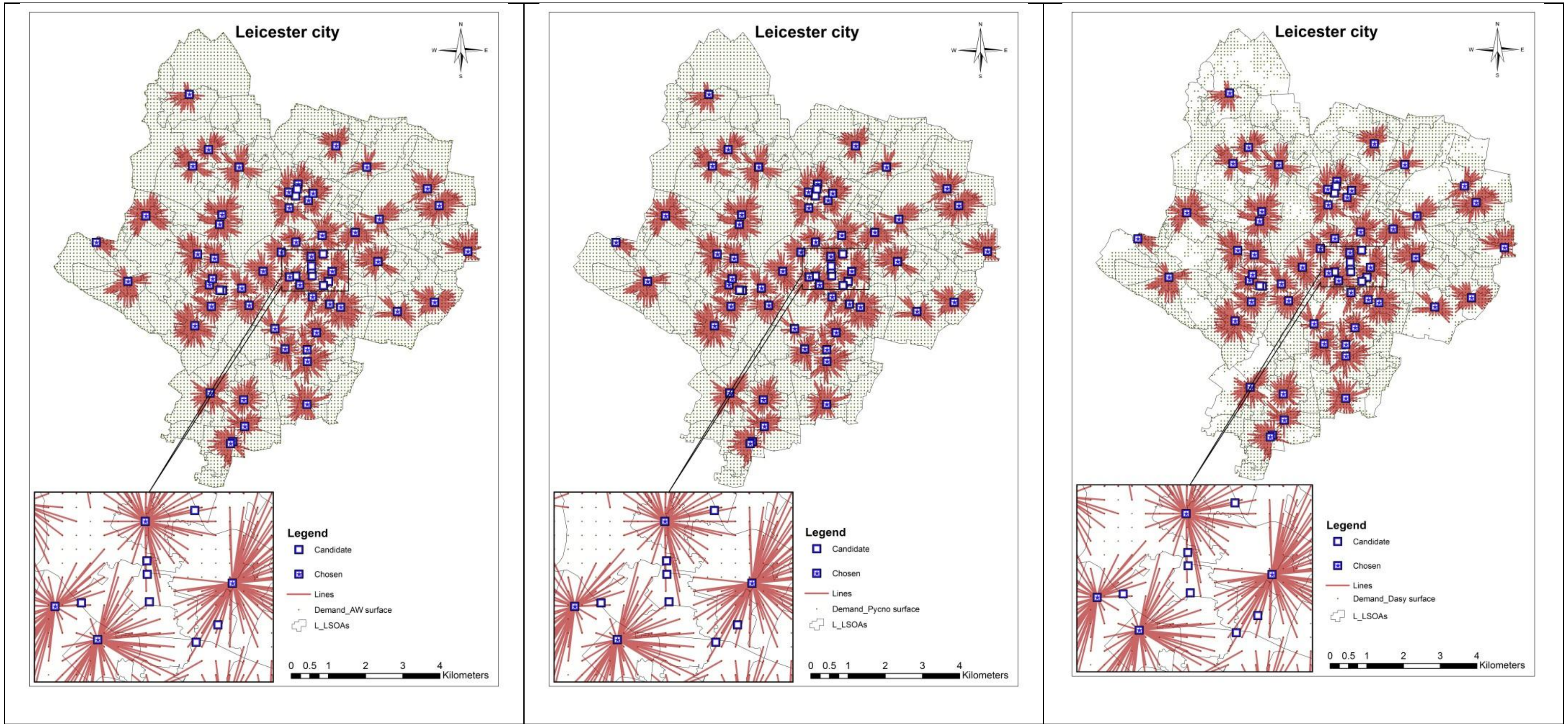
a) AW	b) Pycno	c) Dasy

Figure 2.16: Results of applying the MF model in Leicester within 650 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



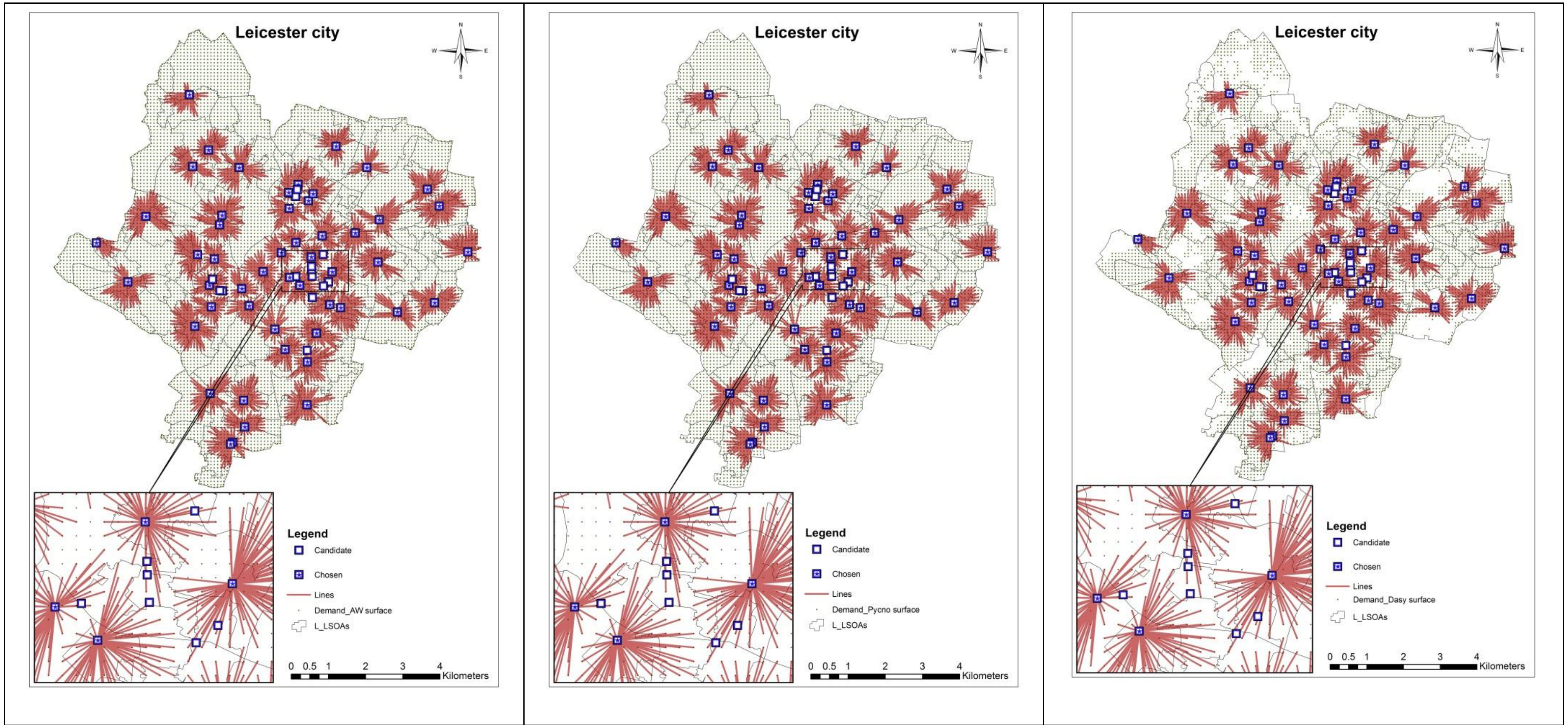
a) AW	b) Pycno	c) Dasy

Figure 2.17: Results of applying the MF model in Leicester within 700 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW	b) Pycno	c) Dasy

Figure 2.18: Results of applying the MF model in Leicester within 750 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW	b) Pycno	c) Dasy

Figure 2.19: Results of applying the MF model in Leicester within 850 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

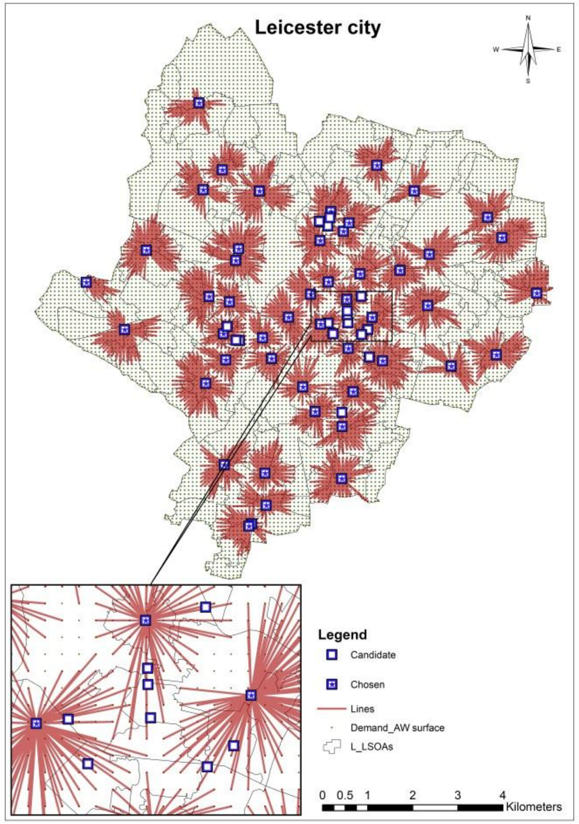
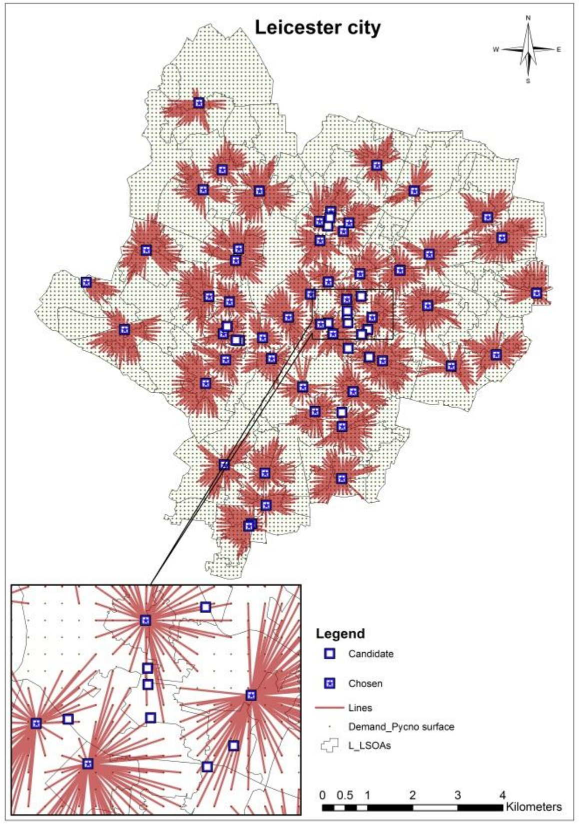
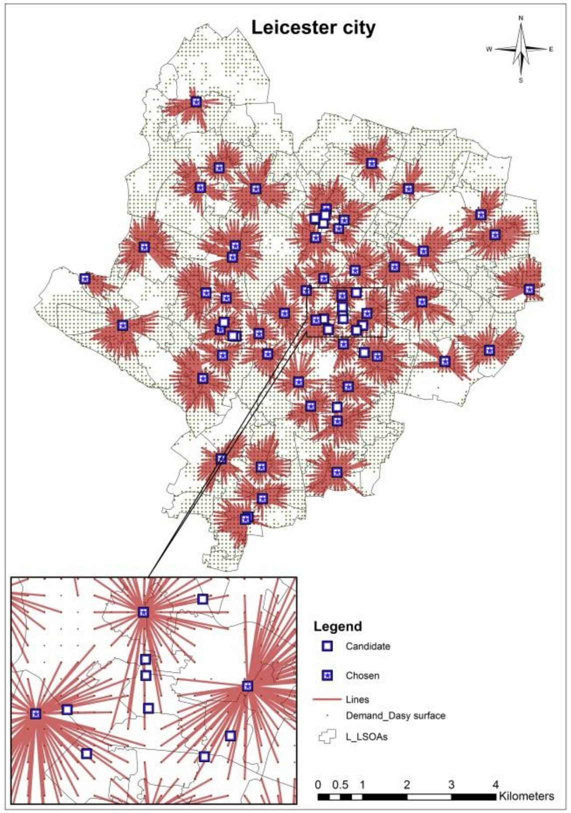
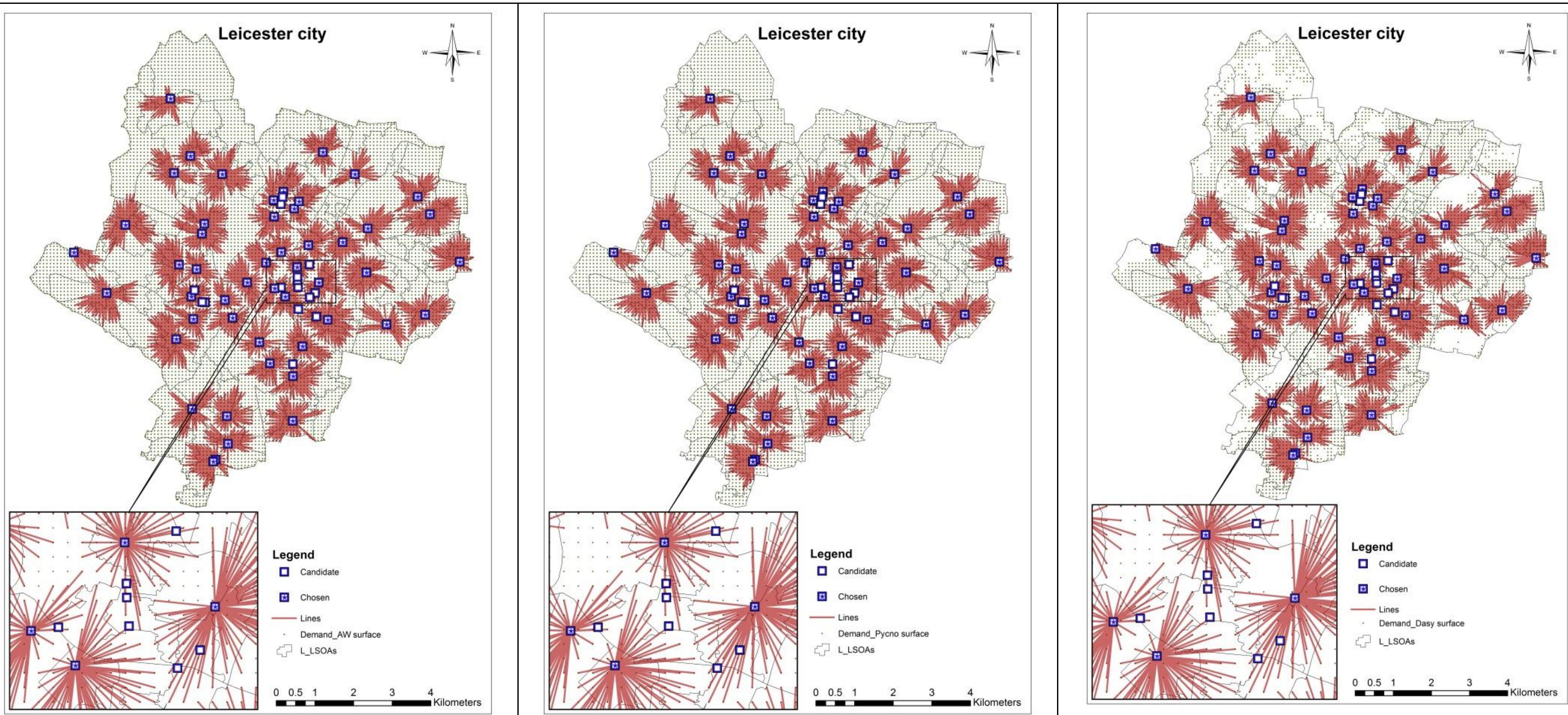
		
a) AW	b) Pycno	c) Dasy

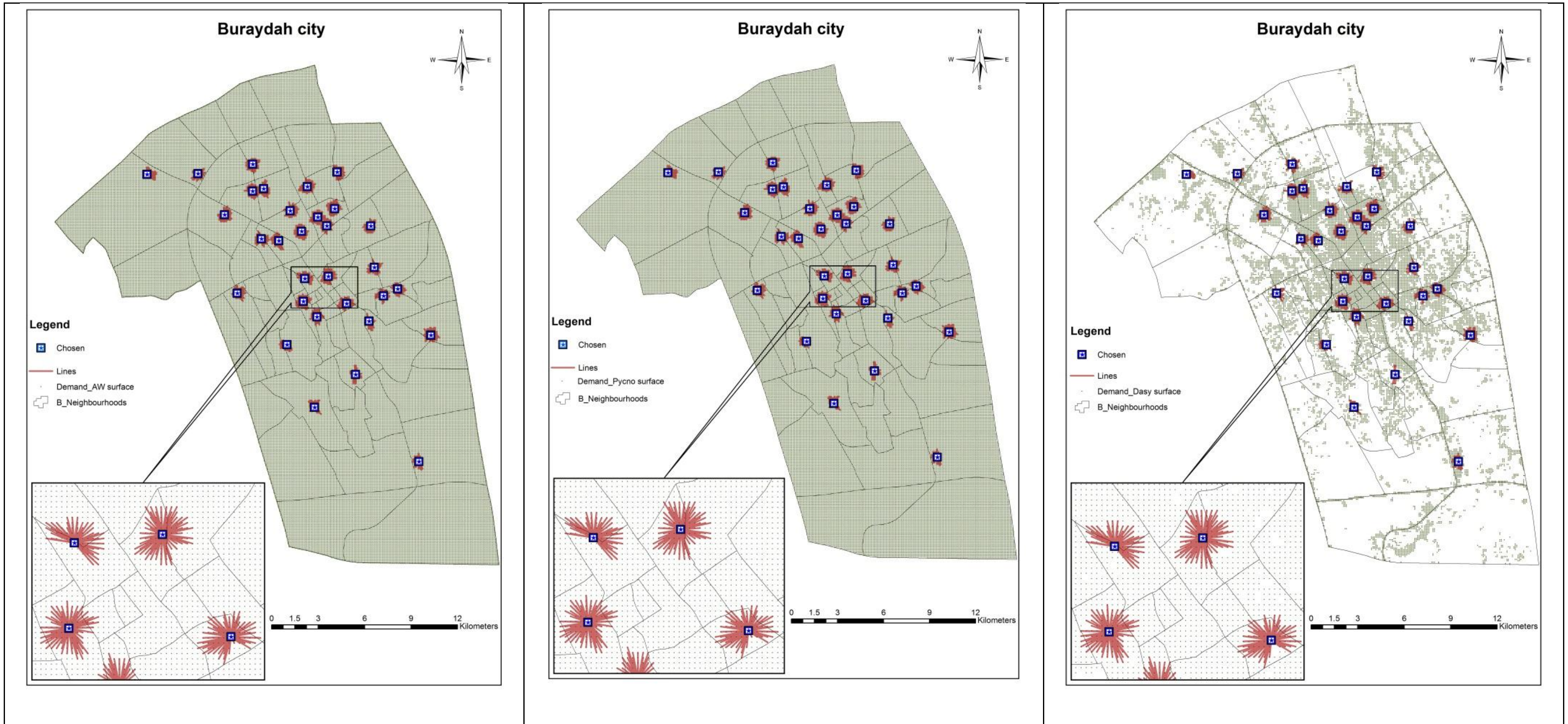
Figure 2.20: Results of applying the MF model in Leicester within 900 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW | b) Pycno | c) Dasy

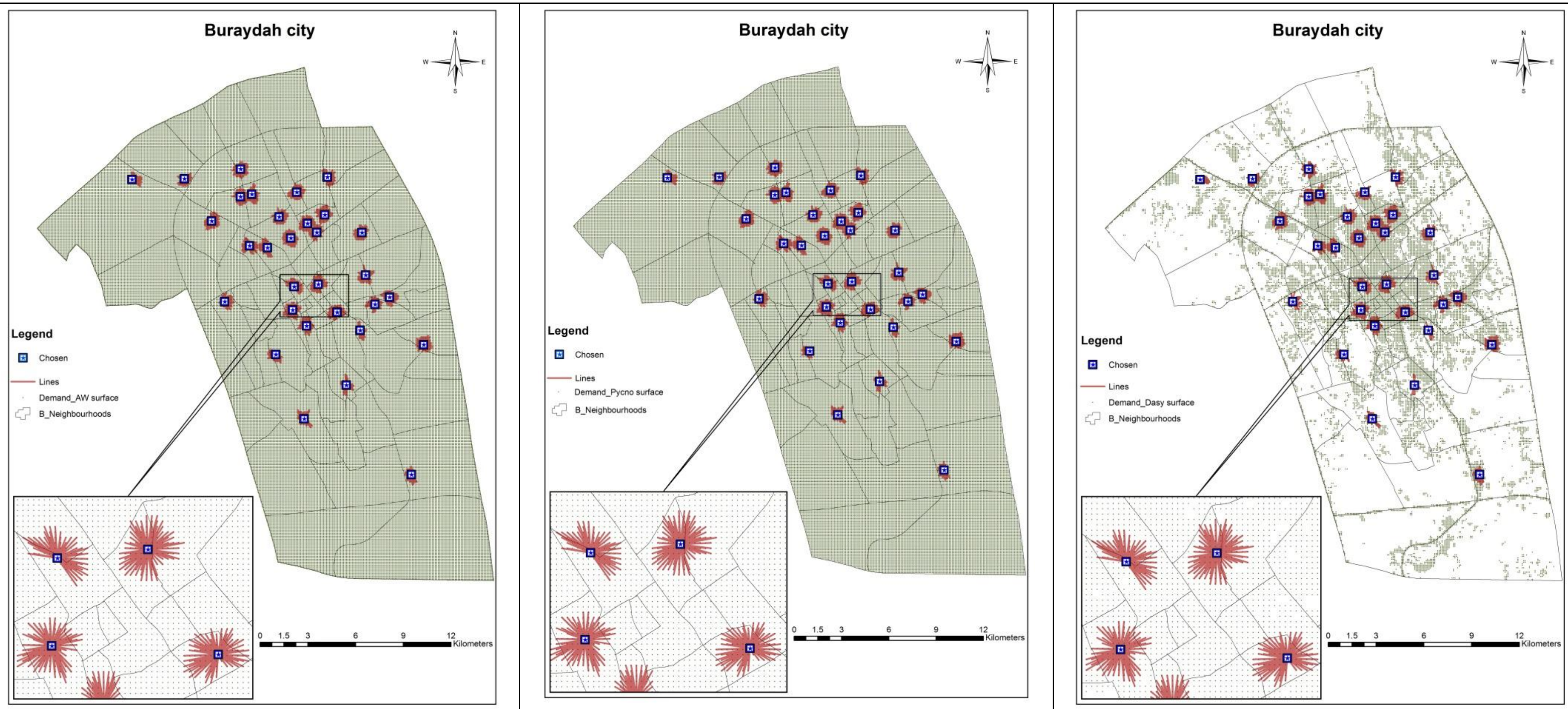
Figure 2.21: Results of applying the MF model in Leicester within 950 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

2.2.2 Results of the MF model for Buraydah



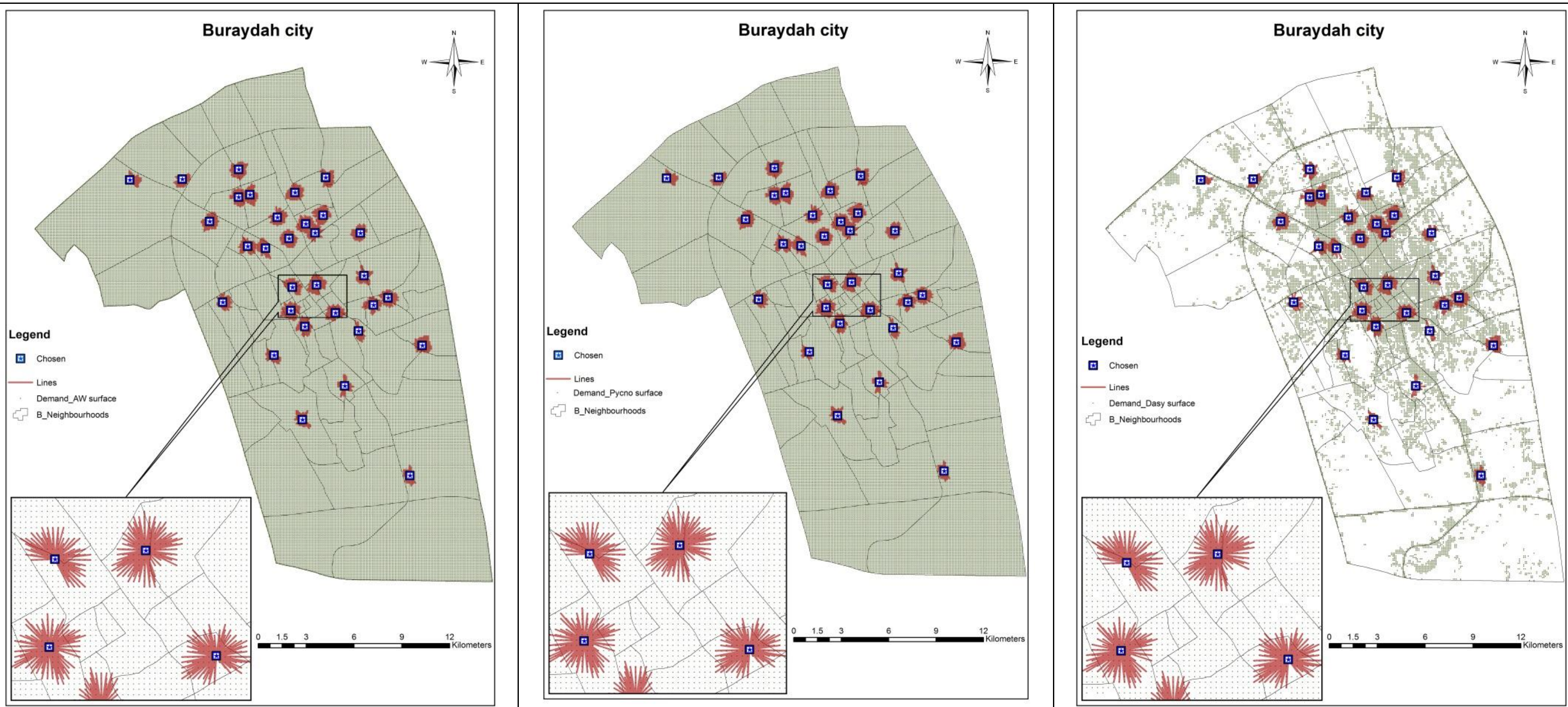
a) AW	b) Pycno	c) Dasy

Figure 2.22: Results of applying the MF model in Buraydah within 650 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



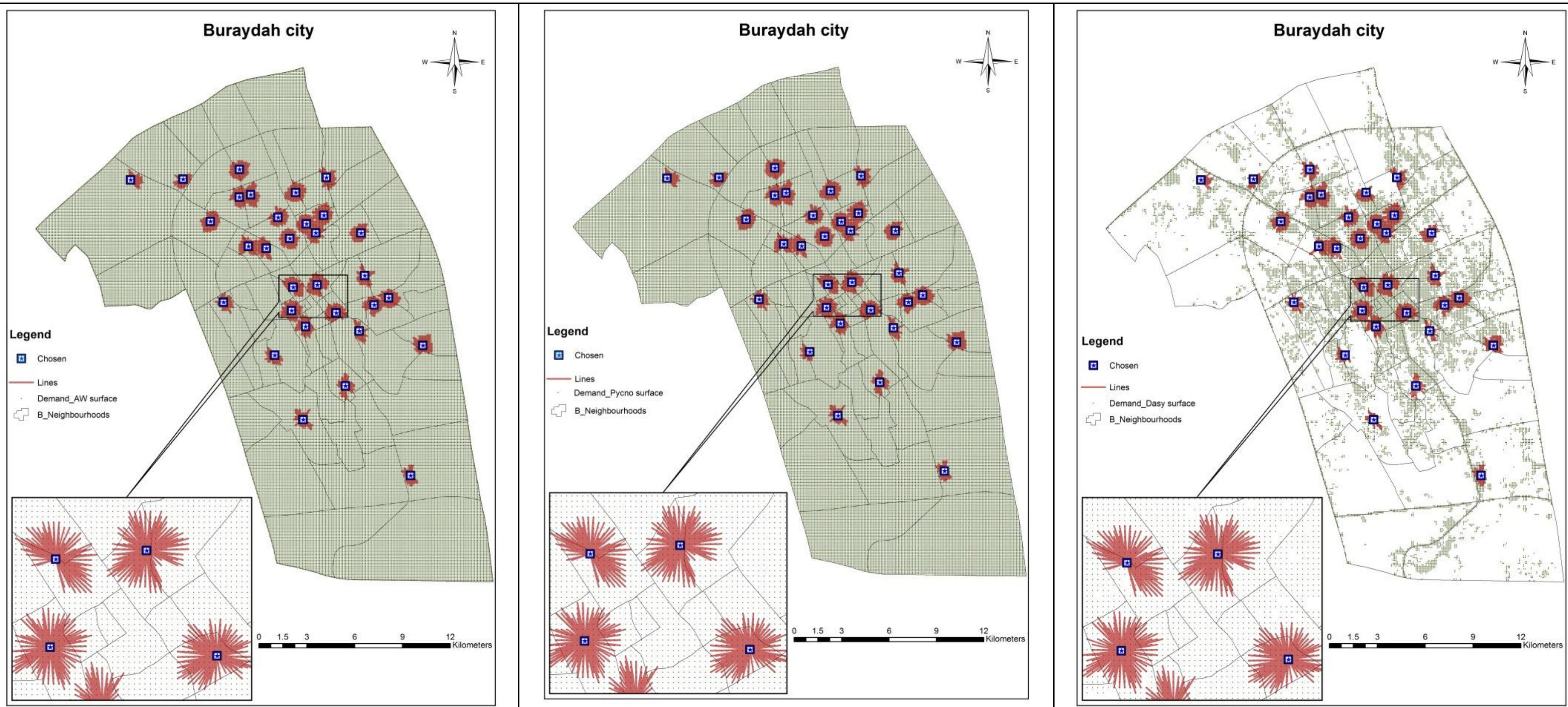
a) AW	b) Pycno	c) Dasy

Figure 2.23: Results of applying the MF model in Buraydah within 700 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



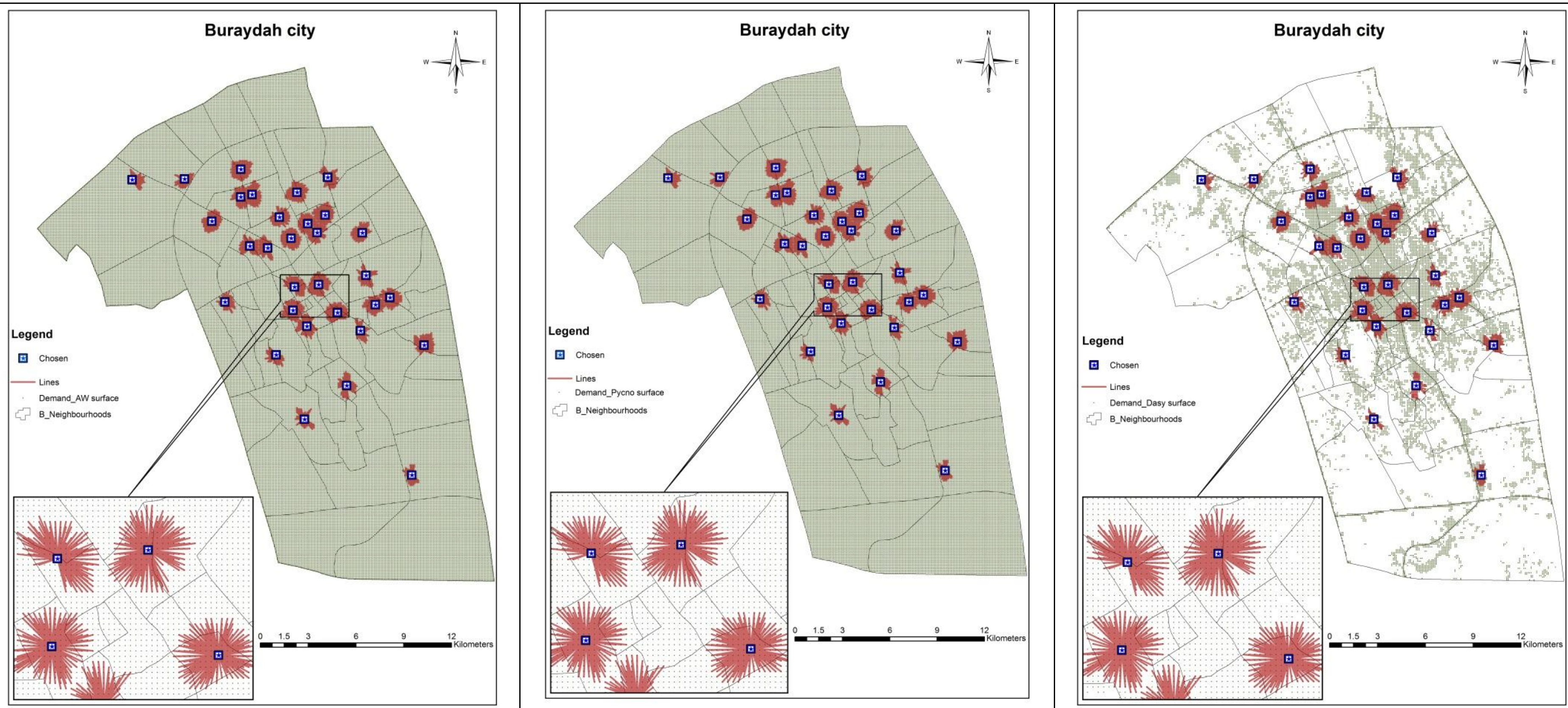
a) AW	b) Pycno	c) Dasy

Figure 2.24: Results of applying the MF model in Buraydah within 750 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



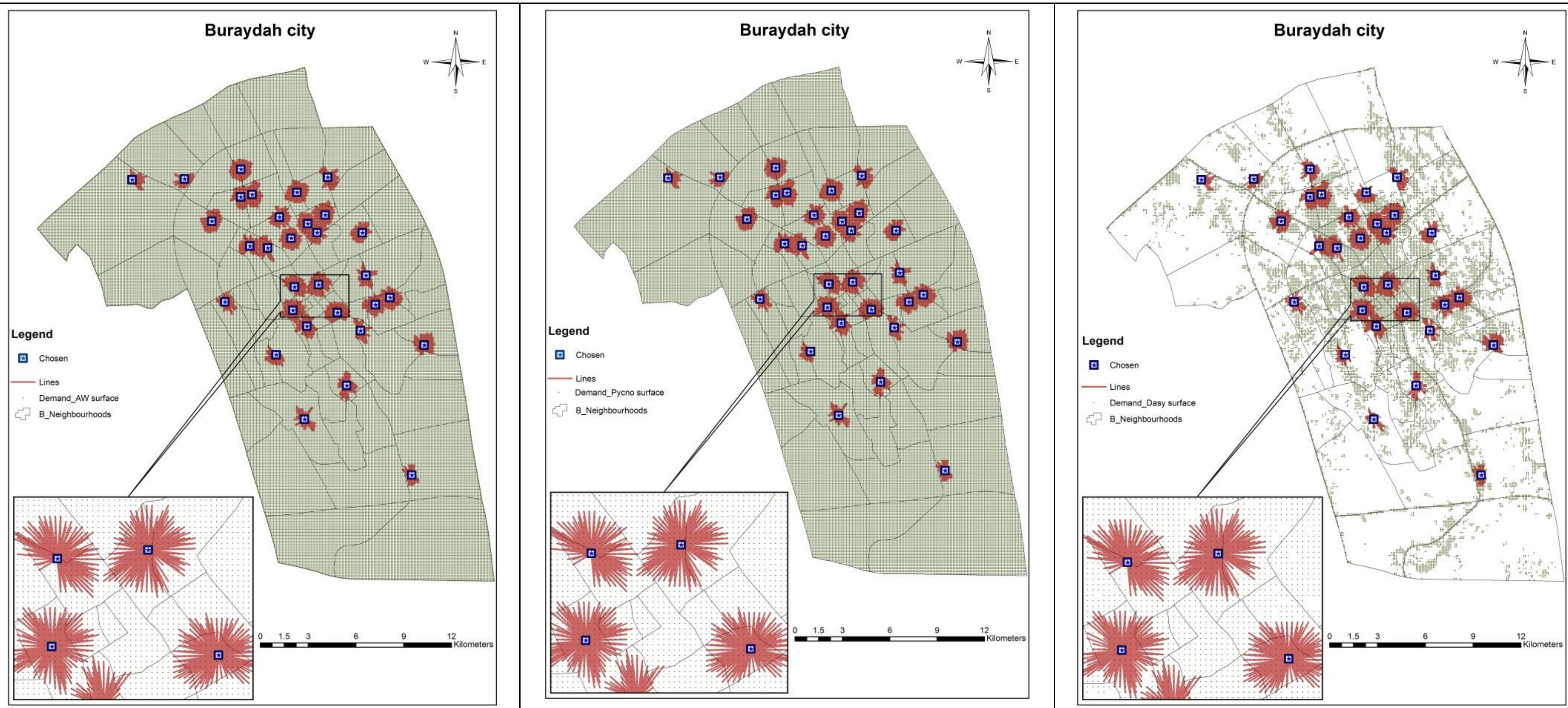
a) AW	b) Pycno	c) Dasy

Figure 2.25: Results of applying the MF model in Buraydah within 850 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

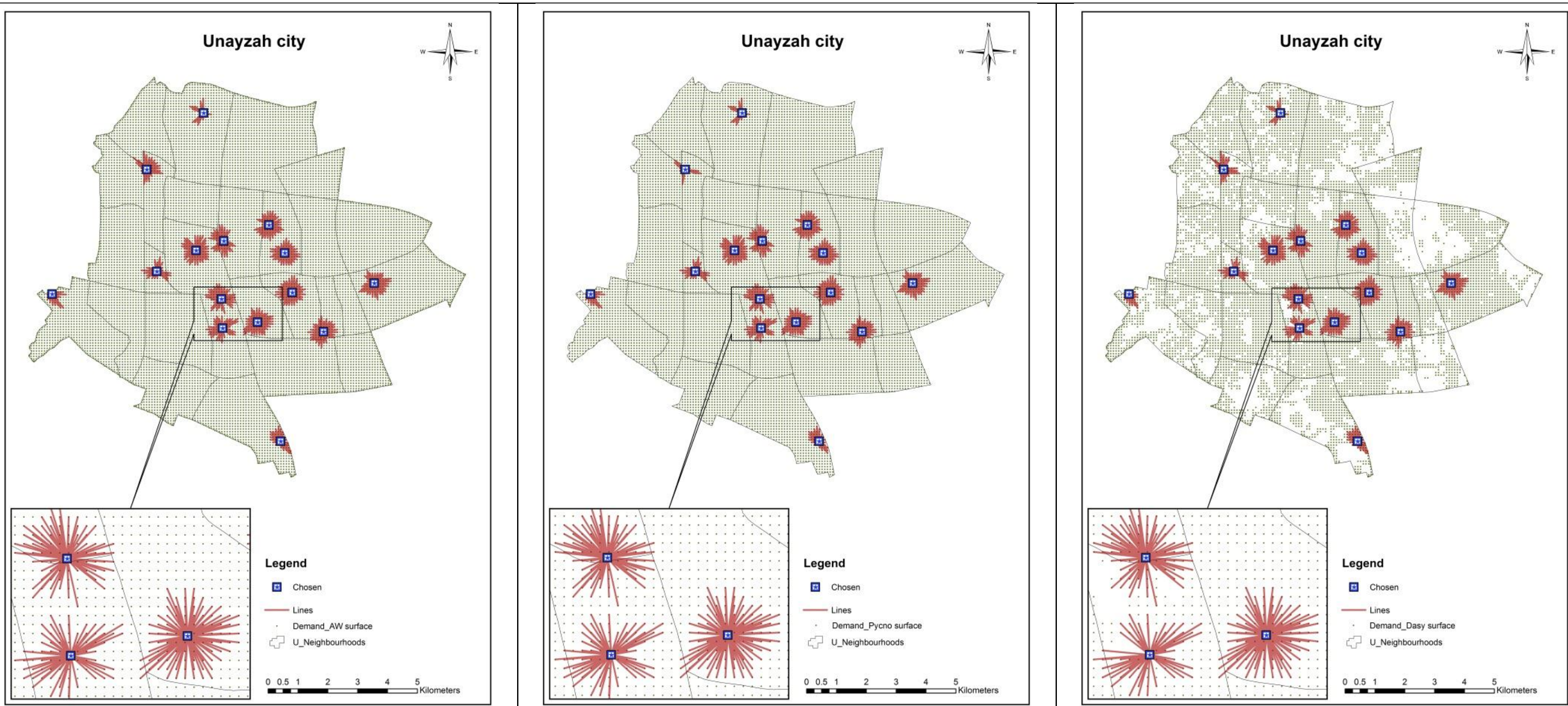
Figure 2.26: Results of applying the MF model in Buraydah within 900 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

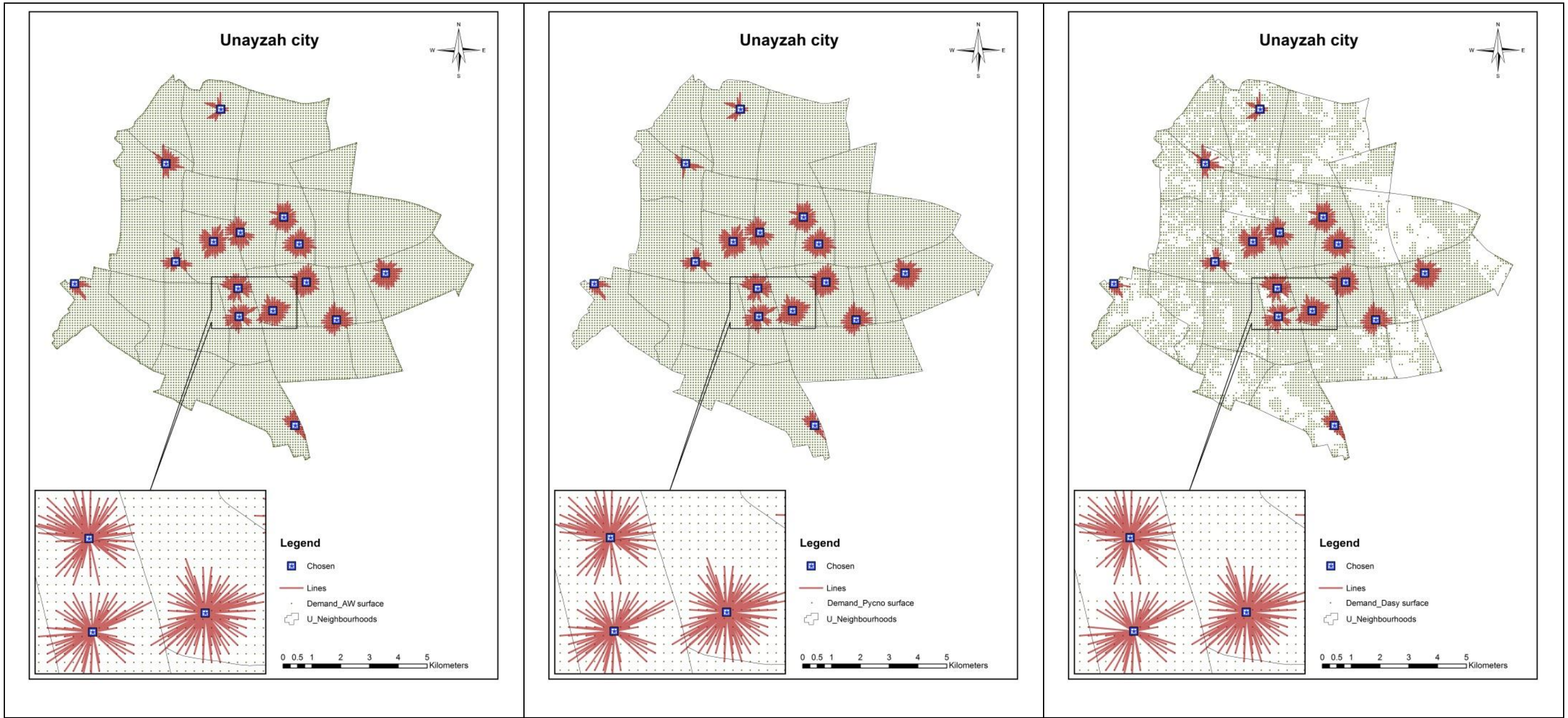
Figure 2.27: Results of applying the MF model in Buraydah within 950 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

2.2.3 Results of the MF model for Unayzah



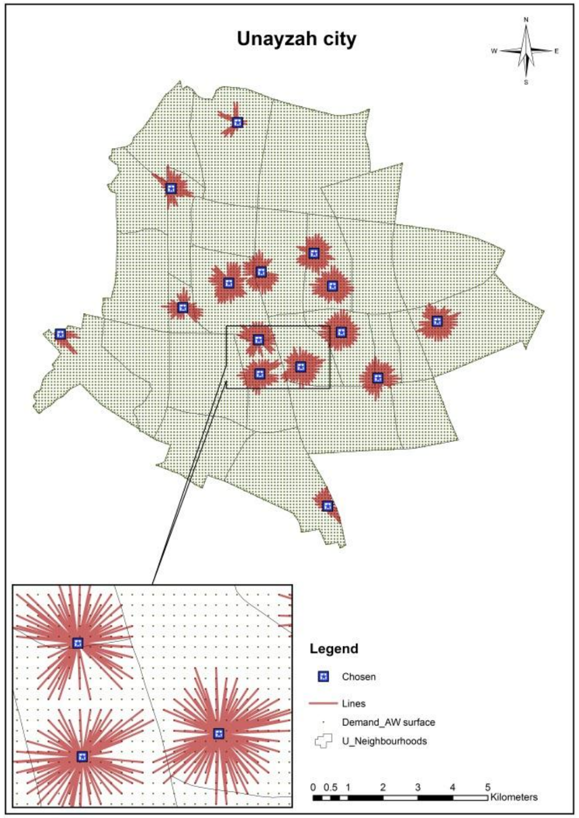
a) AW	b) Pycno	c) Dasy

Figure 2.28: Results of applying the MF model in Unayzah within 650 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

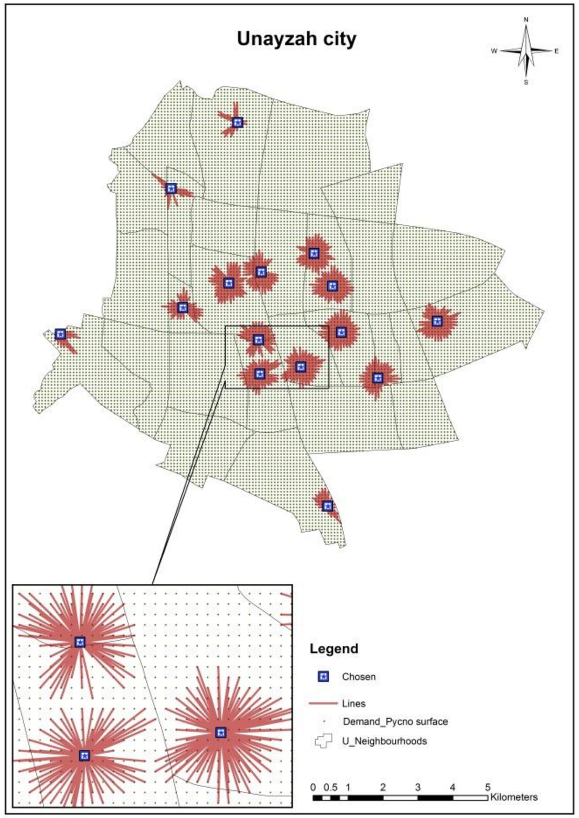


a) AW	b) Pycno	c) Dasy

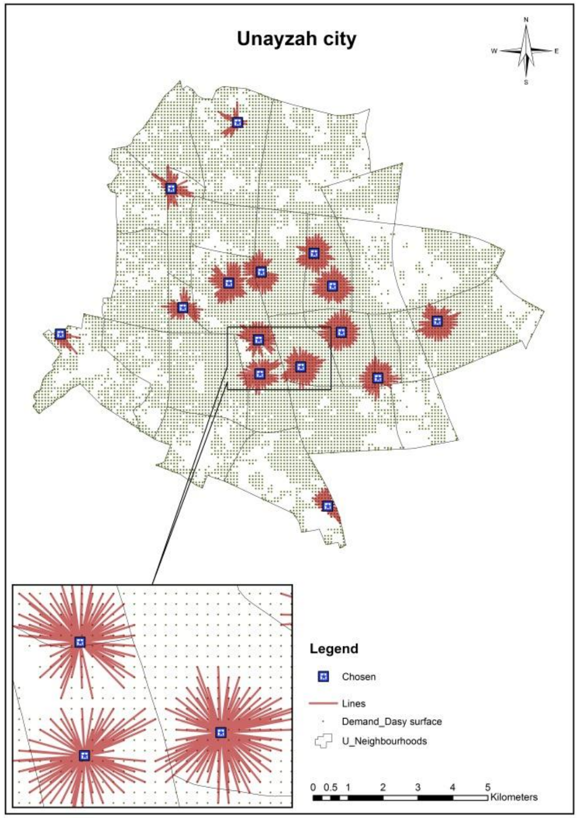
Figure 2.29: Results of applying the MF model in Unayzah within 700 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW

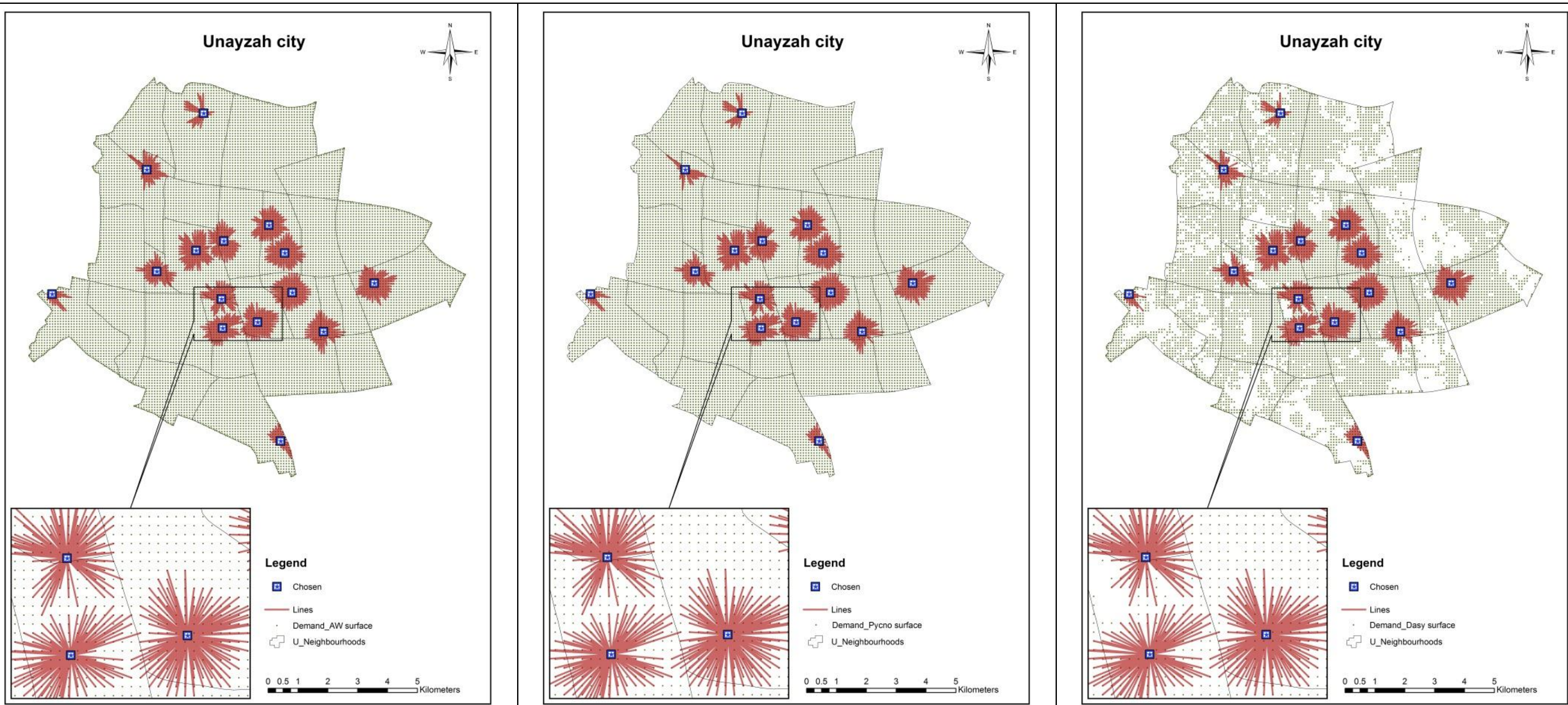


b) Pycno



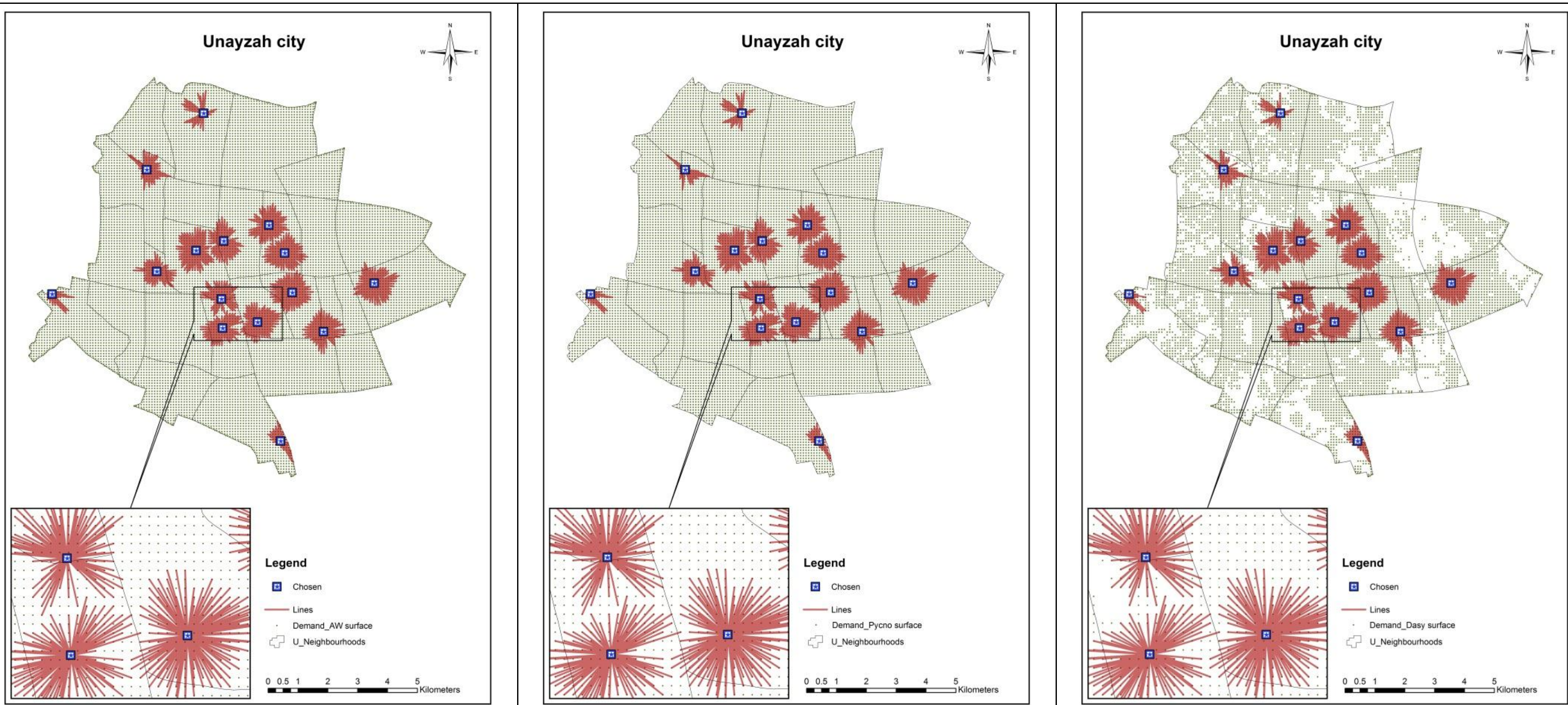
c) Dasy

Figure 2.30: Results of applying the MF model in Unayzah within 750 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



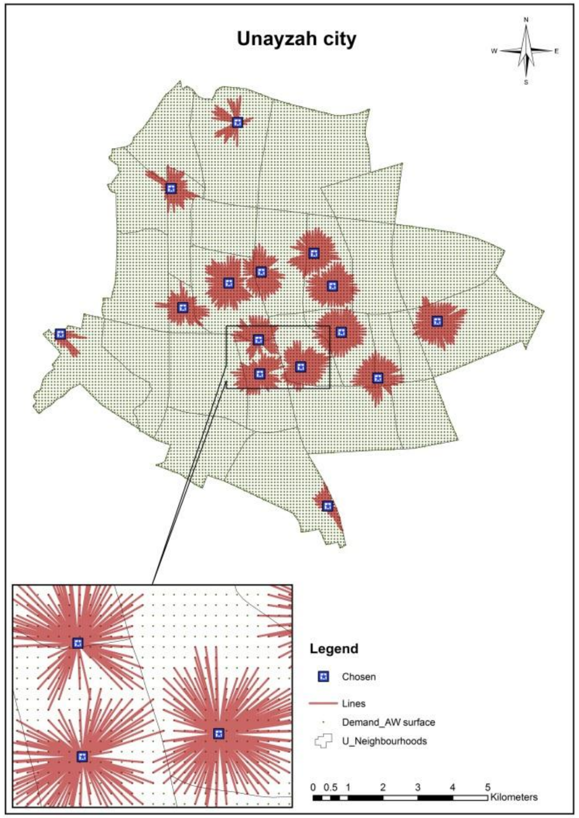
a) AW	b) Pycno	c) Dasy

Figure 2.31: Results of applying the MF model in Unayzah within 850 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

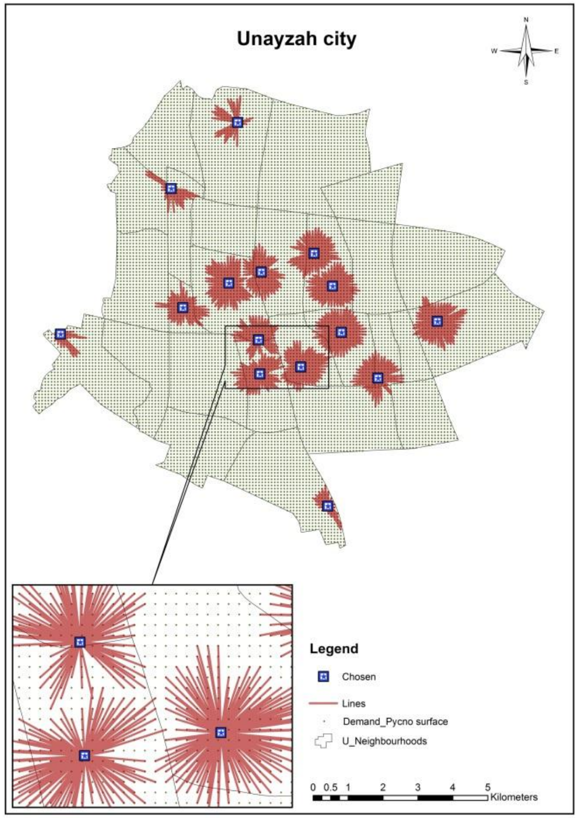


a) AW	b) Pycno	c) Dasy

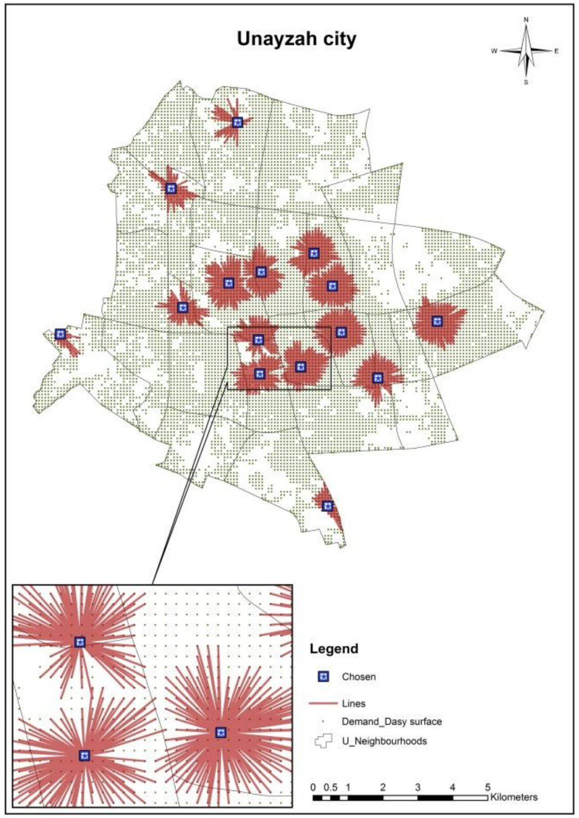
Figure 2.32: Results of applying the MF model in Unayzah within 900 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW



b) Pycno

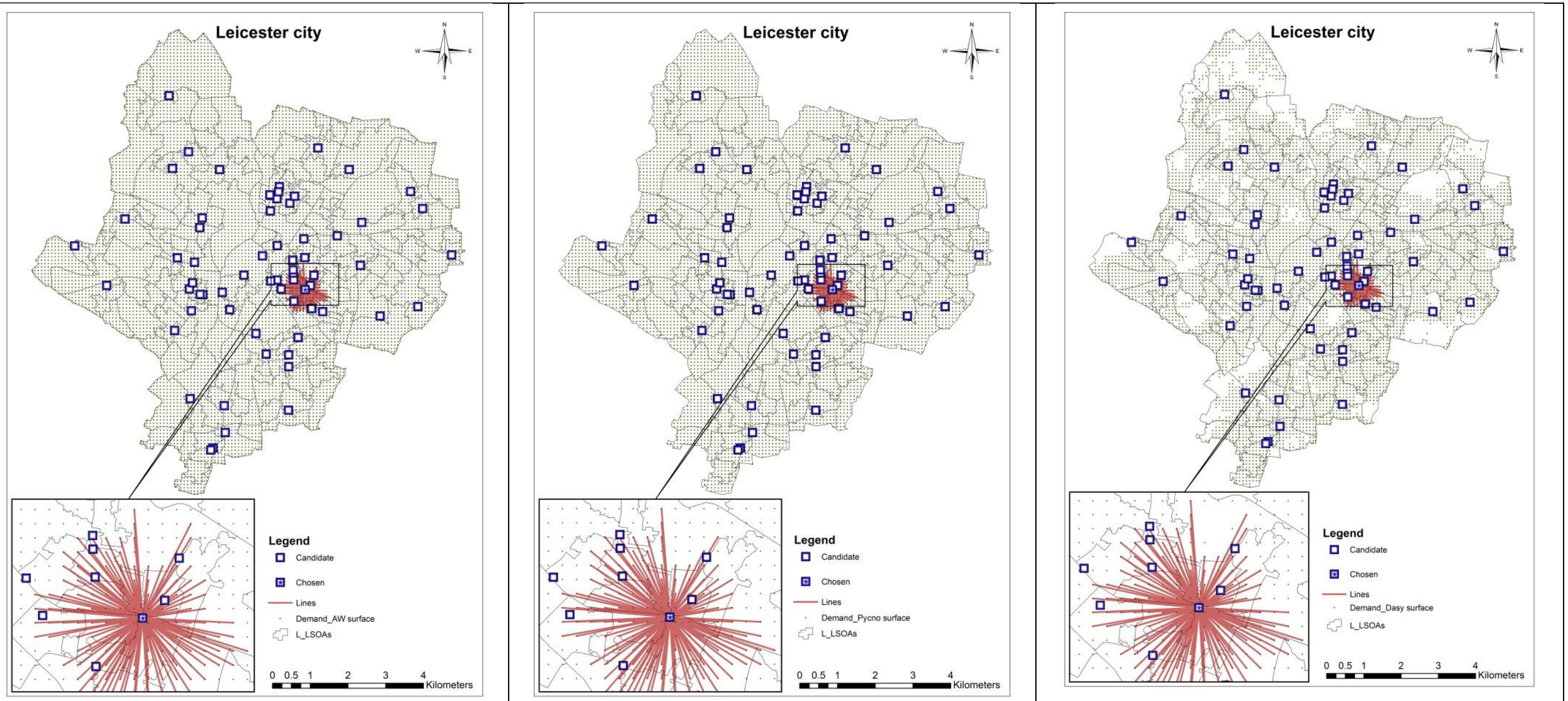


c) Dasy

Figure 2.33: Results of applying the MF model in Unayzah within 950 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

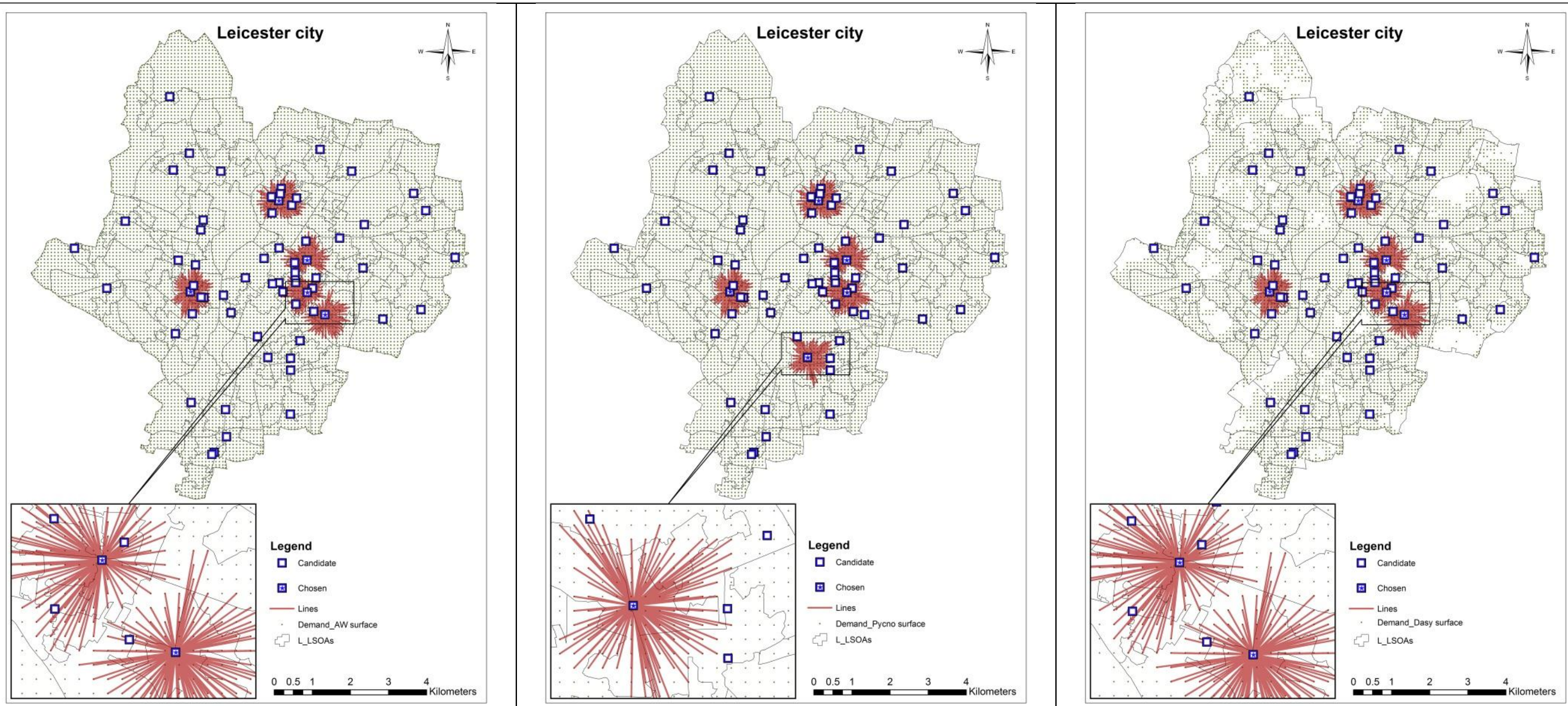
2.3 Results of the MA model

2.3.1 Results of the MA model for Leicester



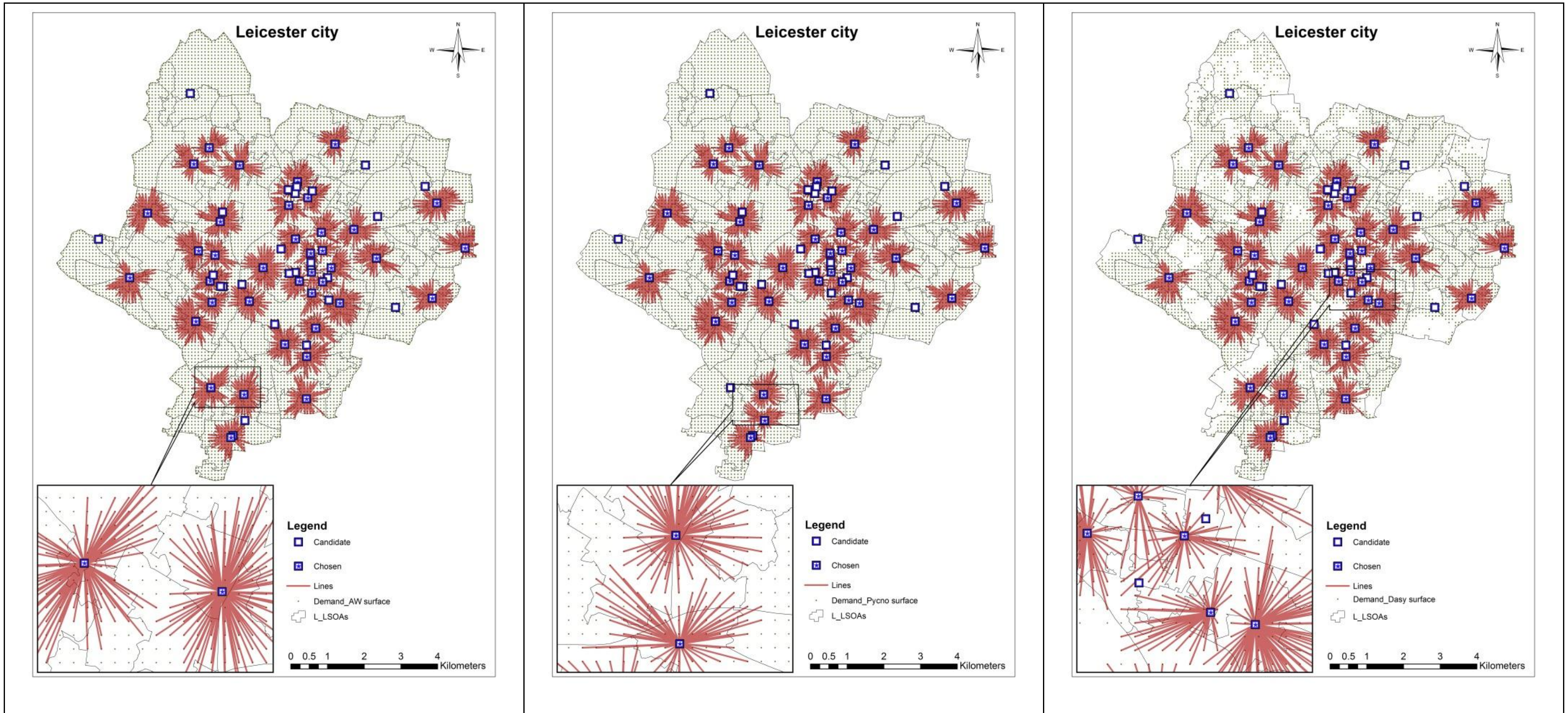
a) AW	b) Pycno	c) Dasy

Figure 2.34: Results of applying the MA model in Leicester to select the best 1 GP location within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



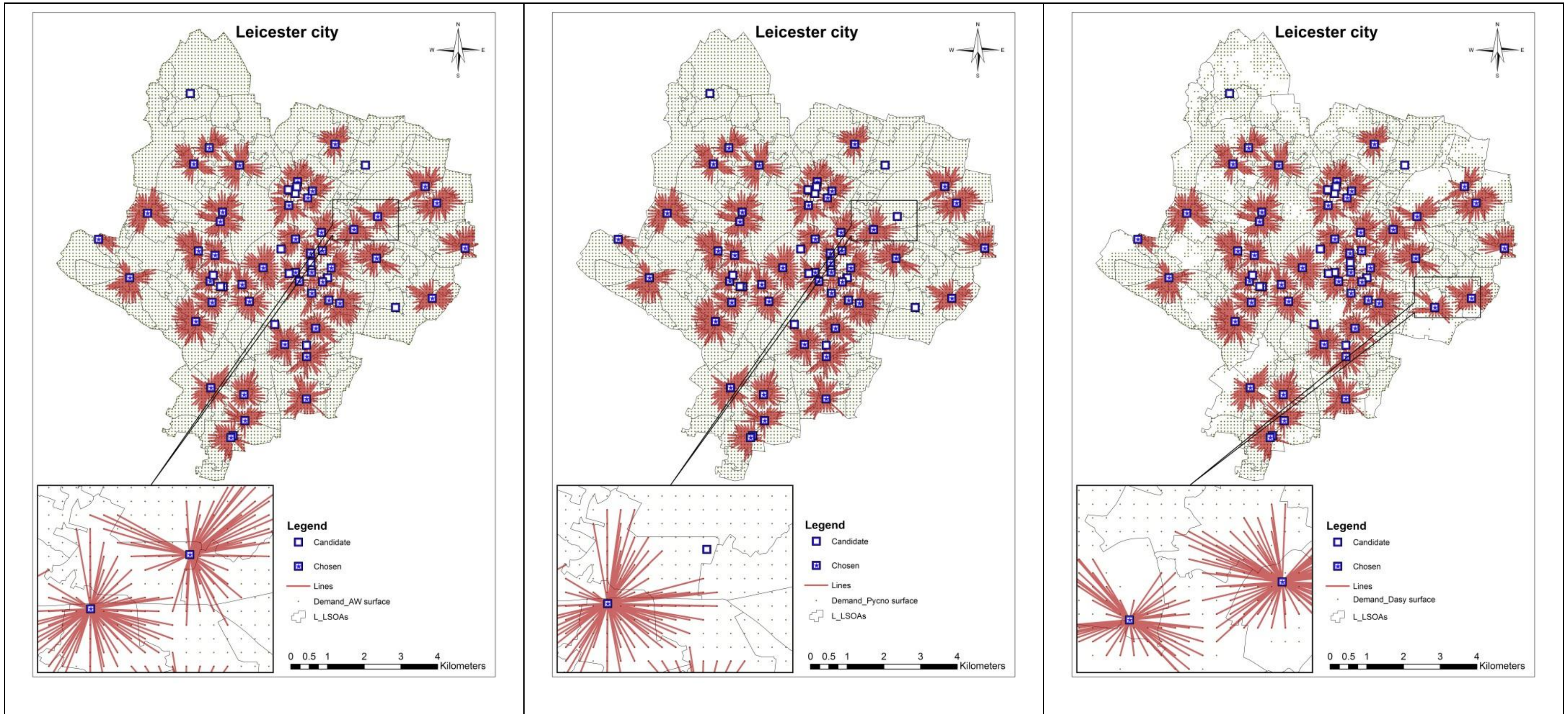
a) AW	b) Pycno	c) Dasy

Figure 2.35: Results of applying the MA model in Leicester to select the best 5 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



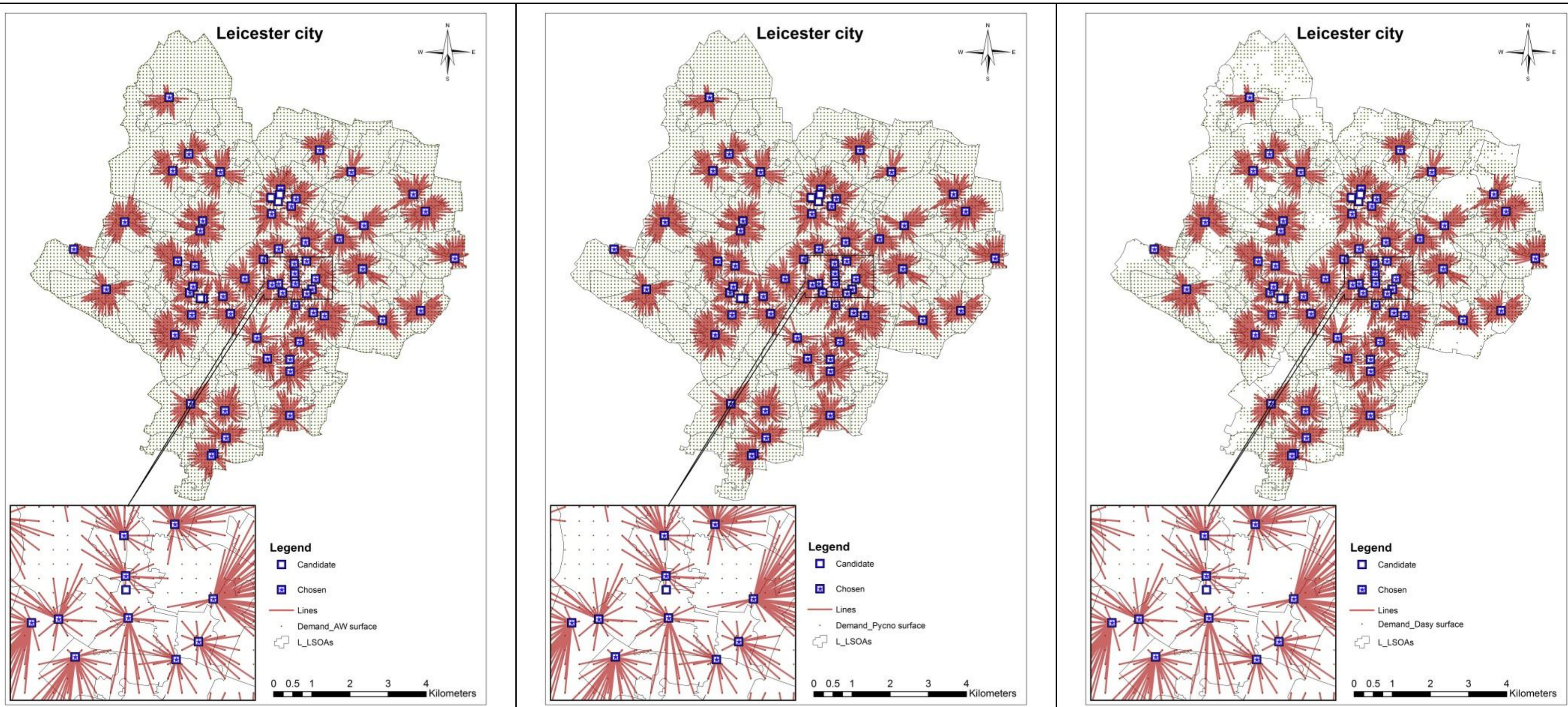
a) AW	b) Pycno	c) Dasy

Figure 2.36: Results of applying the MA model in Leicester to select the best 40 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW	b) Pycno	c) Dasy

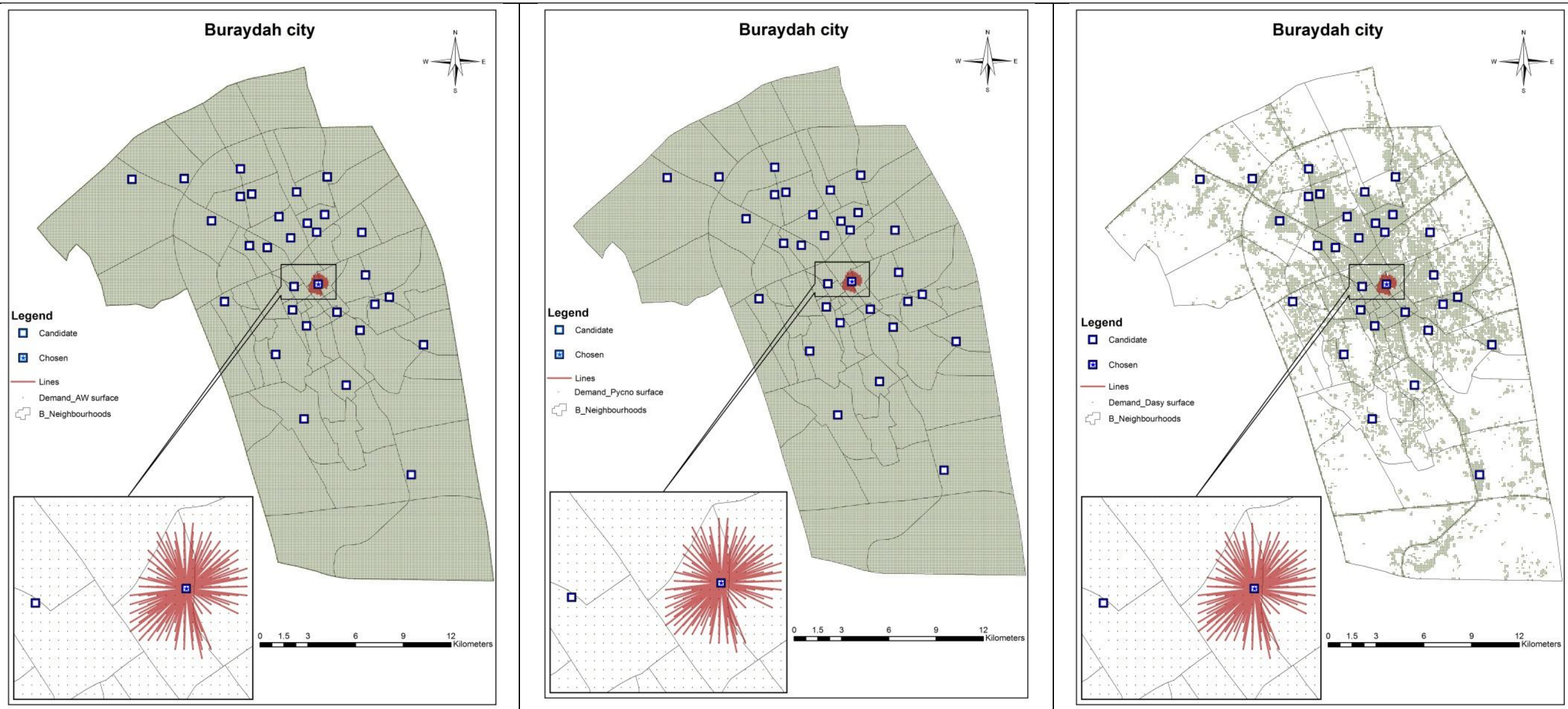
Figure 2.37: Results of applying the MA model in Leicester to select the best 50 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.



a) AW | b) Pycno | c) Dasy

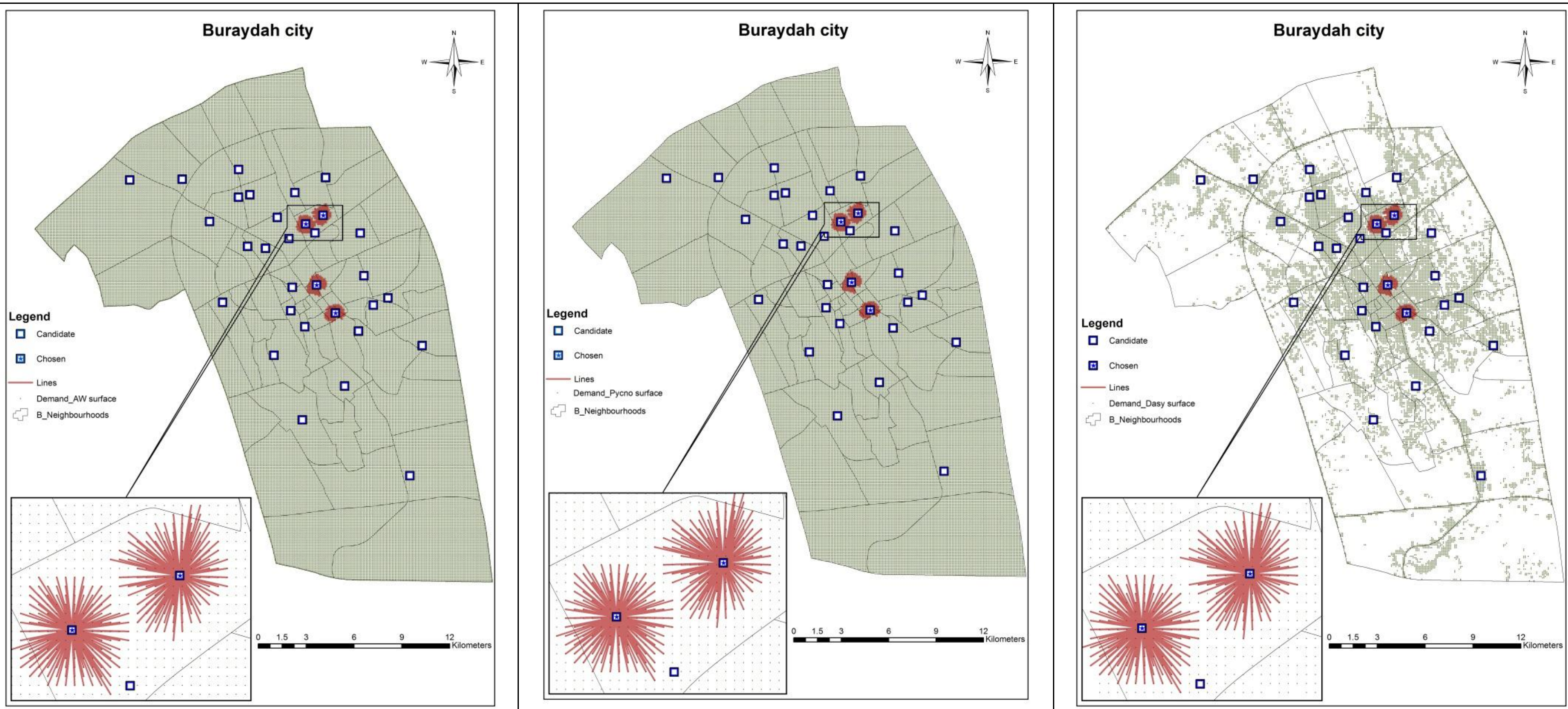
Figure 2.38: Results of applying the MA model in Leicester to select the best 60 GP locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities. The LSOAs boundaries are © Crown Copyright for Ordnance Survey 2012.

2.3.2 Results of the MA model for Buraydah



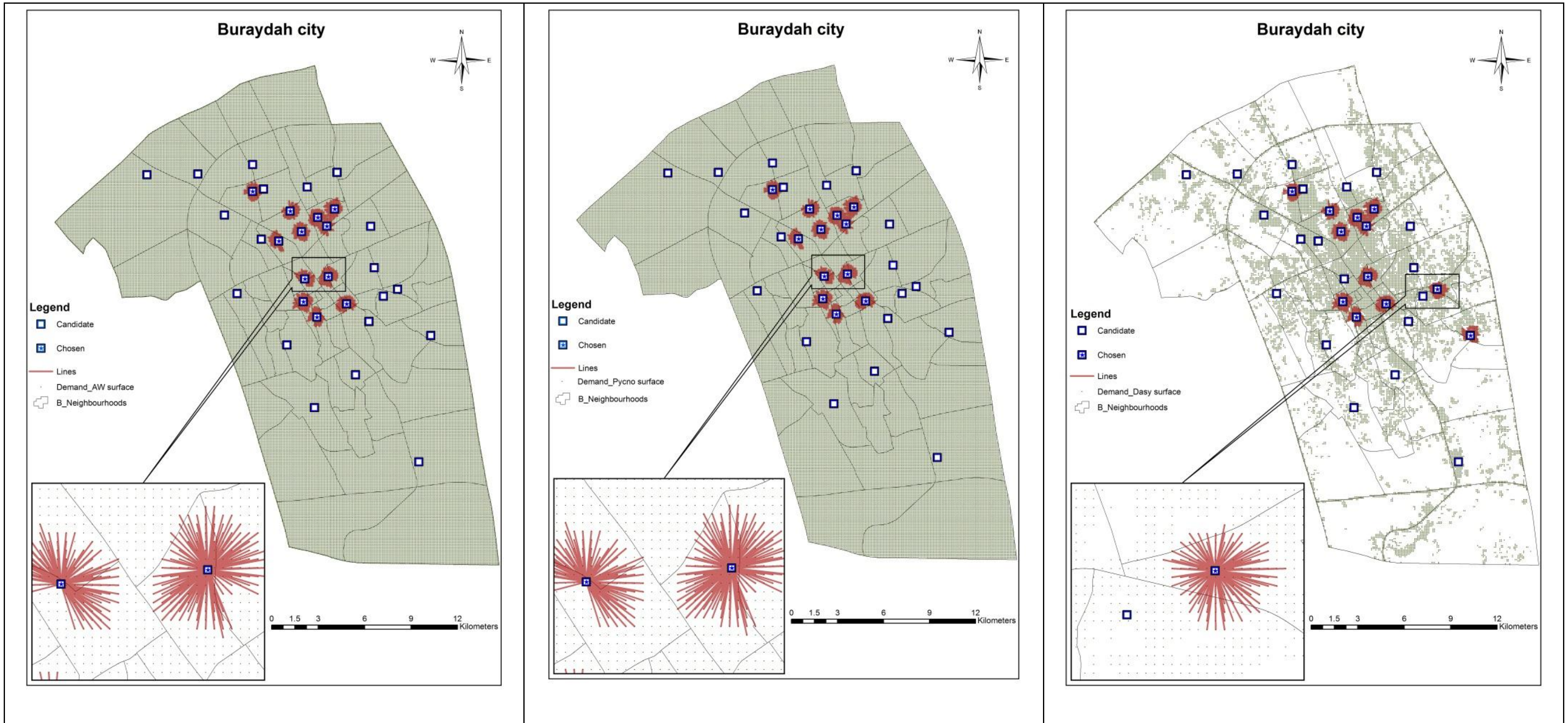
a) AW	b) Pycno	c) Dasy

Figure 2.39: Results of applying the MA model in Buraydah to select the best 1 PHCC location within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



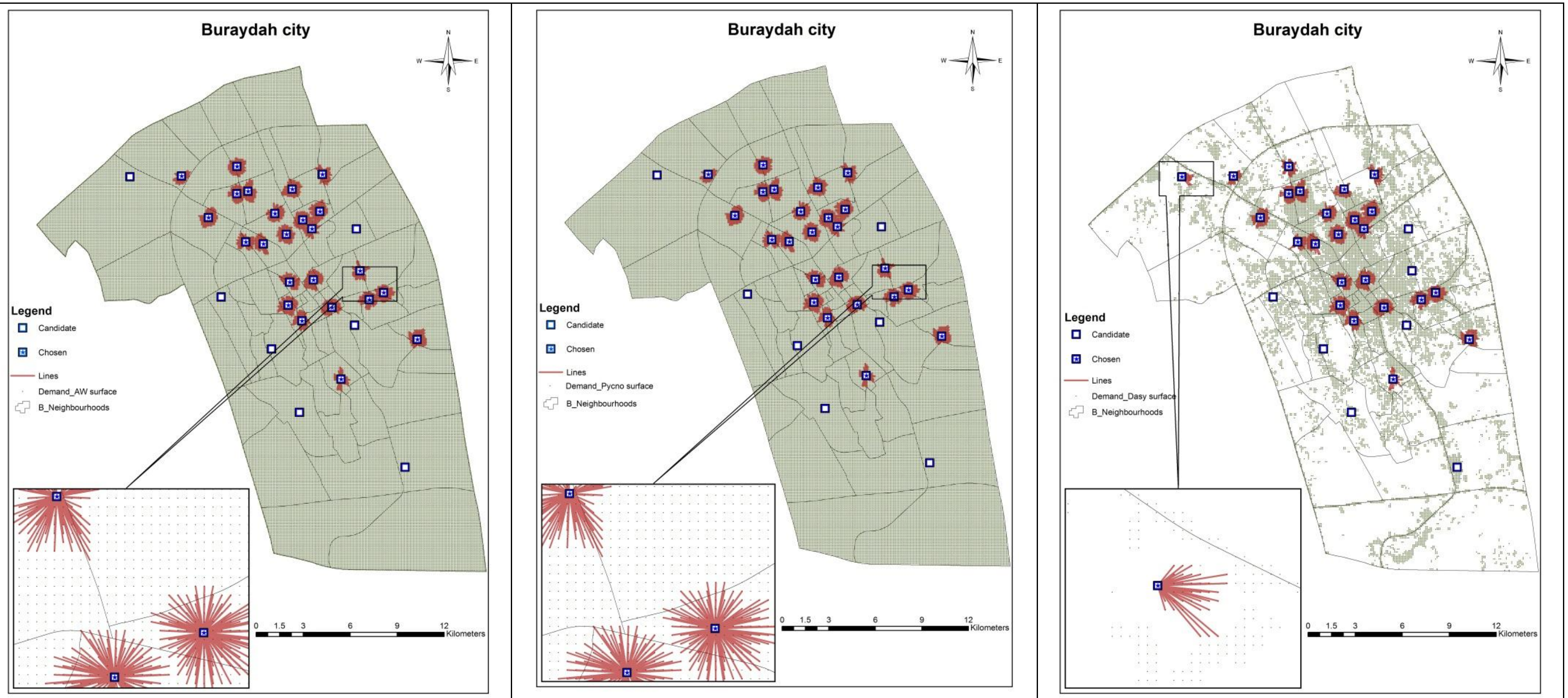
a) AW | b) Pycno | c) Dasy

Figure 2.40: Results of applying the MA model in Buraydah to select the best 4 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



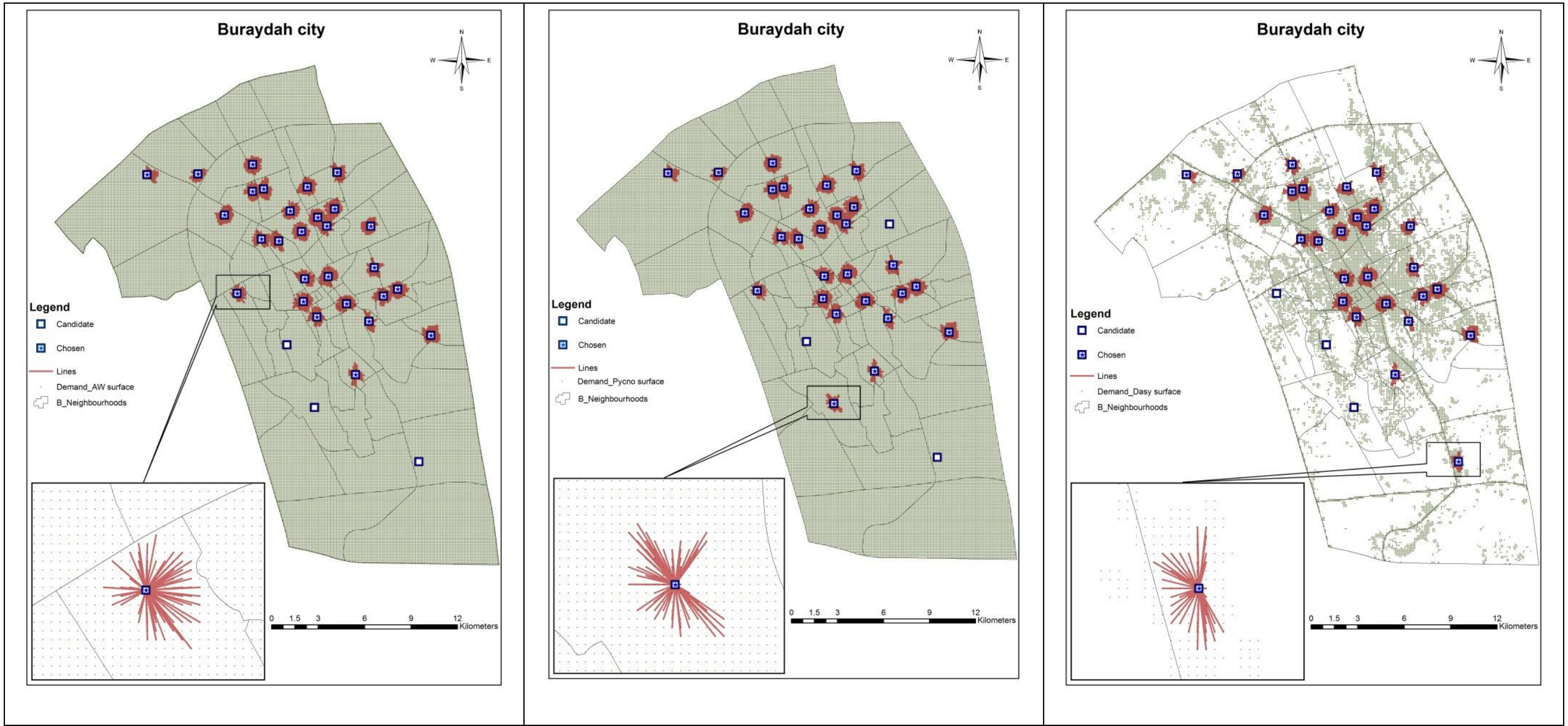
a) AW | b) Pycno | c) Dasy

Figure 2.41: Results of applying the MA model in Buraydah to select the best 12 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

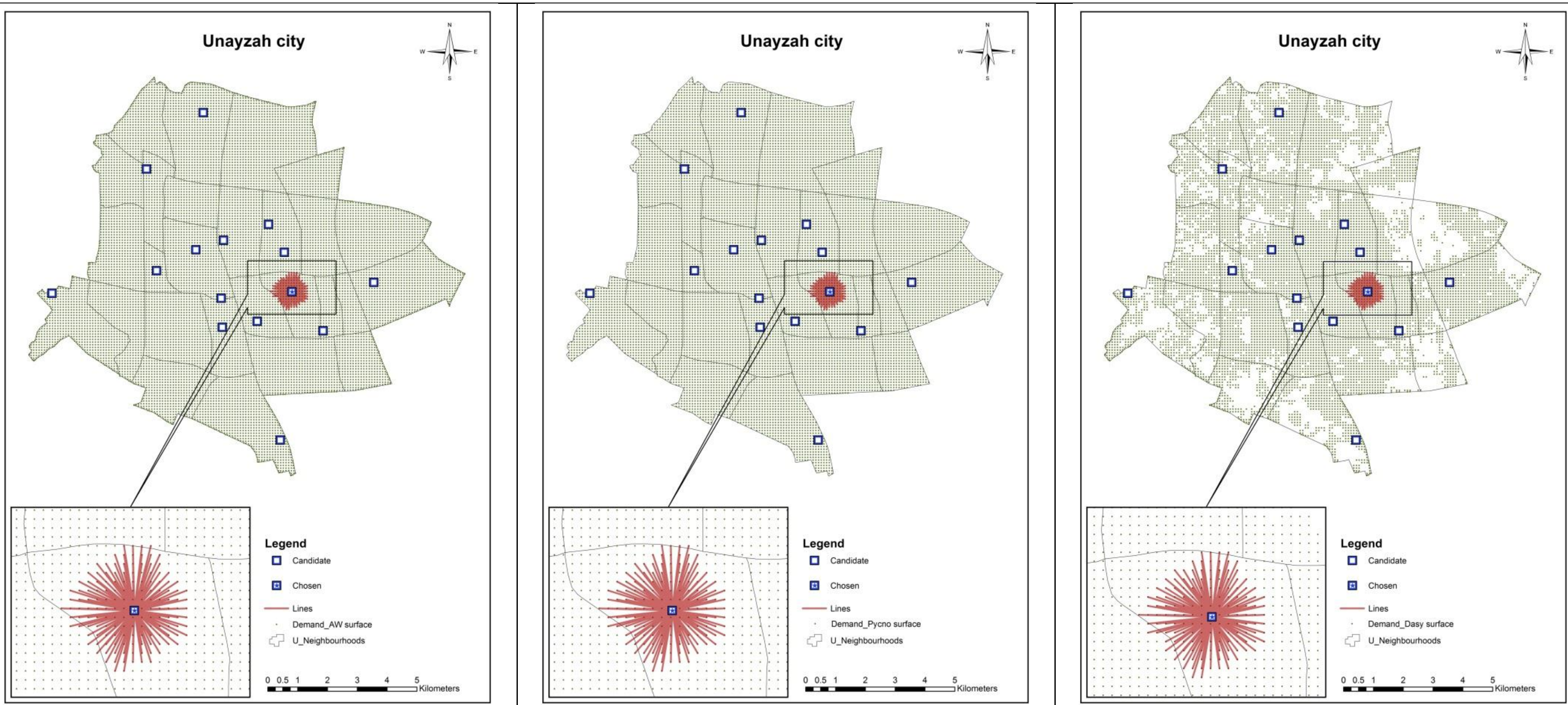
Figure 2.42: Results of applying the MA model in Buraydah to select the best 24 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

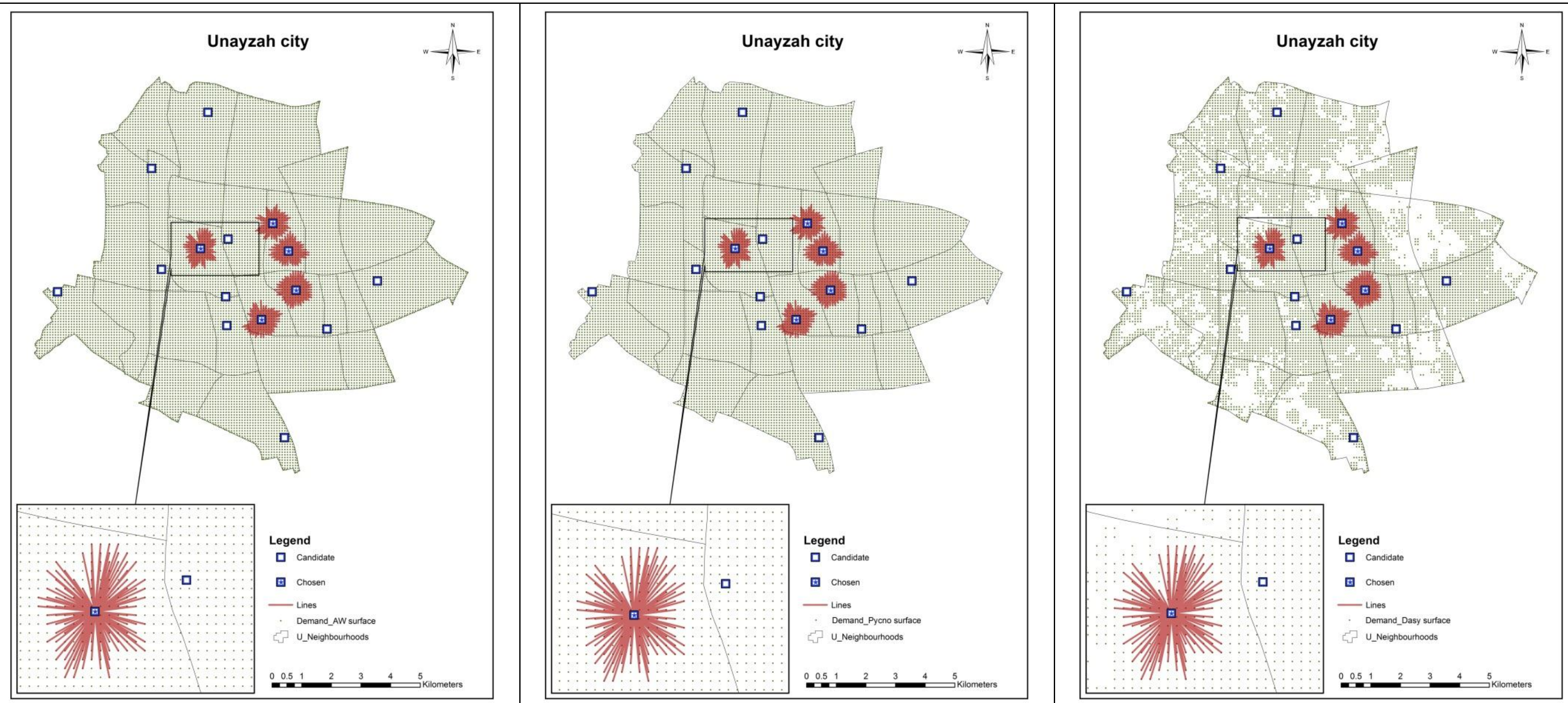
Figure 2.43: Results of applying the MA model in Buraydah to select the best 28 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.

2.3.3 Results of the MA model for Unayzah



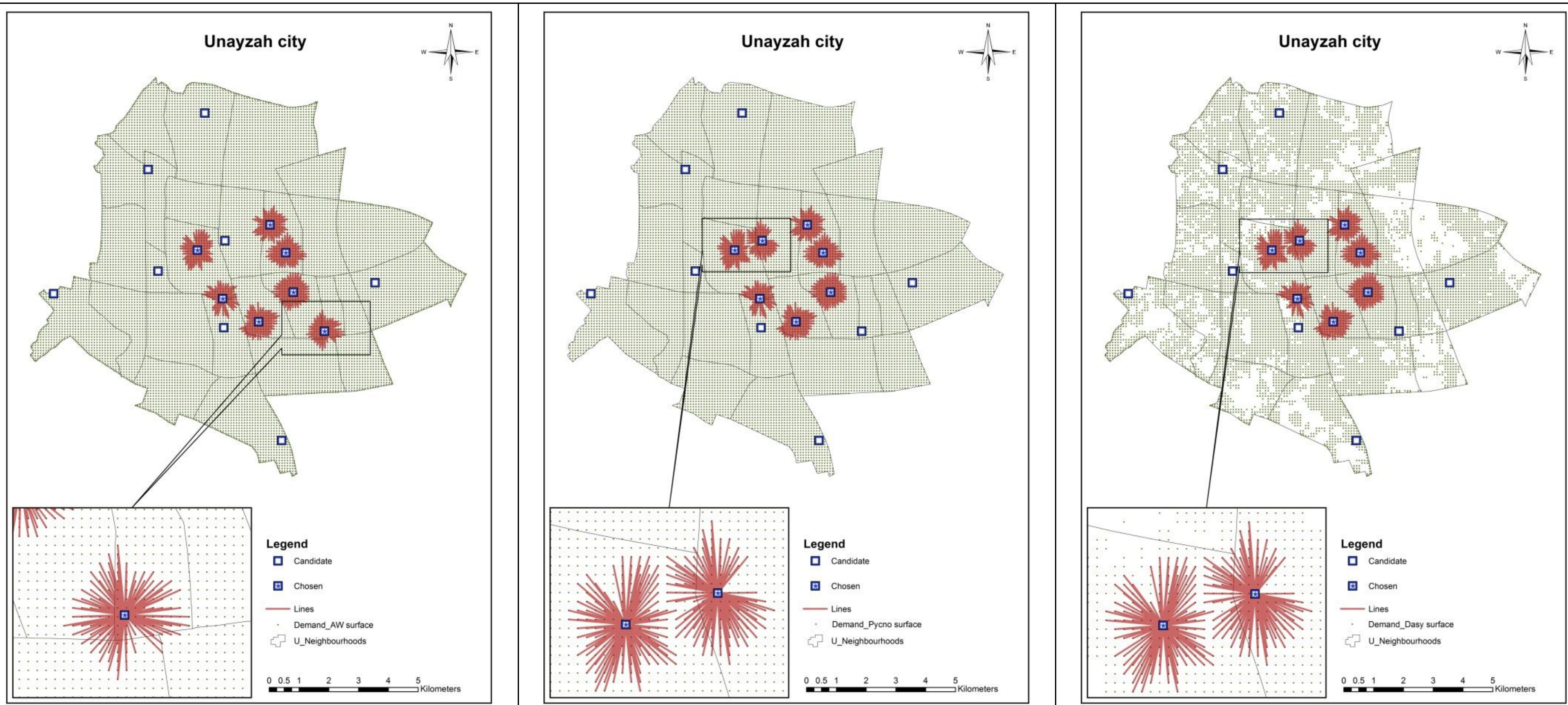
a) AW	b) Pycno	c) Dasy

Figure 2.44: Results of applying the MA model in Unayzah to select the best 1 PHCC location within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



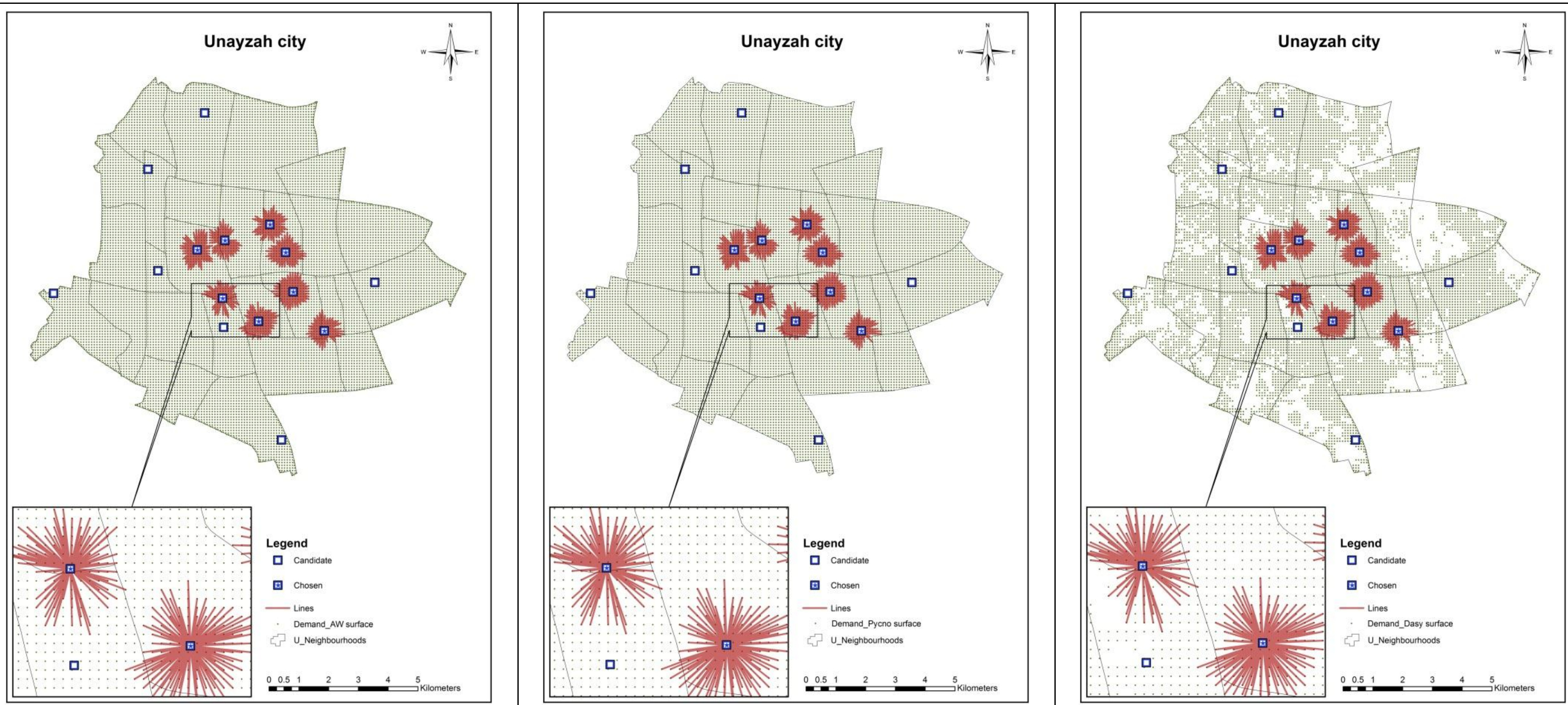
a) AW	b) Pycno	c) Dasy

Figure 2.45: Results of applying the MA model in Unayzah to select the best 5 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



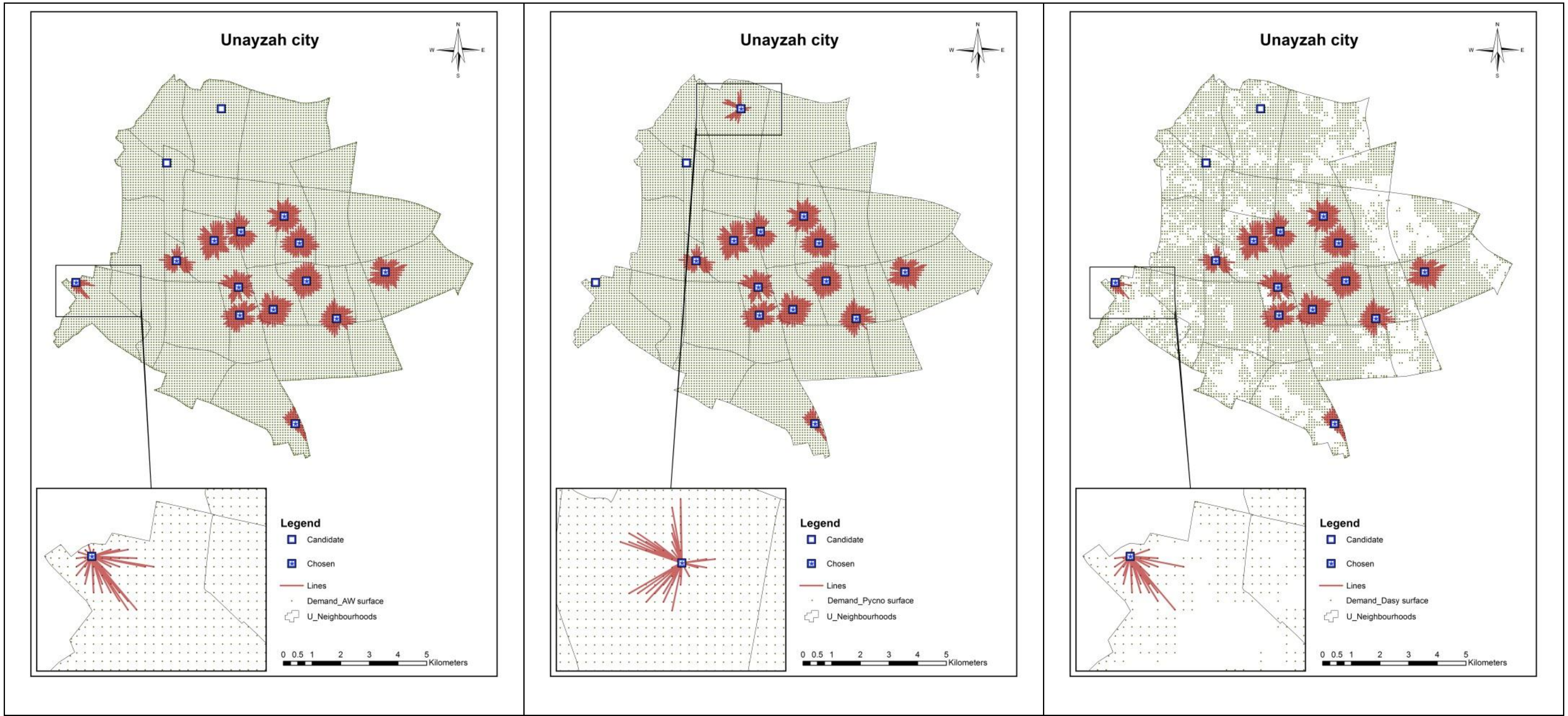
a) AW	b) Pycno	c) Dasy

Figure 2.46: Results of applying the MA model in Unayzah to select the best 7 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 2.47: Results of applying the MA model in Unayzah to select the best 8 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.



a) AW	b) Pycno	c) Dasy

Figure 2.48: Results of applying the MA model in Unayzah to select the best 13 PHCC locations within 800 metres: a) AW surface; b) Pycno surface; and c) Dasy surface. The points represent the demand distribution and the lines indicate the demand points covered by the selection of facilities.