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Local Ideal Point Method for GIS-based Multicriteria Analysis: A Case Study in London, Ontario

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A thesis submitted in partial fulfillment of the requirements for the degree in Master of Science

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**Local Ideal Point Method for GIS-based Multicriteria Analysis:
A Case Study in London, Ontario**

(Thesis format: Monograph)

by

Xue Qin

Graduate Program

in

Geography

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science

The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

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Abstract

GIS-based multicriteria analysis (GIS-MCA) is a procedure for transforming and combining geographic data and value judgments (preferences) to evaluate a set of alternatives with respect to relevant criteria. Ideal Point Method (IPM) is one of the most often used GIS-MCA techniques. It has been applied in many research/planning areas including environmental planning, urban/regional planning, waste management, water resource management and agriculture. One of the limitations of IPM is that it has conventionally been used as a global approach based on the implicit assumption that its parameters do not vary as a function of geographic space. The conventional IPM assumes a spatial homogeneity of its parameters within the whole study area. This thesis proposes a new IPM called local IPM. The local version of IPM is developed by localizing two parameters (criterion weights and ideal/nadir points) based on the range-sensitivity principle. The IPM methods are used to evaluate and analyse the spatial patterns of the quality of employment in London, Ontario. The case study shows that there are significant differences between the spatial patterns generated by the local and conventional IPM. The local IPM not only can display the general ‘spatial trend’ of the quality of employment in London, but also is able to highlight the areas with relatively high quality of employment in different neighborhoods. Furthermore, the local IPM provides a tool for visualizing and exploring spatial patterns. The parameters influencing the local IPM results can be mapped and further examined with GIS.

Keywords: GIS, Multicriteria Analysis, Ideal Point Method

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Chapter 1

Introduction

Multicriteria analysis (MCA) is a set of methods and procedures for structuring and evaluating decision alternatives on the basis of multiple attributes and objectives (Voogd, 1983; Zeleny, 1982). Over the last two decades or so, the MCA methods have been successfully integrated into Geographic Information System (GIS) for tackling a variety of spatial decision and evaluation problems (Malczewski, 2006). GIS is a widely used technology that can store, analyze, manage and display different types of geographical information. It facilitates decision-making and evaluation procedures through its analytical capabilities of processing spatial information. GIS-based MCA (GIS-MCA) assists in solving those decision-making problems which involve geospatial information.

One of the underlying assumptions of the conventional GIS-MCA is concerned with spatial homogeneity of the GIS-MCA model parameters. This implies that the values of evaluation criteria (attributes and objectives) and preferences associated with the criteria are independent of a local context. This shortcoming can be addressed by developing a local form of the global (conventional) GIS-MCA. There are two major objectives of this study: (i) to propose a new GIS-MCA method which assumes a spatial heterogeneity of its parameters within the study area, and (ii) to demonstrate the differences between the conventional GIS-MCA and local forms of GIS-MCA using a case study of quality of employment evaluation in London, Ontario.

Ideal Point Method (IPM) is one of the most commonly used MCA techniques (Zeleny, 1976, 1982). It is based on a calculation of the weighted absolute distance between the ideal set of scores and the actual scores for an alternative (Carver, 1991;

Zeleny, 1976). Over the last 20 years, there has been a great progress in the development and applications of IPM. Tkach and Simonovic (1997) proposed a new approach that combined IPM with GIS technology that can capture the spatial distribution of the criteria values associated with the various alternatives. Malczewski (1996) developed a new IPM which took a group of decision makers into consideration. Malczewski et al. (1997) integrated IPM with four techniques to enhance the visualization of GIS-MCA. Jankowski et al. (2001) presented prototype software named DECADE (Dynamic Exploratory Cartography for Decision Support) which integrated maps with IPM using highly an interactive, exploratory map to further improve the visualization of GIS-MCA. The uncertainty of GIS-based MCA has also been progressed. Prato (2008) combined IPM and stochastic dominance with respect to a function (SDRF) to develop a stochastic multiple attribute evaluation. Elaalem et al. (2011) introduced Fuzzy Analytical Hierarchy Process and weighted fuzzy maps into IPM. Some researchers also adopted GIS-based IPM (GIS-IPM) as a support method for their new developed systems or tools. GIS-IPM has been applied in many spatial decision and evaluation problems (Carver, 1991; Pereira and Duckstein, 1993; Sante-Riveira et al., 2011; Tkach and Simonovic, 1997). All of those studies applied conventional (global) approaches to GIS-MCA.

The conventional GIS-IPM contains two sets of parameters: criteria weights and ideal/nadir scores (or points). The purpose of criterion weight is to express the relative importance of each criterion. This is often achieved by considering the preferences of decision makers or experts. There are many criterion weighting techniques including pairwise comparison, ranking, and trade-off analysis (Malczewski, 1999). The purpose of determining the ideal/nadir scores is to measure the separation (or distance) between the ideal or nadir scores and the actual criteria scores for each decision alternative (or an object of evaluation such as location, site or area). In the previous GIS-IPM studies these two parameters have been determined based on the whole study area. In other words, the criteria weights and ideal/nadir scores can be applied to any location (or region) within the study area. All the locations are assigned the same parameters regardless of their spatial heterogeneity. Therefore, the conventional IPM can be viewed as global IPM (see Chapter 3). One of the main limitations of global IPM is that it assumes spatial homogeneity of the criteria weights and ideal/nadir scores.

Several GIS-MCA studies addressed the problem of spatial heterogeneity by ‘localizing’ the conventional GIS-MCA (e.g. Feick and Hall, 2004; Ligmann-Zielinska

and Jankowski, 2008; Malczewski, 2011). Feick and Hall (2012) presented a method to evaluate changes of the criteria weights and to visualize the spatial dimension of weighting sensitivity to show the localized variations of decision outcomes. Ligmann-Zielinska and Jankowski (2008) adopted sensitivity analysis as a part of spatial MCA from the perspective of three aspects (spatiality, scope, and cardinality) in order to strengthen its exploratory role. They argued that the spatiality of GIS-MCA should take spatial criteria and spatial weights into account, and the local-global dichotomy in the spatial sensitivity analysis can be extended to GIS-MCA procedures in general. Malczewski (2011) has argued that most of the researchers did not successfully integrate the theories and principles of MCA with explicitly spatial components of GIS-MCA. He developed a local version of Weighted Linear Combination (WLC) model which interrelated concepts of local criterion weight and local range of criteria values based on range sensitivity principle.

Although some progress has been made in localizing GIS-MCA, the previous studies mainly focused on detecting and demonstrating the necessity or feasibility of localizing conventional GIS-MCA by using spatial sensitivity analysis (e.g. Feick and Hall, 2004; Ligmann-Zielinska and Jankowski, 2008). None of the previous studies placed their focus on localizing global IPM. Therefore, the main aim of this study is to propose a local GIS-IPM.

The main difference between the local and global IPM is that each decision alternative (location) has its own parameters (criteria weights and ideal/nadir score) which are calculated based on a local area instead of the whole area of study (see Chapter 4). The local area or neighborhood is determined by the spatial information of each alternative. This study uses two main methods for defining the neighborhood: adjacency measure and distance based method (Fotheringham et al., 2000, 2002; Lloyd, 2010; Malczewski, 2011). Once the neighborhood is defined, the parameters (criteria weights and ideal/nadir points) are localized based on the range sensitivity principle (Fischer, 1995; von Nitzsch and Weber, 1993). The principle suggests that, other things being equal, the greater the range of values for a given criterion, the greater the weight that should be assigned to the criterion (Fischer, 1995; Malczewski, 2011; von Nitzsch and Weber, 1993). To this end, the local version of the global IPM model is developed by localizing criteria weights and ideal/nadir points using the range sensitivity principle and related concept of spatial neighborhood. The value of range is defined as the difference between the maximum and minimum criterion values, and it depends on the definition of neighborhood.

This thesis provides a comparative analysis of the global and local IPM using a case study of evaluating quality of employment in London, Ontario. MCA methods are often used to evaluate the quality of life by aggregating a number of relevant criteria (Federation of Canadian Municipalities, 2001; Janzen, 2003; Malczewski and Rinner, 2005; Rinner, 2007). Quality of employment is one of the main aspects that reflect people's quality life. In this study, quality of employment is defined based on the Federation of Canadian Municipalities (FCM) quality of life reporting system. Specifically, the FCM's system defines quality of employment as a component of an index that measures the quality of life in Canadian communities. Consequently, the quality of employment is related to the community (residential neighborhood) level rather than workplace.

Many studies on quality of life (and quality of employment) use multivariate statistics and/or MCA procedures (Bayless and Bayless, 1982; Can, 1992; Goode, 1997; Janzen, 2003; Malczewski and Rinner, 2005). MCA method can combine a variety of criteria and propose an overall score (or index) of the quality of employment by residential neighborhood. All the previous studies about measuring the quality of life or employment are based on the global MCA. This study evaluates the quality of employment using both global and local IPM (see Chapter 5). The results of this study show that the global and local IPM provide different information about the spatial patterns of quality of employment. The global IPM shows the absolute values in the whole study area, while the local IPM displays the relative values within each neighborhood.

1.1 Objectives

There are two main objectives for this study:

1. to develop the local form of GIS-based Ideal Point Method (GIS-IPM), and
2. to demonstrate the differences between the conventional (global) and local forms of GIS-IPM using a case study of quality of employment evaluation in London, Ontario.

1.2 Thesis Organization

The rest of the thesis is organized as follows. Chapter 2 provides an overview of GIS-MCA. Two types of the global IPM along with their implementation and limitations are presented in Chapter 3. Chapter 4 focuses on developing the local form of global IPM. The differences between the global and local IPM are analyzed based on a case study which evaluates the quality of employment in London, Ontario are presented in Chapter 5. The concluding chapter provides a brief discussion and suggestions for future research.

Chapter 2

GIS-based Multicriteria Analysis

Multicriteria Analysis (MCA) is a set of methods and procedures for tackling decision (or evaluate) problems with multiple, conflicting objectives and attributes (Voogd, 1983; Zeleny, 1982). The conventional MCA techniques have very limited capabilities to analyse or visualize geospatial data/information. To address this limitation, MCA methods can be integrated with Geographic Information System (GIS). GIS-based MCA can be defined as a set of methods and procedures for combining geographic information (criterion maps) and preferences (criterion weights) to obtain an overall value for each decision (or evaluation) alternative. In the context of this study, the decision alternative is a location (or area) that is to be evaluated on the basis of a set of relevant attributes associated with that location using GIS-MCA.

There are several advantages to combining GIS and MCA. First, GIS is a tool for performing deterministic analyses on all types of geographical data. Second, GIS provides a suitable framework for the application of spatial analysis methods, such as MCA, using its capability of the capture, storage, retrieval, editing, transformation and display of spatial data. Third, MCA procedures provide GIS with the means of performing complex trade-offs on multiple and conflicting criteria while taking the expert (decision maker) knowledge (preferences) into account. Fourth, GIS-MCA has the potential to provide a more rational, objective and unbiased approach for tackling spatial decision (or evaluation) problems (Carver, 1991).

2.1 Multiobjective vs. Multiattribute Analysis

The term ‘criterion’ includes both the concept of objective and attribute. Therefore, multicriteria analysis is a generic term which includes both multiobjective and multiattribute analysis. Table 2.1 shows the differences between multiobjective and multiattribute decision problems.

Table 2.1: Comparison of Multiobjective and Multiattribute Decision Problem *Source: Malczewski (1999, p.86) and Huang and Yoon (1981, p.4)*

	Multiobjective Decision Problem	Multiattribute Decision Problem
Criteria defined by:	Objectives	Attributes
Objectives defined:	Explicitly	Implicitly
Attributes defined:	Implicitly	Explicitly
Constraints defined:	Explicitly	Implicitly
Alternatives defined:	Implicitly	Explicitly
Number of alternatives:	Infinite(large)	Finite(small)
Decision makers control:	Significant	Limited
Decision modeling paradigm:	Process-oriented	Outcome-oriented
Relevant to:	Design/search	Evaluation/choice

An objective is something to be pursued to its fullest, which indicates the desired direction of change (Hwang and Yoon, 1981). Objectives are functionally related to, or derived from, a set of attributes (Malczewski, 1999). Multiobjective analysis usually has explicit objectives defined as its criteria. It views the attributes of alternatives as the means to reach objectives. Therefore, this type of decision problem is especially suitable for design/planning approaches, which aims at achieving the optimal goals by considering the various interactions within a given set of constraints (Tzeng and Huang, 2011). In other words, multiobjective decision problem is referred to as a designing problem which aims at finding the best alternatives from an infinite set of alternatives defined by explicit constraints. Multiobjective decision problems are also known as continuous decision problems.

An attribute should provide a means of evaluating objective (Hwang and Yoon, 1981). The criteria in multiattribute analysis are defined in terms of attributes. Multiattribute analysis requires that choices be made among alternatives described by their attributes (Malczewski, 1999). In this case, the attributes are actually viewed as objectives. However, attributes are more concrete and specific than objectives. In

multiattribute decision problem, the decision space is finite, which means there is an explicit list of predetermined alternatives. Solving a multiattribute decision problem is an evaluation and selection process, as opposed to a design process. Therefore, multiattribute decision problems are sometimes referred to as discrete decision problems or evaluation problems. This study focuses on multiattribute analysis. Hereafter, the terms multiattribute analysis and multicriteria analysis will be used interchangeably.

2.2 Framework for GIS-based Multicriteria Analysis

The framework of GIS-MCA consists of seven components in terms of the sequence of activities involved in GIS-MCA. They include: evaluation problem, evaluation criteria, alternatives, criteria weights, decision rules, sensitivity analysis and outcomes (Malczewski, 1999). Figure 2.1 shows the relationship of the seven components.

Any GIS-MCA starts with the statement of the evaluation (or decision) problem to be solved. At this initial stage, GIS assists in the data storage, management and analysis in order to better address the problems. The next step is to establish or select a set of relevant evaluation criteria. They are represented as a set of criterion (or attribute) maps in GIS. A criteria map represents a unique attribute of the alternatives (locations or areas) that can be used to evaluate their performance.

The third step is to identify the alternatives (or locations). Each alternative is associated with a set of evaluation criteria. The fourth step of GIS-MCA involves criteria weighting. The weights represent the levels of importance of each criterion relative to other criteria. The criterion weighting is the major step to incorporate preferences or judgments into the analysis. The evaluation criteria, alternatives and criteria weights are typically organized in the form of an evaluation matrix.

Selecting decision rules is the fifth step. A decision rule dictates how the one-dimensional measurements (geographic data layers) and judgments are integrated to obtain the ordering of the set of alternatives. A decision rule provides an ordering (ranking) of all alternatives according to their performance with respect to the set of evaluation criteria. In this study the Ideal Point Methods are used as decision rules for integrating criterion maps and associated criterion weights.

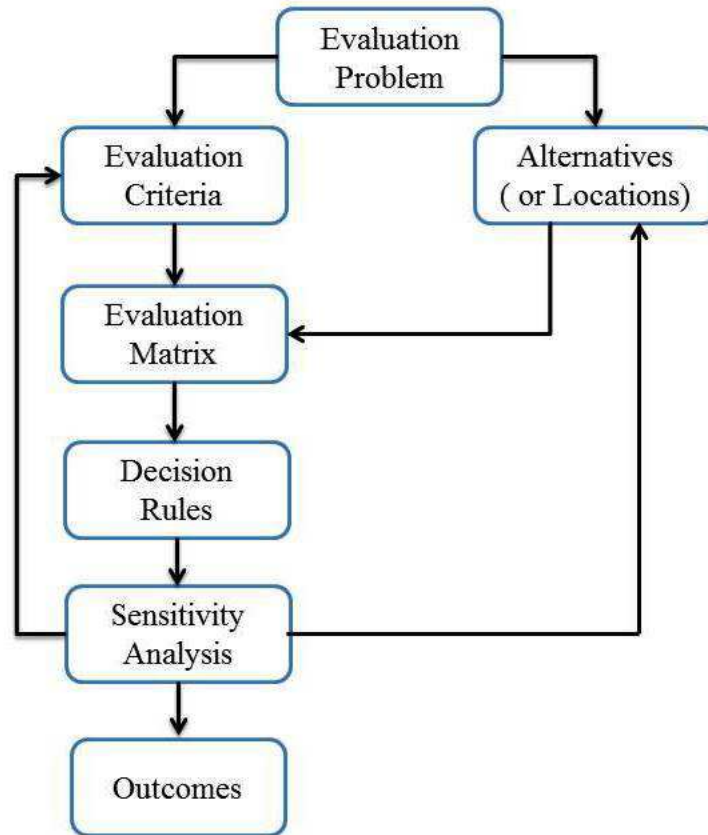


Figure 2.1: Framework of GIS-based Multicriteria Analysis

The next step aims at testing the robustness of the ranking of alternatives. Sensitivity analysis is used to show how the outcome (ranking of alternatives) changes with the variations of input data (geographical data and judgments). A ranking is considered to be robust if variations of input data insignificantly affect the output. This step helps us to know how the evaluation criteria and criteria weights interact with the outcomes. The final step is to show the outcomes of the analysis (or evaluation). Visualization techniques, such as maps and graphs, should be used for communicating the results.

2.3 Summary

Multicriteria analysis (also referred to as multicriteria evaluation) is a well-known area of decision-making methods that logically structure and evaluate problems with

multiple attributes and objectives. Multicriteria problems can be classified into two main groups: multiobjective and multiattribute decision problems. This study focuses on the multiattribute (or multicriteria) evaluation problem. The problem is tackled using GIS-based MCA. GIS-MCA combines a set of criterion values (maps) and preferences (criterion weights) to obtain overall value for each spatial unit (location) in the study area.

Chapter 3

Global Ideal Point Methods

Ideal Point Methods (IPM) evaluate and order the decision alternatives based on their deviations or distance from the ideal point. The methods are also referred to as multicriteria ‘distance’ methods. The ideal point represents a hypothetical alternative that consists of the most desirable weighted standardized levels (the best values) for criteria across all alternatives under consideration. The overall aim of the methods is to find the alternative that comes as close as possible to the ideal alternative (Karni and Werczberger, 1995; Zeleny, 1982). IPM avoids some of the difficulties associated with the interdependence-among-attributes (i.e., correlation between two attributes). In the ideal point approaches, an alternative is treated as an inseparable bundle of attributes for which it would be meaningless to treat dependence as separable and assess value and preferential dependence (Pereira and Duckstein, 1993; Zeleny, 1982). Thus, IPM is an attractive approach for those decision or evaluation problems that involve complex interdependencies between attributes.

IPM has traditionally been used as a global approach based on the implicit assumption that its parameters do not vary as a function of geographical space. Therefore, the conventional IPM is referred to as global method. The criteria weights and ideal/nadir point can be called global weights and global ideal/nadir point, respectively. The first section of this chapter is concerned with the two major types of global IPM: Compromise Programming (CP) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). In the case study of this research, TOPSIS is used for evaluating the quality of employment in London, Ontario. Then, the following section reviews the implementation of IPM in the GIS environment over the

past twenty years or so. The third section of this chapter discusses the limitations of IPM.

3.1 Ideal Point Methods

The two ideal point models: Compromise Programming (CP) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) are based on some assumptions. They require that each criterion has a monotonically increasing or decreasing utility. The monotonically increasing utility indicates that the larger the criteria value is, the better the alternative is. The monotonically decreasing utility identifies the better alternative as the one has a smaller criteria value. In addition, the models assume that the preferences or judgment on criterion (criteria weights) are specified in the cardinal form. Also, all the qualitative criteria should be transformed into quantitative form by means of appropriate scaling (standardization) techniques.

3.1.1 Compromise Programming

Compromise Programming (CP) is a multicriteria method originally developed in the 1970s (Freimer and Yu, 1976; Yu, 1973, 1985; Zeleny, 1974, 1976). CP is a technique appropriate for a continuous multiobjective context that has also been modified for the analysis of discrete problems (Duckstein and Opricovic, 1980). CP identifies the alternatives (solutions) that are closest to the ideal point as determined by some distance measures (Goicoechea et al., 1982). The solutions identified as the nearest to the ideal point are called compromise solutions and constitute the compromise set. In a multicriteria decision problem, the set of feasible alternatives to be evaluated is represented as (Zeleny, 1982):

$$A = (a_1, a_2, a_3, \dots, a_m) \quad (3.1)$$

All alternatives are evaluated based on n attributes, corresponding to the map layers in GIS. The i -th feasible alternative is an n -dimensional vector (see rows in Table 3.1). Each dimension a_{ik} represents the performance of the i -th alternative for k -th criterion. Therefore, each row in Table 3.1 is a vector of n values, assigned to

each alternative and synthesized for all available information about that alternative in terms of possibly incommensurable, quantitative and qualitative criteria (Zeleny, 1982). A vector with m values represents the k -th attribute or evaluation criterion (or map layer in GIS) (see columns in Table 3.1). Each column in Table 3.1 represents the levels of performance of all alternatives for the k -th criterion. Among these values, there is at least one best (or so called ideal) value.

Table 3.1: m alternatives based on n attributes (or criteria)

	Attribute 1	Attribute 2	Attribute 3	...	Attribute k	...	Attribute n
Alternative 1	a_{11}	a_{12}	a_{13}	...	a_{1k}	...	a_{1n}
Alternative 2	a_{21}	a_{22}	a_{23}	...	a_{2k}	...	a_{2n}
Alternative 3	a_{31}	a_{32}	a_{33}	...	a_{3k}	...	a_{3n}
...
Alternative i	a_{i1}	a_{i2}	a_{i3}	...	a_{ik}	...	a_{in}
...
Alternative m	a_{m1}	a_{m2}	a_{m3}	...	a_{mk}	...	a_{mn}

$$a^* = (a_1^*, a_2^*, a_3^*, \dots, a_n^*) \quad (3.2)$$

The vector a^* represents the ideal point (or ideal alternative) that consists of the best scores of each criterion. It is usually an infeasible alternative. The best scores of every criterion can be the values that are unavailable within a given set of alternatives. However, the definition above makes it easier to conceptualize the ideal point, since all its characteristics can be directly experienced, being derived from existing alternative choices (Zeleny, 1982). In CP, all available alternatives are rated based on their multidimensional distance to the ideal point (Pereira and Duckstein, 1993). The distance from the ideal point, which is calculated for each alternative, is a function of the criteria values themselves, the relative importance of the various criteria, and the importance of the maximal deviation from ideal solution. Equation 3.3 is the operational expression of a generalized family of distance matrices based on the parameter p .

$$s_i^p = \left\{ \sum_{k=1}^n \left(w_k \frac{a_k^* - a_{ik}}{a_k^* - a_{k*}} \right)^p \right\}^{\frac{1}{p}} \quad (3.3)$$

where:

s_i^p is the distance (or separation) between the value associated with i -th alternative and the ideal point based on parameter p ;

a_k^* denotes the best value of the k -th criteria;

a_{k*} is the worst value of the k -th criteria;

a_{ik} is the actual value of i -th alternative for the k -th criteria;

w_k is the weight of the k -th criteria.

The $\frac{a_k^* - a_{ik}}{a_k^* - a_{k*}}$ element in Equation 3.3 can be interpreted as the normalized difference between the anticipated performances of alternative i and the ideal point with respect to criterion k (Karni and Werczberger, 1995). To ensure the same range of values for every criterion, the performance measures are normalized or mapped into the interval $[0, 1]$ by dividing the range of values for criteria k , that is $(a_k^* - a_{k*})$ (Duckstein and Opricovic, 1980). As a consequence, however, the compromise solution does not satisfy the independence of irrelevant alternatives property, as the addition or elimination of suboptimal alternatives to or from a set of feasible alternatives may affect the ranking of the remaining solutions (Karni and Werczberger, 1995). The reason is that the magnitude of the distance between an alternative and the ideal point depends not only on the performance of the alternative considered, but also on the whole set of alternatives that defines the set of a_k^* and a_{k*} (Zeleny, 1982).

The range of parameter p is $[1, \infty)$. Different p values indicate different contributions of individual separations from ideal point. The greater the parameter p is, the greater emphasis is placed on the larger separations. If the $p = 1$, Equation 3.3 indicates that the overall score of alternative i is the sum of weighted deviations associated with all criteria. In this case, total compensation between criteria is assumed, which means that a decrease of one unit of one criterion can be totally compensated by equivalent gain on any other criterion (Pereira and Duckstein, 1993). As the p value increases, the term of $w_k \frac{a_k^* - a_{ik}}{a_k^* - a_{k*}}$ with higher scores has greater influence on the overall score, while the impacts from other terms may become negligible. The best solution should be the one that has the smallest overall score. Therefore, the decision criteria in selecting the compromise solution become the 'avoidance of low performance in any criteria' as the increased value of p (Karni and Werczberger, 1995).

3.1.2 Technique for Order Performance by Similarity to Ideal Solution

The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was developed by Hwang and Yoon (1981). The basic concept of this method is that the selected best alternative from a finite set of alternatives should have the shortest distance from the ideal point and the farthest distance from the negative ideal point (or nadir) in a geometrical sense (Olson, 2004; Triantaphyllou and Lin, 1996). Although the TOPSIS method can be implemented in the raster and vector GIS environment, the technique is especially suitable for the raster data structure (Malczewski, 1996; Pereira and Duckstein, 1993). The GIS-based TOPSIS procedure involves the following steps:

1. Determine the set of feasible alternatives.
2. Standardize each criterion map layer by transforming the various criteria dimensions (a_{ik}) to unidimensional criteria (v_{ik}).
3. Define the weights (w_k) assigned to each criterion; the criteria weights should be in the range of $[0, 1]$ and $\sum_{k=1}^n w_k = 1$.
4. Determine the best value for each criterion or standardized map, and these best values constitute the ideal point: $v^* = (v_1^*, v_2^*, v_3^*, \dots, v_n^*)$.
5. Determine the worst value for each standardized criteria map, the worst values constitute the negative ideal point (or nadir point): $v_* = (v_{1*}, v_{2*}, v_{3*}, \dots, v_{n*})$.
6. Calculate the deviations from the ideal point for each alternative with respect to certain criterion, the equation is $\frac{v_k^* - v_{ik}}{v_k^* - v_{k*}}$. Since $v_k^* - v_{k*} = 1$, the equation can be rewritten as $v_k^* - v_{ik}$.
7. Calculate the deviations from the negative ideal point for each alternative with respect to certain criterion, the function is $\frac{v_{ik} - v_{k*}}{v_k^* - v_{k*}}$, where $v_k^* - v_{k*} = 1$.
8. Calculate the weighted distance between the ideal point and each alternative for a given value of the parameter p (see Equation 3.4). All dimensions of the ideal point equal to 1, because the ideal point is selected based on the whole study area where the best standardized value of each criterion is always equal to 1. Thus, Equation 3.4 can be rewritten as Equation 3.5

$$s_i^p = \left\{ \sum_{k=1}^n (w_k (v_k^* - v_{ik}))^p \right\}^{\frac{1}{p}} \quad (3.4)$$

$$s_i^p = \left\{ \sum_{k=1}^n (w_k (1 - v_{ik}))^p \right\}^{\frac{1}{p}} \quad (3.5)$$

9. Use the same method to calculate the weighted distance between the negative ideal point and each alternative under the same parameter p by Equation 3.6. Since the $v_{k^*} = 0$, Equation 3.6 becomes Equation 3.7.

$$d_i^p = \left\{ \sum_{k=1}^n (w_k (v_{ik} - v_{k^*}))^p \right\}^{\frac{1}{p}} \quad (3.6)$$

$$d_i^p = \left\{ \sum_{k=1}^n (w_k v_{ik})^p \right\}^{\frac{1}{p}} \quad (3.7)$$

10. Calculate the relative closeness (overall score f_i^p) to ideal point using Equation 3.8.

$$f_i^p = \frac{d_i^p}{s_i^p + d_i^p} \quad (3.8)$$

where f_i^p ranges from 0 to 1; an alternative is closer to the ideal point as f_i^p approaches to 1.

11. Rank the alternatives in the descending order of f_i^p ; the alternative with highest value of f_i^p is the best alternative.

3.2 Implementation of Ideal Point Method in GIS

The ideal point approach have been applied in many areas including environmental planning (Pereira and Duckstein, 1993), urban/regional planning (Sante-Riveira et al., 2011), waste management (Carver, 1991), water resources (Tkach and Simonovic, 1997), agriculture (Salt and Dunsmore, 2000). Pereira and Duckstein (1993) suggested that simple rules of combination impose an oversimplification on the MCA problem when at least one criterion is measured by continuous interval-scaled data

and its discretization, or in complex situations characterized by several discrete criteria, each one with multiple categories. To overcome this limitation, Pereira and Duckstein (1993) proposed an alternative methodology by applying CP approach within a raster GIS environment (IDRISI) to solve land suitability problem. They evaluated the potential locations based on a set of relevant criteria and CP model. Sensitivity analysis for various values of parameter p was applied to identify which parameter p value produced the best binary classification. However, only one distance matrix was generated for the whole region under certain value of parameter p .

Tkach and Simonovic (1997) extended the approach by Pereira and Duckstein (1993) and proposed a new IPM approach called Spatial Compromise Programming (SCP) that combined CP with GIS. SCP can capture the spatial distribution of the criteria values associated with the various alternatives. Tkach and Simonovic (1997) compared this approach with the traditional CP within a raster GIS environment by analyzing potential flood plain management strategies. The conventional CP considered the region as a whole study area, which means it identified the best strategies for the whole region. However, the SCP technique showed that the strategy generated by conventional CP may not necessarily be the best for all locations. Tkach and Simonovic (1997) took localized impacts associated with each alternative into consideration in their applications of the SCP technique. The resulting maps generated by SCP contained a distance matrix value for each raster cell that corresponds to the relative impact produced by each strategy. By comparing the distance matrix values of feasible strategies, the best strategy for a certain raster cell is the one that has the smallest value. The two main contributions of their work are: (1) the replacement of a single distance matrix for the whole region with a distance matrix for each potential flood protection alternative; and (2) the comparison of distance matrix values for each alternative (strategy) at each geographic location (Tkach and Simonovic, 1997).

Malczewski (1996) developed an IPM by combining TOPSIS with Borda's choice rule for multicriteria group decision-making in a raster IDRISI environment in order to enhance the utility of the GIS-based multicriteria evaluation method. He emphasized the importance of visualization techniques in the GIS-MCA (see also Malczewski et al. 1997). Integrating visual techniques with MCA provides a tool for better understanding the results of MCA, especially in situations involving large amounts of data. Malczewski et al. (1997) pointed out that multivariate data display techniques were typically used to visualize multicriteria problems in criterion outcome space, rather than in geographic space. It is argued that the multicriteria approach requires

the decision problem to be visualized in both the criteria and decision space (Church et al., 1992; Malczewski et al., 1997; Schilling et al., 1982). To enhance the visualization of multicriteria location analysis, Malczewski et al. (1997) integrated IPM with four techniques (decision matrix, payoff matrix, multicriteria scatterplot/map matrix, and value path/map display) within a raster GIS environment to solve a site selection problem. A decision matrix is used to visualize the standardized criteria in IPM. The payoff matrix helps to select the ideal and nadir point. The multicriteria scatterplot/map matrix and value path/map display methods provide tools to analyze the problem in the decision space and the criterion outcome space simultaneously (Malczewski et al., 1997). In a nutshell, results of different steps in IPM can be visualized through these four techniques, which helps decision makers obtain insights into the solution of decision problems.

Malczewski et al. (1997) pointed out that the value path display method is particularly useful for visualizing a decision problem with a small number of alternatives. In addition, another limitation of value path display method is that it also set implicit requirement on the number of criteria (Jankowski et al., 2001). More specifically, there are natural limitations on the number and size of maps to be displayed simultaneously on the computer screen because the value path display method shows ‘partial optimums’ on separate maps. Jankowski et al. (2001) argue that maps have been used predominantly as presentation media either to display the results of spatial decision analysis or to inform about the location of decision options, and they rarely played roles in structuring multicriteria decision problems. Jankowski et al. (2001) developed DECADE (Dynamic Exploratory Cartography for Decision Support) that integrated maps with MCA using highly interactive, exploratory map displays coupled with the IPM and data mining algorithms.

Prato (2008) proposed a stochastic multiattribute evaluation that adopted TOPSIS and stochastic dominance with respect to rank feasible land use policies. Elaalem et al. (2011) used GIS-IPM for evaluating agriculture land suitability based on the weighted fuzzy maps. They also compared the fuzzy Analytic Hierarchy Process (AHP) and fuzzy IPM, and concluded that fuzzy AHP is more appropriate for the case study because fuzzy IPM may be biased on selecting positive and negative ideal values.

Natividade-Jesus et al. (2007) developed a multicriteria decision support system for housing evaluation. This decision support system, that applied IPM as one of

decision methods, assists its users in keeping and structuring information, obtaining historical and statistical analysis, and providing decision aid by enabling to rationalise the comparisons among non-dominated alternatives in construction and housing evaluation. Jankowski et al. (2008) presented a web-based multicriteria evaluation tool that viewed multicriteria evaluation as a stand-alone methodology and a potential spatial decision support systems component, by presenting a design as well as prototype implementation utilizing web-based technologies. This web-based multicriteria evaluation tool used IPM for evaluating a set of alternatives. Sante-Riveira et al. (2011) presented a planning support system for rural land-use allocation called RULES in a GIS environment. IPM was applied as a technique in two basic stages in a rural land-use planning model (land suitability evaluation and spatial allocation of land-uses). IPM was selected as the technique for evaluating land suitability, and then the method was integrated with other techniques to generate the final land use map in the GIS-based planning support system for rural land-use allocation.

3.3 Limitations of Ideal Point Methods

The GIS-MCA procedures are mostly derived from general decision theory and analysis (Malczewski, 1999). The spatial variability is mainly reflected in defining evaluation criteria based on the concept of spatial relations such as proximity, adjacency, and contiguity (Ligmann-Zielinska and Jankowski, 2008; van Herwijnen and Rietveld, 1999). The parameters in GIS-MCA do not vary with different geographic information. The conventional GIS-MCA evaluates all the alternatives under the same standard regardless of their spatial heterogeneity. It assumes a spatial homogeneity of preferences or value judgments within the study area. This implies that two key elements (the criteria weights and ideal point) of the conventional IPM do not vary over geographical space. The method assigns the same weight to each alternative (location) in the whole study area for a given criteria map layer. One can argue that the homogeneous criteria weights may be inappropriate in certain regions (neighborhoods) of the study area (Ligmann-Zielinska and Jankowski, 2008; Malczewski, 2011; van Herwijnen and Rietveld, 1999) .

Also, the ideal/nadir point in the conventional IPM is determined based on the whole study area. One can suggest that it is unreasonable to set a uniform standard for different decision alternatives (locations). Moreover, a single value function is

used to standardize criteria in the conventional IPM. This ignores the fact that the form of the function may depend on the local context (Malczewski, 2011). Therefore, the conventional IPM can be viewed as the global IPM. The assumption of spatial homogeneity of the global IPM parameters (i.e., the criterion weights and the ideal point) is one of the main limitations of the method. To address this limitation, one can propose a local form of the traditional IPM for GIS-based MCA.

Several GIS-MCA studies made some ‘improvement on localizing’ the conventional GIS-MCA (Feick and Hall, 2012; Ligmann-Zielinska and Jankowski, 2008; Malczewski, 2011). Chakhar and Mousseau (2008) proposed a framework for incorporating explicitly spatial components into GIS-MCA based on the topological relationship between decision alternatives (locations and areas). Tkach and Simonovic (1997) developed a new IPM called SCP capable of capturing the spatial distribution of the criteria values associated with the various alternatives. This new IPM technique addressed uneven spatial distribution of criteria values in the evaluation and ranking of alternatives (Tkach and Simonovic, 1997). Makropoulos and Butler (2006) used a similar concept to develop spatial Ordered Weighted Averaging (SOWA). They applied different decision rules to different alternatives based on their spatial characteristics. SOWA takes the spatial variation of the risk-averse attitude of the decision maker into account by using different weights per alternative (Makropoulos and Butler, 2006).

Rinner and Heppleston (2006) took spatial factors into consideration in MCA in two ways: one is to classify decision criteria into three groups based on spatial relations (location, proximity, and direction), the second is to evaluate the final scores of alternatives based on distance-based adjustment of evaluation scores. Distance-based adjustment of evaluation scores, which uses the performance of neighbouring properties to smooth the distribution of scores across the study area, allows decision makers to consider the environment of locations. Ligmann-Zielinska and Jankowski (2012) extended the work of Rinner and Heppleston (2006) by adjusting the individual criteria weights rather than the final composite evaluation scores. They used the concept of proximity to capture spatial heterogeneity of the criteria values and associated criteria weights.

However, the previous studies mainly focused on the limitations of the implicitly spatial GIS-MCA (e.g. Chakhar and Mousseau, 2008; Tkach and Simonovic 1997; Rinner and Heppleston, 2006). Malczewski (2011) introduced range sensitivity principle to localize conventional GIS-based MCA methods. However, he focused only on

integrating the principle in the context of GIS-based Weighted Linear Combination modeling. None of the previous researchers propose a local IPM to overcome homogeneity aspects of its conventional form. This study aims at localizing the global IPM in a GIS environment.

3.4 Summary

This chapter introduced introduced the conventional IPM, its implementations, and limitations. The method has two main versions. One is known as Compromise Programming (CP), and another is called Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). TOPSIS in fact can be viewed as an extension of CP because it not only compares all the alternatives with ideal point but also examines the deviation between alternatives and nadir point. In the past 20 years or so, significant progress has been made in the development of GIS-based IPM. However, one of the major limitations of the conventional or global IPM is that it has an implicit assumption that the model parameters (criteria weights and ideal/nadir points) do not vary over geographical spaces. Although, several approaches explicitly integrated spatial concepts into the conventional GIS-MCA methods, there has been no attempt to develop a local form of the conventional IPM. In this study, a new method called local IPM will be proposed. In addition, this study will demonstrate the differences between the global and local IPM using a case study (see Chapter 5).

Chapter 4

Local Ideal Point Method

As mentioned in Chapter 3, one of the main limitations of conventional IPM is that it assumes spatial homogeneity; that is, the IPM model parameters (i.e., criteria weights and ideal/nadir point values) do not vary over geographical space. This assumption contradicts the fact that conditions vary from one location to another. Also, MCA requires a specific relation between the range of criterion values and the weight for that criterion: the greater the range, the greater the weight has to be (von Nitzsch and Weber, 1993). This relationship is known as the range sensitivity principle.

This chapter aims at developing a local IPM based on the range sensitivity principle. The first section shows the process of developing the local IPM. Sections 4.2 throughout 4.7 illustrate how to localize the parameters: criteria weights and ideal point. Section 4.8 presents the local form of TOPSIS.

4.1 Developing The Local Ideal Point Method

Figure 4.1 shows a flowchart for developing a local form of IPM. The concept of spatial heterogeneity and range sensitivity principle play central roles in the proposed approach. Spatial heterogeneity implies that conditions vary over the earth surface. Consequently, local factors may influence the parameters of the IPM model. Thus, one needs to determine the local context. In this study, the concept of neighborhood is used for defining the local area. The neighborhood refers to the spatial relationships between geographic units. Once the neighborhood is determined, one can identify

the range of criterion values in each neighborhood. According to the range sensitivity principle, the local weights can be determined based on the global weight and the global and local ranges. Malczewski (2011) presented a local value function (local standardization) based on the local range. This form of value function for the local standardization will be used. After obtaining local criteria values, the ideal/nadir points can be identified for each neighborhood. These points are referred to as the local ideal/nadir points. The global IPM model then can be rewritten as the local IPM model by replacing the global weights and ideal/nadir points with the local weights and ideal/nadir points.

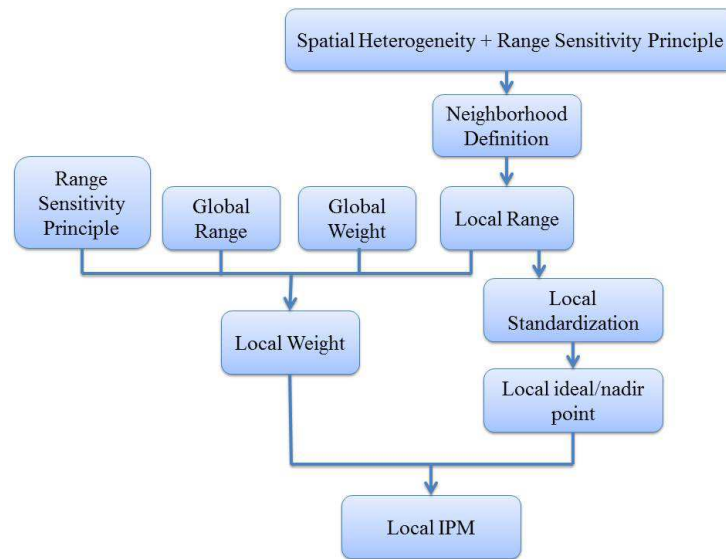


Figure 4.1: Flowchart for developing a local form of IPM

4.2 Range Sensitivity Principle

The criterion weights and ranges are interdependent. The relationship is addressed by the range sensitivity principle (von Nitzsch and Weber, 1993). The principle is a normative property concerned with the dependence of the criterion weights on the upper and lower limits of criterion values (Malczewski, 2011). It states that the criteria weights should be adjusted so that they are proportional to the ranges of the criterion values: other things being equal, the greater the range of values for the criterion, the greater the weight should be assigned to that criterion, and small range should yield correspondingly small weight (Malczewski, 2011; Monat, 2009).

Malczewski (2011) localized the criterion weights and value functions of the weighted linear combination method based on the range sensitivity principle.

In this research, the range sensitivity principle is used as the central concept for developing the local IPM. The proposed model is based on the local form of weighted linear combination developed by Malczewski (2011) (see Section 4.5 and 4.7). Additionally, the ideal/nadir point is determined based on the local context. The following sections discuss how to localize the global IPM.

4.3 Neighborhood Definition

The range sensitivity principle defines a relationship between criteria weights and ranges of criteria. Moreover, local context may have influences on the parameters of IPM model (that is, the criteria weights and ideal/nadir points). The local IPM is based on a definition of neighborhood. The concept of neighborhood has to be quantified so that it can be applied for determining the local criterion range. In other words, one has to define the neighborhood first in order to identify the local ranges and then localize the criteria weights and value functions. The definition of neighborhood is based on the spatial relationships of geographical units.

This section focuses on different ways of defining neighborhood. In general, there are two methods for grouping geographical units to form a neighborhood. First, the study area is divided into different discrete ‘functional’ units such as economic regions, land use zones or watersheds. Second, a neighborhood is defined using the concept of moving window (Fotheringham et al., 2000, 2002; Lloyd, 2010; Malczewski, 2011). Moving window is the most widely used approach to local adaptation in spatial analysis (Lloyd, 2010). The window consists of a focal unit and its vicinity. The size of the moving window can be fixed or floating. In GIS raster data, the size of moving window is usually fixed because all the units have the same shape and size. In GIS vector data the size is floating. Generally, there are two methods to determine the size of the moving window: adjacency measure and distance based method. The following subsections introduce these two methods. In the case study of this research, this study will only use the vector data and adopt the Queen’s case (see Subsection 4.3.1) and one of the distance based methods to define neighborhood (see Subsection 4.3.2).

4.3.1 Adjacency Measure

The adjacency measure is concerned with the immediate neighbors of a spatial unit. This means that two units can be defined as neighbors if they share their boundaries. There are two main types of this method: Rook's case and Queen's case.

In Rook's case, if two units share two or more than two points, then they are neighbors. Figure 4.2 shows an example of Rook's case for vector data. For example, if polygon A is the focal polygon, then the Rook's neighborhood of A includes polygon A, B, C, D, E, G, and H. Polygon I is excluded from the neighborhood because it has only one shared point with the focal polygon.

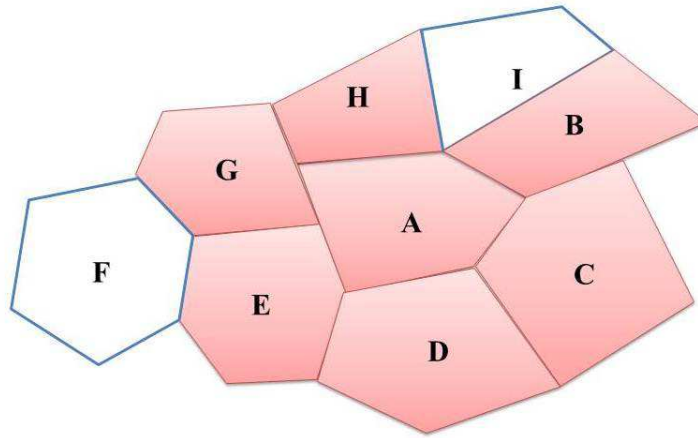


Figure 4.2: Neighborhood of polygon A: Rook's case

The Queen's case neighborhood includes all units the surrounding the focal unit. The neighbors of the focal unit have one or more than one shared point with the focal unit. Figure 4.3 demonstrates the Queen's case neighborhood of polygon A. In this case, polygon I is one of A's neighbors because they share one point. In the Queen's case neighborhoods have typically more spatial units than those the Rook's case neighborhoods. The Queen's case will be applied in the case study for defining neighborhoods.

4.3.2 Distance Based Method

Another common way to define neighborhood is the distance based method. According to the geographic concept of distance decay, the intensity of spatial activities

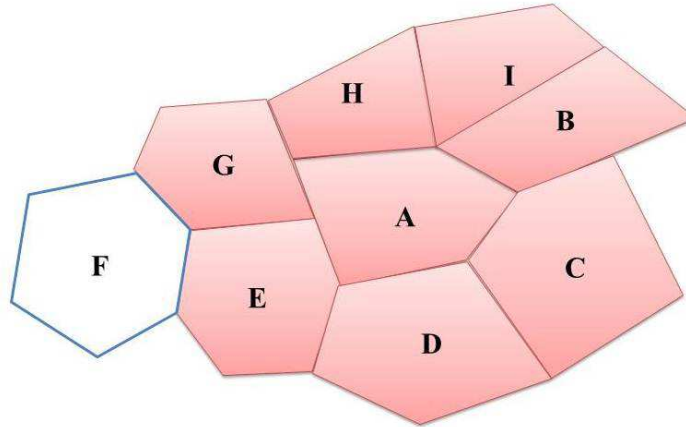


Figure 4.3: Neighborhood of polygon A: Queen's case

between two distant places is said to be less than the intensity of activities between places that are closer together, assuming that all places have the same characteristics (Lee and Wong, 2001). Therefore the distance can be viewed as an indicator of the spatial relationship between two locations (areas or polygons). The distance is measured between the centroids of each polygon. There are two main types in distance based method.

The first type defines the neighborhood based on a standard distance. More specifically, if the distance between the centroids of a spatial unit and the focal unit is less than a given distance, that spatial unit can be viewed as the neighbor of the focal unit. In this case, we have to first determine the centroids of all spatial units and then select a distance d as the standard distance. The next step is to draw a circle using distance d as the radius, and centroid of the focal unit as the center of the circle. If the centroids of the spatial units fall into this circle, those spatial units can be defined as the neighbors of the focal unit. Figure 4.4 displays the neighborhood of polygon A using the distance based method. The neighbors of polygon A are polygons D and H.

The second type of distance based method determines the neighborhood based on the nearest distance. In this case, the distances between the focal unit and its surrounding units is measured first and the distances are ranked from shortest to longest, and then the top number of units (e.g. top 5, 10, or 15) are selected as the neighbors of the focal unit based on the ranking. The method is also known as the K -nearest neighbors method. According to this method all the spatial units in the study area

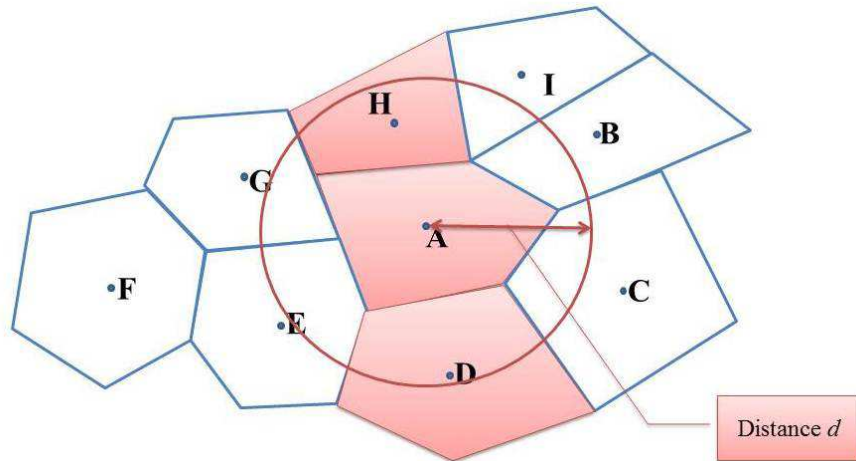


Figure 4.4: Neighborhood of polygon A: distance based method

have the same number of neighbors based on the ordering of distances between them and their surrounding units. Figure 4.5 shows an example of defining neighborhood using the K -nearest neighbors method for $K = 4$. The top four polygons are chosen to be the neighbors of polygon A based on the distance between polygon A and its surrounding polygons.

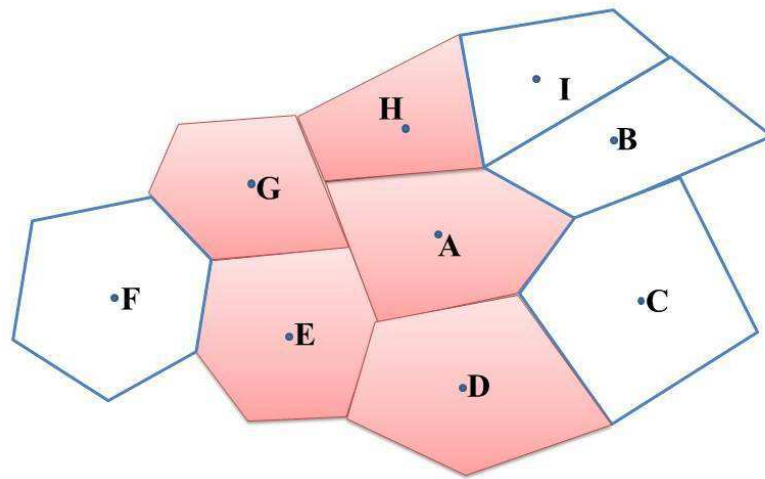


Figure 4.5: Neighborhood of polygon A: the K -nearest neighbor method for $K = 4$

Compared to the first type of distance based method, the K -nearest neighbor method sets a standard on number of neighbors instead of distance. In other words, a given number of neighbors are applied for defining the neighborhood in the second type, which means all the units have the same number of neighbors. A given distance

is used to determine the neighborhood in the first type, which means the number of neighbors may vary from one focal unit to another because it depends on the number of centroids of spatial units falling into the circle that has a standard distance as its radius. Thus, extreme situations may exist in the first type of distance based method. For instance, some spatial units may have a dozen of neighbors, while others may only have one or two neighbors due to the size and shape of the spatial units. To avoid this situation, the second type of distance based method is recommended. Therefore, the data determines which type of distance based method should be applied. If the shape and size of units are similar within the whole study area, both types can be used to define neighborhood. Otherwise, the second type is preferred. Based on the data of this case study, the first type of distance based method will be used to define neighborhoods.

4.4 Local Range

The Range sensitivity principle states that the greater the range of criterion values is, the greater the criterion weight should be (Malczewski, 2011). Therefore, one needs to determine the local range in order to localize criterion weights. The local range is the difference between the maximum and minimum criterion scores in a given neighborhood. Formally, it can be defined as follows:

$$r_k^q = \max_k^q \{a_{ik}\} - \min_k^q \{a_{ik}\} \quad (4.1)$$

where:

$\min_k^q \{a_{ik}\}$ is the minimum criterion value for the k -th criterion in the q -th neighborhood;

$\max_k^q \{a_{ik}\}$ is the maximum criterion value for the k -th criterion in the q -th neighborhood.

The local range is the base for localizing standardization and criteria weights (see Sections 4.5 and 4.7)

4.5 Local Standardization

Standardization is an important step in GIS-MCA. It transforms different scales used for measuring criteria into the same comparable scale. A number of techniques can be applied to convert incommensurately criteria into a standardized form (Hwang and Yoon, 1981; Malczewski, 1999, 2011; Massam, 1988). The approach most often used for standardization in GIS-MCA is the score range procedure (Malczewski, 1999, 2006). This standardization procedure uses different functions for benefit criterion (the larger the raw score, the better the performance) and cost criterion (the lower the raw score, the better the performance). The functions can be written as follows:

$$v(a_{ik}) = \begin{cases} \frac{a_{ik} - \min_k\{a_{ik}\}}{r_k} & \text{for the } k\text{-th criterion to be maximized} \\ \frac{\max_k\{a_{ik}\} - a_{ik}}{r_k} & \text{for the } k\text{-th criterion to be minimized} \end{cases} \quad (4.2)$$

where $v(a_{ik})$ is the standardized score of the k -th criterion for the i -th alternative; a_{ik} is the raw score of the k -th criterion for the i -th alternative (location or area); $\min_k\{a_{ik}\}$ and $\max_k\{a_{ik}\}$ represent the minimum and the maximum criterion values for the k -th criterion, respectively; r_k is the difference between $\min_k\{a_{ik}\}$ and $\max_k\{a_{ik}\}$, that is the global range of the k -th criterion.

According to Equation 4.2, the standardized scores are calculated based on the whole study area. It is the global standardization (value function) procedure, which ignores the spatial heterogeneity of the relationship between the criteria scores, a_{ik} , and the worth or value of that score, $v(a_{ik})$. The preferences (values) are assumed to be homogeneous regardless of the local context and factors that may influence the level of worth associated with a particular criterion score. Consequently, Malczewski (2011) proposed a local value function, v_k^q . The local value function transforms different levels of the k -th criterion associated with the alternatives within the q -th neighborhood. It can be written as the follows:

$$v_k^q = \begin{cases} \frac{a_{ik} - \min_k^q\{a_{ik}\}}{r_k^q} & \text{for the } k\text{-th criterion to be maximized} \\ \frac{\max_k^q\{a_{ik}\} - a_{ik}}{r_k^q} & \text{for the } k\text{-th criterion to be minimized} \end{cases} \quad (4.3)$$

where $\min_k^q\{a_{ik}\}$ and $\max_k^q\{a_{ik}\}$ denote the minimum and maximum criterion

value for the k -th criterion for the i -th alternative in the q -th neighborhood respectively; r_k^q is local range which can be calculated by Equation 4.1. The local standardized value, v_k^q , ranges from 0 to 1. The value of 1 represents the most-desirable alternative in the q -th neighborhood, while 0 denotes the least-desirable alternative in that neighborhood.

The local standardization is used in this study to develop local IPM, and further applied in the case study to standardize raw scores of all criteria locally. However, according to the equation of local standardization, it sets an implicit requirement for the raw criterion values; specifically, the value of the local range must be different. The local range must be greater than 0; if the range is equal to 0, then the local standardization formula is invalid.

4.6 Local Ideal/Nadir Point

Local ideal point, v^{q*} , consists of all the best standardized criteria scores in the q -th neighborhood, while the worst standardized scores of criteria within neighborhood constitute the local nadir point, v_*^q . Both of them are n -dimensional vectors. They can be represented by Equation 4.4 and 4.5.

$$v^{q*} = (v_1^{q*}, v_2^{q*}, v_3^{q*}, \dots, v_n^{q*}) \quad (4.4)$$

$$v_*^q = (v_{1*}^q, v_{2*}^q, v_{3*}^q, \dots, v_{n*}^q) \quad (4.5)$$

The difference between local ideal/nadir point and global ideal/nadir point is that the former is the relatively best/worst point in each neighborhood, while the latter is the best/worst point for the whole study area. The ideal/nadir point may vary due to the effects of local conditions.

4.7 Localizing Criterion Weights

MCA problems typically involve criteria with varying importance. The relative importance of criteria is usually expressed by assigning weights to each criterion. There are many methods for estimating criterion weights including: ranking, rating, pairwise comparisons, and trade-off analysis (Hwang and Yoon, 1981). All of these approaches estimate weights based on the whole study area. In other words, each alternative is assigned the same set of weights. Consequently, the criterion weights are global. A global weight ignores the fact that the relative importance of criterion may change over geographical space. The localized form of the global weights is based on the range sensitivity principle as well as the definition of neighborhood. The local weight, w_k^q , is determined as follows:

$$w_k^q = \frac{\frac{w_k r_k^q}{r_k}}{\sum_{k=1}^n \frac{w_k r_k^q}{r_k}} \quad 0 \leq w_k^q \leq 1 \quad \text{and} \quad \sum_{k=1}^n w_k^q = 1 \quad (4.6)$$

Thus, the local weight, w_k^q , is a function of global weight (w_k), global range (r_k), and local range (r_k^q). Once the study area is determined, the global weight and range do not change. The values of local weight depend only on the local range that is defined based on the neighborhood q . Consequently, the values of local weight indirectly depend on the neighborhood scheme used for subdividing the study area. Therefore, the local weight can also be viewed as the neighborhood-based criterion weight (Feick and Hall, 2012; Malczewski, 2011).

It is important to indicate an essential difference between the concept of global and local weight. Global weight is obtained by expressing an individual or group of individuals (decision makers or experts) preferences with respect to the relative importance of evaluation criteria. It is determined empirically using one of the approaches for assessing criteria weights (Hwang and Yoon, 1981; Malczewski, 1999). The local weight is developed on the basis of a normative theory; that is, the range sensitivity principle. This principle assumes that “once the global weight for a given criterion has been determined, the local weight for that criteria can be estimated as a function of the global criterion weight modified by the relationships between the criterion local and global range” (Malczewski, 2011). Local weighting takes both the preferences and spatial heterogeneity into consideration and assigns different criteria weights to different alternatives.

4.8 Local TOPSIS

In this section, the local TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) will be presented. Compromise Programming (CP) can be viewed as part of TOPSIS. It determines the best alternative based on the weighted deviation between the ideal set of criteria values and the actual criteria values (see Section 3.1), while TOPSIS not only compares the weighted deviation but also the distance between the negative ideal set of criteria values and the actual criteria values. The basic concept of TOPSIS is that the selected best alternative from a finite set of alternatives should have the shortest distance from the ideal solution and the farthest distance from the negative ideal solution in a geometrical sense (Olson, 2004; Triantaphyllou and Lin, 1996). The local TOPSIS can be formulated as follows:

$$s^{p,q} = \left\{ \sum_{k=1}^n \left(w_k^q \frac{(v(a_{ik})^{q*} - v_k^q)}{v(a_{ik})^{q*} - v(a_{ik})_*^q} \right)^p \right\}^{\frac{1}{p}} \quad (4.7)$$

$$d^{p,q} = \left\{ \sum_{k=1}^n \left(w_k^q \frac{(v_k^q - v(a_{ik})_*^q)}{v(a_{ik})^{q*} - v(a_{ik})_*^q} \right)^p \right\}^{\frac{1}{p}} \quad (4.8)$$

$$f^{p,q} = \frac{d^{p,q}}{s^{p,q} + d^{p,q}} \quad (4.9)$$

where $s^{p,q}$ is the weighted distance between the local ideal point and i -th alternative based on the parameter p within the q -th neighborhood; $d^{p,q}$ is the weighted distance between the local nadir point and i -th alternative based on the parameter p within the q -th neighborhood; w_k^q is the local weight; $v(a_{ik})^{q*}$ and $v(a_{ik})_*^q$ are the best and worst standardized values of the k -th criterion for the i -th alternative within the q -th neighborhood, respectively; $f^{p,q}$ is relative closeness to the local ideal point for i -th alternative.

4.9 Summary

The aim of this chapter was to develop a local IPM to overcome the major limitation of the global IPM. The global IPM assumes preferences of decision makers (or experts) and the ideal/nadir point does not vary as the function of geographical space. In

other words, it assumes spatial homogeneity across the whole study area. The local IPM model was developed based on the following concepts:

1. Range Sensitivity Principle suggests that the criteria weights should be adjusted so that they are proportional to the ranges of the criterion values; other things being equal, the greater the range of values, the greater the weight that should be assigned to that criterion.
2. Neighborhood Definition; the whole study area is subdivided into local areas using a neighborhood scheme.
3. Localized Parameters; each alternative has its own parameters (local standardized values, local weights and local ideal/nadir points), which reflects the influences of the local context.

This research has achieved the first objective mentioned in Chapter 1; it has developed a new approach for GIS-MCA: the local IPM. The second objective of this study is to demonstrate the differences between global and local IPM.

Chapter 5

Case Study: The Quality of Employment in London, Ontario

This chapter focuses on the case study of evaluating the quality of employment in the City of London, Ontario to demonstrate the applicability of the local IPM model and compare the results generated by the local and global IPM. The first two sections of the chapter provide a short description of the study area and the input data. Then, the two IPM models are applied for evaluating and examining the spatial patterns of quality of employment. According to various ways of defining neighborhood, the local IPM adopts the Queen's case, and the 850m, 1600m and 2400m distance parameters for determining the neighborhood. Section 5.4 compares the results generated by the global and local IPM. The results show that these two methods generate substantially different spatial patterns of quality of employment in London (see Subsection 5.4.1). In addition, Moran's I test and t -test are used to show there is significant difference between the results generated by the global and local IPM (see Subsection 5.4.2).

5.1 Study Area

The study area is the City of London, Ontario. The city is located in Southwestern Ontario, Canada, midway between Toronto, Ontario and Detroit, Michigan. It has a metropolitan area population of approximately 458,000; and the City proper has a population of 352,000. London is one of the largest urban municipalities in Ontario and the 10th largest metropolitan area in Canada. The study area covers the central

part of the London metropolitan area (see Figure 5.1). It consists of 494 dissemination areas (which are geographic units designed by Statistics Canada). The dissemination areas are small, relatively stable geographic units composed of one or more census blocks. It is the smallest standard geographic area for which most census data are disseminated.

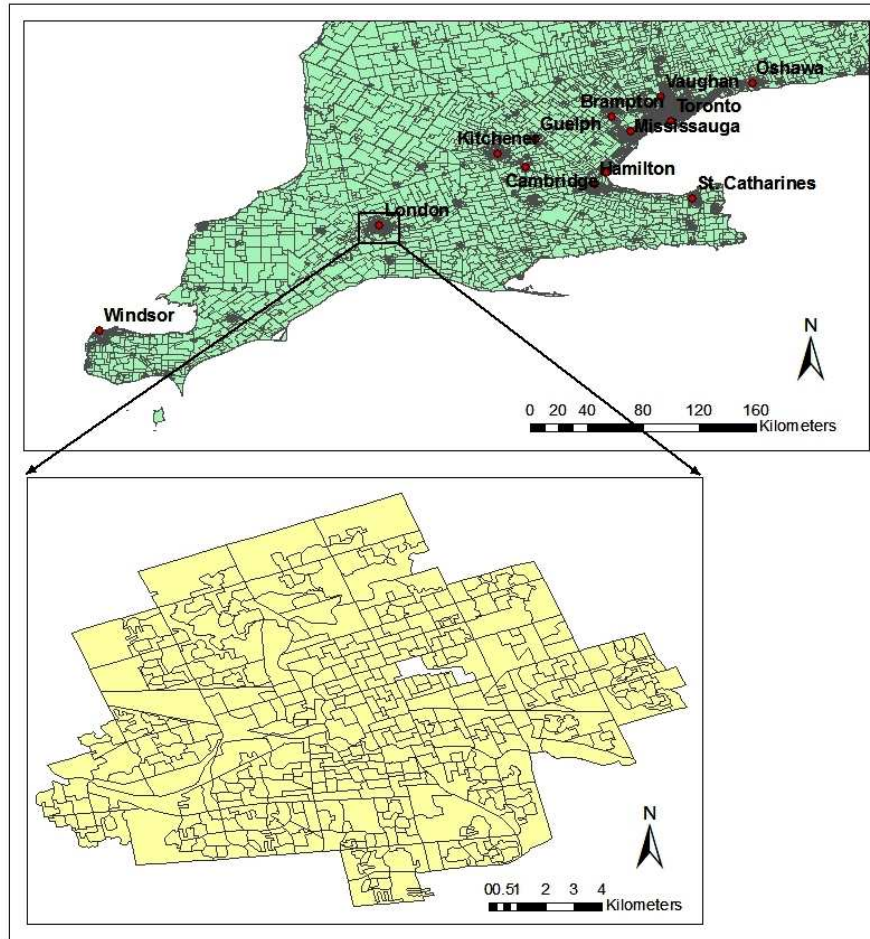


Figure 5.1: Study area: the City of London, Ontario. *Source: Map Library, UWO*

The best spatial unit of the data for the local IPM would be the census block. The relevant data sets about quality of employment are unavailable at the census block level. Therefore, the study uses the dissemination area as the basic spatial unit of analysis. Also, it is important to note that London Airport and military areas have been excluded from the analysis (see Figure 5.1).

5.2 Data

The case study aims at evaluating the quality of employment in London. The data (criterion) selection is based on the report by the Federation of Canadian Municipalities (Federation of Canadian Municipalities, 2001). The Federation initiated a project on a reporting system to monitor quality of life in the Canadian municipalities. Employment is one of the key aspects of participation in society for most people and families (Federation of Canadian Municipalities, 2001). In the FCM report, the quality of employment measures contain six aspects and nine criteria (indicators) including: employment rate, unemployment rate, permanent, temporary, self-employment, families receiving employment insurance, wages, long-term unemployment, and employment income as a percentage of total income.

Based on the categories provided by Census Canada and the FCM report, eight indicators are selected from the 2006 Census as the criteria for evaluating the quality of employment. They were: employment rate, unemployment rate, median income, and government transfer payments rate, percentage of paid workers, percentage of self-employed, percentage of without incomes, and percentage of incidence of low-income. The criteria are measured based on the population aged 15 years and over.

According to the local IPM model the local range must be greater than 0. This is because if the local range equals 0, then the local standardized criterion value is inadmissible due to the 0 value of the denominator of the local standardization formula (see Equation 4.3). For this reason, two criteria: unemployment rate and percentage of without incomes have been removed from the initial set of criteria. Table 5.1 shows the final set of 6 criteria be used in this study. The ‘MAX’ type of criterion indicates the greater the criterion value is, the greater its contribution to quality of employment; while the ‘MIM’ type represents the smaller the criterion value is, the greater its contribution to quality of employment (see Table 5.1).

Table 5.1: Criteria for evaluating the quality of employment in London, Ontario

#	Name	Description	Type
1	EMP_RAT	Employment rate (population 15 years and over)	MAX
2	MED_INC	Median income (population 15 years and over)	MAX
3	GOV_PAY	% of government transfer payment (composition of total income)	MIN
4	PAI_WOR	% of paid workers (population 15 years and over)	MAX
5	SEL_EMP	% of self-employed (population 15 years and over)	MAX
6	LOW_INC	Incidence of low income (population 15 years and over)	MIN

5.3 Data Analysis

In this section, two GIS-MCA methods (the global IPM and local IPM) are applied to evaluate the quality of employment in London, Ontario. The following two subsections discuss the procedure of these two methods.

5.3.1 Global Ideal Point Method

The global IPM method consists of four steps: (1) standardization, (2) global ideal and nadir point selection, (3) global weights assignment, (4) computation of overall score.

Criterion Standardization

Standardization is a method for transforming the raw criterion values into the value score ranging from 0 to 1 (see Section 4.5). This ensures that criteria measured on different scales are comparable. For example, some criteria, such as employment rate and percentage of paid workers, are measured using a percentage scale, while some criteria, such as median income, are measured on a monetary scale in dollars. Thus, it is impossible to obtain the overall scores by combining these map layers, which

have different units. Consequently, standardization is necessary to obtain a set of commensurate criteria.

One can interpret the standardization scores using the concept of value function. If a_{ik} is the raw score of the k -th criterion for the i -th alternative, then the value function, $v(a_{ik})$, is the worth or desirability of that alternative with respect to that criterion. The range procedure, one of the most often used approaches, is used in this study. The global standardization procedure is computed according to Equation 4.2. The types of criteria in Table 5.1 indicate which equations should be used for the criterion standardization.

Figure 5.2 displays the spatial patterns of the standardized values for each criterion. Figure 5.2a shows the standardized employment rates. It indicates that the downtown, northwest and south parts of London are characterized by high employment rates. The spatial pattern of median income shows the highest values in the northwest and southwest portions of London (see Figure 5.2b). The east part of London has a high government transfer payments rate (Figure 5.2c). According to Figure 5.2d and 5.2e, paid workers and self-employed people tend to concentrate in the downtown and west area of the City, respectively. Comparing Figures 5.2b, 5.2d, and 5.2e, the areas with higher median income usually have higher rates of self-employed and a lower percentage of paid workers. From Figure 5.2f indicates that the downtown area tends to have a higher percentage of incidences of low-incomes.

Global Ideal/Nadir Point

The global ideal/nadir point is the maximum/minimum value of each criterion within the whole study area (see Section 3.1). Given the standardization formula (see Equation 4.2), the maximum standardized criterion value equals 1; and the minimum standardized criterion value is equal to 0. Therefore, the ideal and nadir points have a value score equal to 1 and 0 for each of the six criteria, respectively. The ideal point $v(a_{ik})^*$ and nadir point $v(a_{ik})_*$ can be written as follows:

$$v(a_{ik})^* = (1, 1, 1, 1, 1, 1) \quad (5.1)$$

$$v(a_{ik})_* = (0, 0, 0, 0, 0, 0) \quad (5.2)$$

Global Weights

Criteria weights are used to express the relative importance of each criterion. In the conventional GIS-MCA, all the alternatives are assigned the same criteria weights (see Section 4.7). The pairwise comparison method (Saaty, 1980) is the most often used procedure in GIS-MCA applications (Malczewski, 2006). In this case study, the method is implemented using an Excel spreadsheet. Specifically, the method involves three steps. First, a pairwise comparison matrix is created. The matrix contains the relative importance of criteria based on pairwise comparisons using an underlying scale (see Table 5.2). The scale classifies the importance of two criteria into nine levels, ranging from 1 (equal importance) to 9 (extreme importance). A scenario of pairwise comparisons for demonstrating the concept of global IPM is shown in Table 5.3. The scores located in the upper right corner are integers whose definition can be found in Table 5.2. Calculating the scores of the rest of the pairwise comparison matrix is based on an assumption that the upper right corner can be reciprocal. For example, if the Criterion A is three times more important than Criterion B, then the importance of Criterion B must be equal to 1/3 of the importance of Criterion A. In the same way, one can obtain the rest of the pairwise comparison matrix.

Table 5.2: Scale for Pairwise Comparison, *Source: Adapted from Saaty (1980)*

Intensity of Importance	Definition
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extreme importance

Second, the procedure for computing a set of criteria weights involves the normalization of each column of the pairwise comparison matrix. Specifically, the criteria weights are computed by dividing each pairwise comparison (Table 5.3) by the sum of scores for each criterion and then calculated using an average of the normalized values (see Table 5.4). The third step is to check whether the comparisons are consistent based on a consistency ratio (CR). Typically, the pairwise comparison has a reasonable level of consistency when $CR < 0.10$. If $CR \geq 0.10$, it indicates the pairwise

Table 5.3: Pairwise Comparison Matrix

	MED_INC	EMP_RAT	GOV_PAY	PAI_WOR	SEL_EMP	LOW_INC
MED_INC	1.00	3.00	5.00	5.00	5.00	4.00
EMP_RAT	0.33	1.00	2.00	3.00	4.00	2.00
GOV_PAY	0.20	0.50	1.00	1.00	1.00	1.00
PAI_WOR	0.20	0.33	1.00	1.00	1.00	1.00
SEL_EMP	0.20	0.25	1.00	1.00	1.00	1.00
LOW_INC	0.25	0.50	1.00	1.00	1.00	1.00
Sum	2.18	5.58	11.00	12.00	13.00	10.00

comparisons may be inconsistent. In this case, the comparisons should be reviewed and revised. The CR is defined based on the value of lambda (λ), consistency index (CI), and random index (RI). However, the very first step is to get the consistency vector and weighted sum vector. The weighted sum vector of each criterion is calculated by multiplying the criteria weights (see Table 5.4) by the row of that criterion in Table 5.3. For instance, the weighted sum vector of the median income criterion equals 2.72 (that is, $0.44*1+0.21*3+0.09*5+0.08*5+0.08*5+0.09*4 = 2.72$). The consistency vector of each criterion is determined by dividing the weighted sum vector by its criterion weight. Table 5.5 shows the weighted sum vectors and consistency vectors.

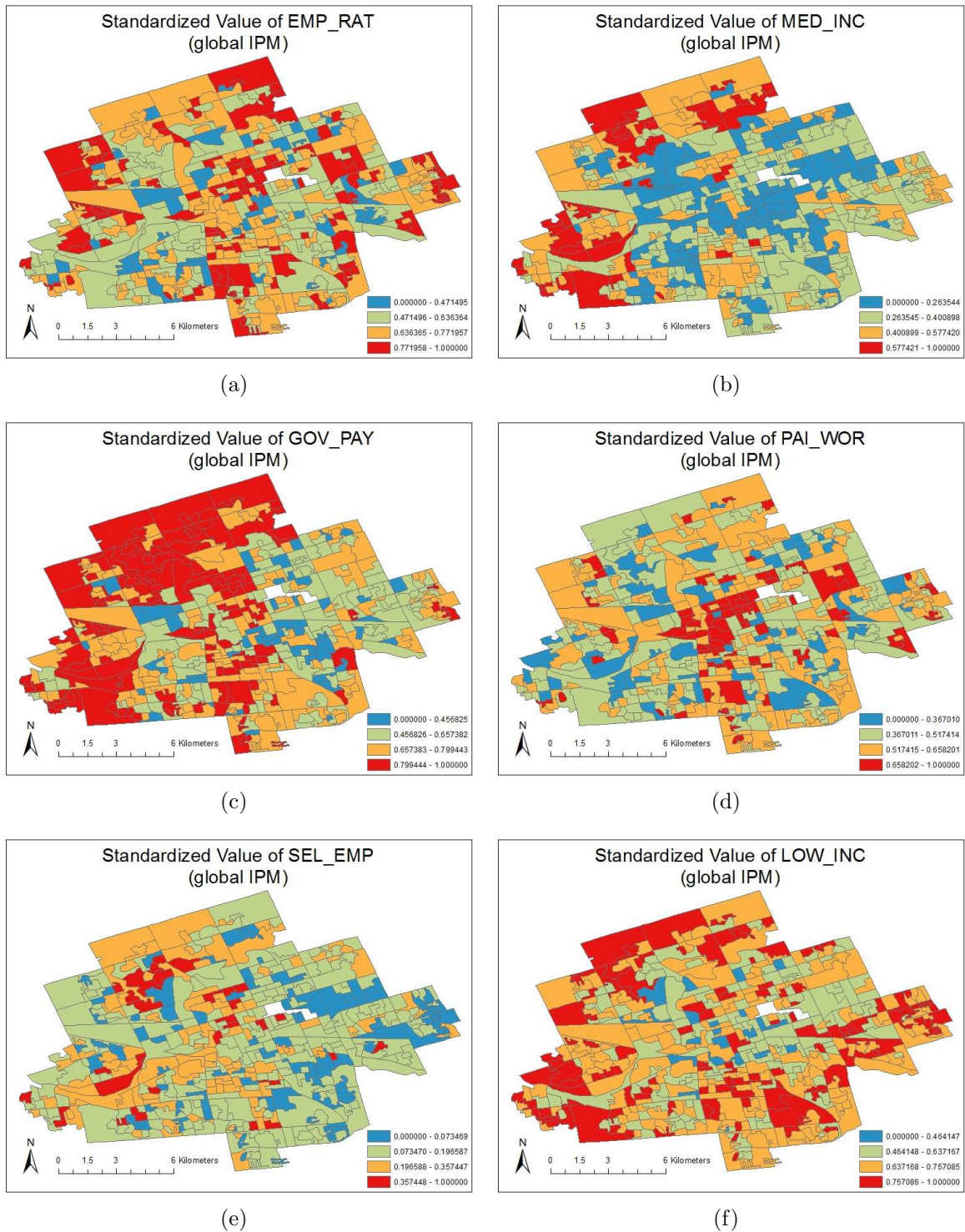


Figure 5.2: Global standardized criterion values of: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

Table 5.4: Criterion Weights

	MED_INC	EMP_RAT	GOV_PAY	PAI_WOR	SEL_EMP	LOW_INC	Weights
MED_INC	0.46	0.54	0.45	0.42	0.38	0.40	0.44
EMP_RAT	0.15	0.18	0.18	0.25	0.31	0.20	0.21
GOV_PAY	0.09	0.09	0.09	0.08	0.08	0.10	0.09
PAI_WOR	0.09	0.06	0.09	0.08	0.08	0.10	0.08
SEL_EMP	0.09	0.04	0.09	0.08	0.08	0.10	0.08
LOW_INC	0.11	0.09	0.09	0.08	0.08	0.10	0.09
Sum	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 5.5: Weighted Sum Vector and Consistency Vector

	MED_INC	EMP_RAT	GOV_PAY	PAI_WOR	SEL_EMP	LOW_INC	Weighted sum	Consistency
MED_INC	0.44	0.64	0.44	0.42	0.41	0.37	2.72	6.15
EMP_RAT	0.15	0.21	0.18	0.25	0.33	0.17	1.29	6.09
GOV_PAY	0.09	0.11	0.09	0.08	0.08	0.08	0.53	6.02
PAI_WOR	0.09	0.07	0.09	0.08	0.08	0.08	0.50	5.96
SEL_EMP	0.09	0.05	0.09	0.08	0.08	0.08	0.48	5.92
LOW_INC	0.11	0.11	0.09	0.08	0.08	0.08	0.56	6.01
							Sum	36.15

Lambda (λ) is the average of the consistency vector. Once the consistency vectors are obtained, lambda can be computed as follows:

$$\lambda = \frac{\text{sum of consistency vectors}}{n} = 36.15/6 = 6.03 \quad (5.3)$$

The value of λ is always greater than or equal to the number of criteria under consideration (n) for positive, reciprocal matrixes, and $\lambda = n$ if the pairwise comparison matrix is a consistent matrix (Saaty, 1980). $\lambda - n$ can be viewed as the degree of inconsistency. The consistency index is calculated as follows:

$$CI = \frac{\lambda - n}{n - 1} = (6.03 - 6)/5 = 0.01 \quad (5.4)$$

Consistency ratio (CR) is defined by Equation 5.5.

$$CR = \frac{CI}{RI} \quad (5.5)$$

RI refers to the random index which depends on a number of criteria. RI can be selected from Table 5.6. For six criteria, the RI equals 1.24. Thus, $CR = 0.01/1.24 = 0.01 < 0.10$, which means that the pairwise comparison matrix has a reasonable level of consistency. The criterion weights can be further used in the following analysis procedure (see Table 5.4).

Table 5.6: Random Index, *Source: Adapted from Saaty (1980)*

n	RI	n	RI	n	RI
1	0.00	6	1.24	11	1.51
2	0.00	7	1.32	12	1.48
3	0.58	8	1.41	13	1.56
4	0.90	9	1.45	14	1.57
5	1.12	10	1.49	15	1.59

Computing the global overall score

To compute the overall scores, f_i^p (see Equation 3.8), the parameter p should be determined. The greater the parameter p is, the greater the emphasis that is placed

on larger separations (see Section 3.1). The criteria in selecting the compromise solution become the avoidance of low value of any criterion as the p increases (Karni and Werczberger, 1995). The parameter $p = 2$ was selected based on previous research (Elaalem et al., 2011; Malczewski et al., 1997; Salt and Dunsmore, 2000; Simonovic, 1989; Tkach and Simonovic, 1997). Therefore, final overall scores can be obtained by inputting all the calculated data to the global IPM Equations 3.5, 3.7 and 3.8. All the computations have been done in an Excel spreadsheet and visualized in ArcGIS (see Figure 5.3).

Figure 5.3 shows a spatial pattern of the quality of employment in London. It indicates that the quality of employment tends to be higher in the north and southwest parts of London than the east and southeast sections. The highest quality of employment areas cluster in the north and southwest. Most areas with lower quality of employment are located in the east and southeast parts of London. A comparison of the spatial patterns of the overall scores to the standardised criteria maps (Figure 5.2) indicates that areas characterized by high overall scores correspond to areas of London with high median income, employment rate, and percentage of self-employment, while the lower overall score areas can be found in sections of London where there are high government transfer payment rates, percentages of paid workers and incidences of low incomes.

5.3.2 Local Ideal Point Method

In this subsection, the quality of employment in London will be evaluated by applying the local IPM model. All the input data are the same as those used in Subsection 5.3.1.

Neighborhood Definition

There are two main ways of defining a neighborhood (see Section 4.3). They are the adjacency measure and distance based method. In this case study, the adjacency measure (Queen's case) and the first type of distance based methods are applied. For the distance based method, a reasonable distance should be selected for defining neighbors. This study uses three different distances (850m, 1600m, and 2400m) to see how they influence the spatial pattern of overall scores. In this case study, the

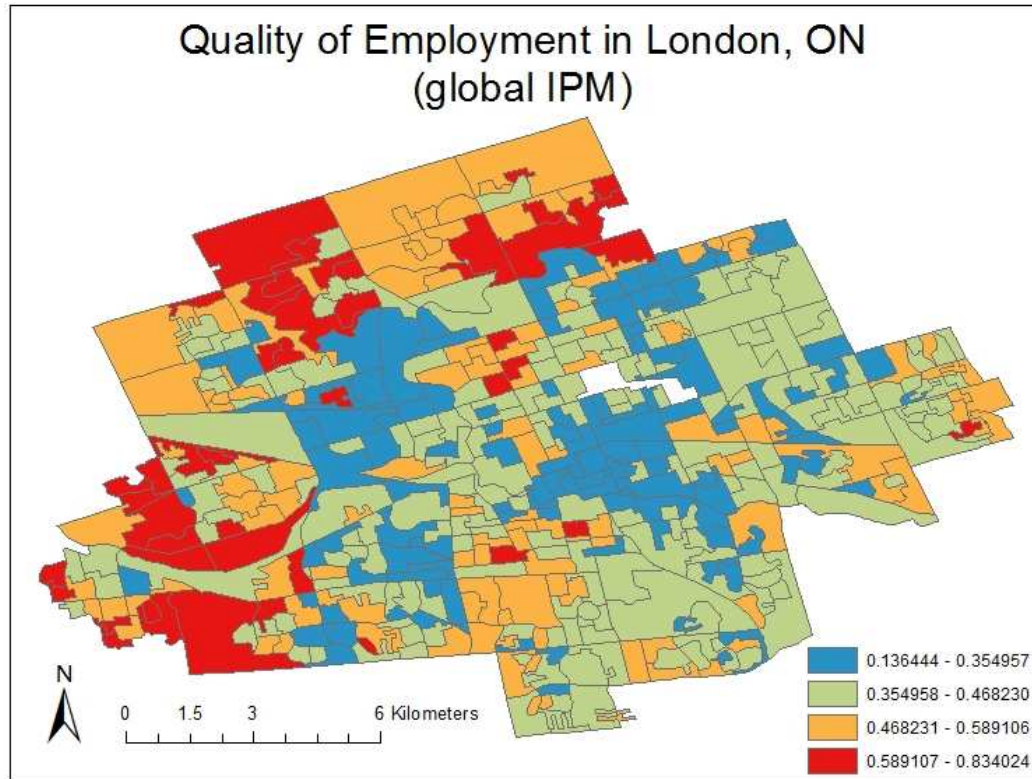


Figure 5.3: Global IPM: Quality of employment

smallest distance (850m) is selected to ensure that each polygon has at least one neighbor. If the polygon has no neighbor, then the local range will be 0, and the following analysis will be meaningless (see Section 4.5). The distance of 2400m is selected based on previous research by Malczewski and Poetz (2005). ArcGIS is used for defining neighborhoods.

Local Standardization

Local standardization differs from the conventional standardization in terms of parameters (the range, minimum and maximum criterion values) used in computation. In conventional standardization, the range and minimum/maximum criterion values do not vary as a function of geographical space, which means all the polygons have the same parameters for calculating their standardized values. However, in local standardization, the geographic space does influence the parameters. The range and minimum/maximum criterion values are determined within each neighborhood, which means each polygon has its own range and minimum/maximum criterion values. This

kind of range is called local range, which can be computed by using Equation 4.1. Local standardization is expressed as Equation 4.3. To this end, each polygon has four different standardized values for every criterion due to the size of its neighborhood. Figures 5.4, 5.5, 5.6, and 5.7 represent the local standardized criteria values based on the neighborhood definition according to: the Queen's case, and distance of 850m, 1600m, and 2400m, respectively. The computation has been programmed in JAVA (see Appendix A).

Local Ideal/Nadir Point Selection

Once the local criterion standardization is completed, the best and worst standardized value for each criterion within a given neighborhood can be selected. The best standardized values in each neighborhood constitute the ideal point of the focal polygon of that neighborhood. The nadir point of each neighborhood is identified by the worst standardized criteria values within that neighborhood. Therefore, every polygon has its own ideal and nadir points. It is important to note that the values of the local ideal and nadir point can be different than 1 and 0, respectively, while the global ideal and nadir point has its value of 1 and 0, respectively (see Subsection 5.2).

Local Weights

Local weights are calculated using Equation 4.6, which is a function of the global weights as well as the global and local ranges. The local weights vary from one polygon to another. Therefore, they can be mapped with GIS to show their spatial patterns. Figures 5.8, 5.9, 5.10, and 5.11 display the spatial patterns of criterion weights based on neighborhoods defined by Queen's case, 850m, 1600m, and 2400m, respectively.

Computing the local overall scores

Equations 4.7, 4.8, and 4.9 are applied to calculate the local overall scores. Parameter p equals 2 to make sure that the local overall scores are comparable with the global scores. Figure 5.12 shows the overall scores generated by the local IPM.

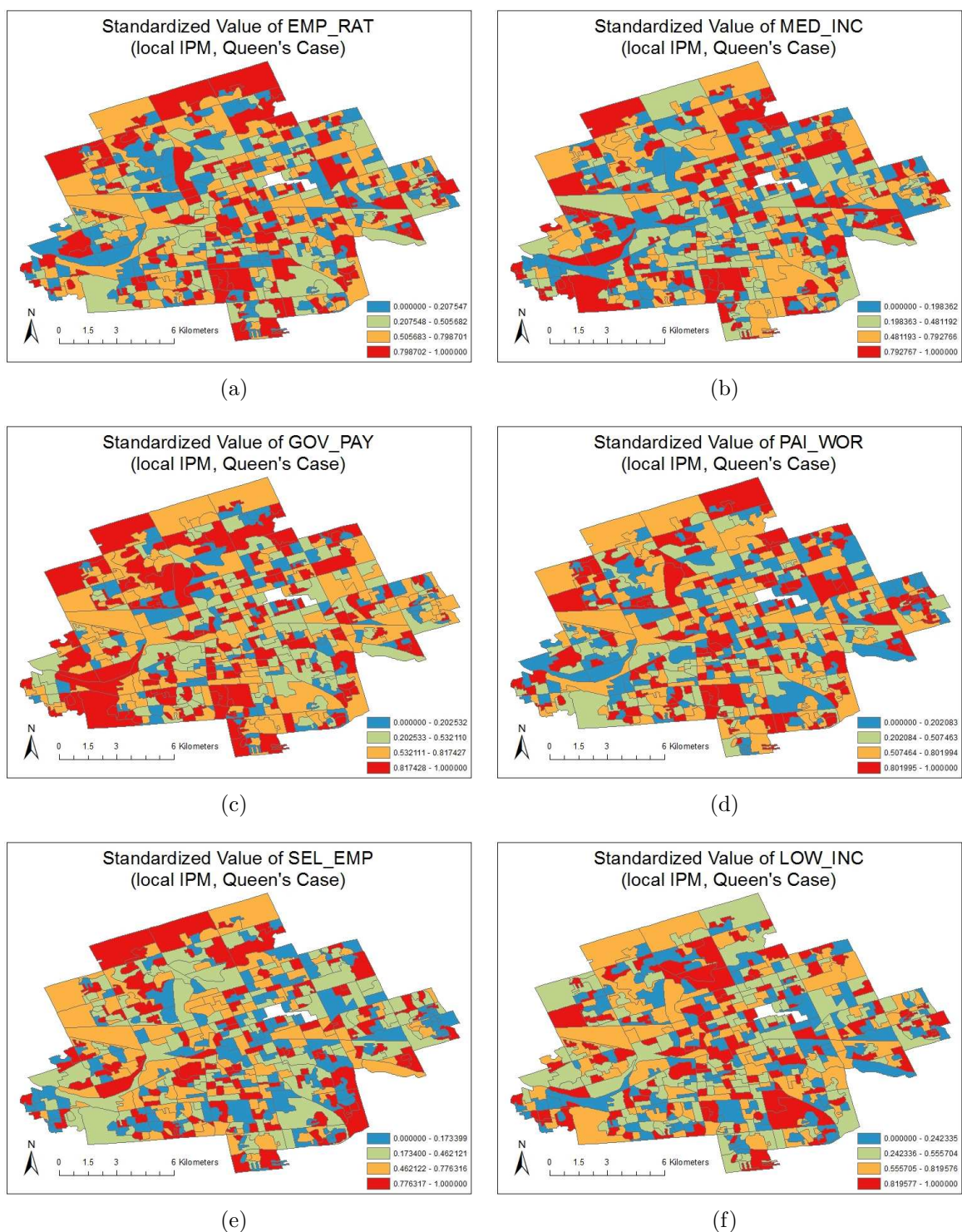


Figure 5.4: Local standardized criterion values based on Queen's case for: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

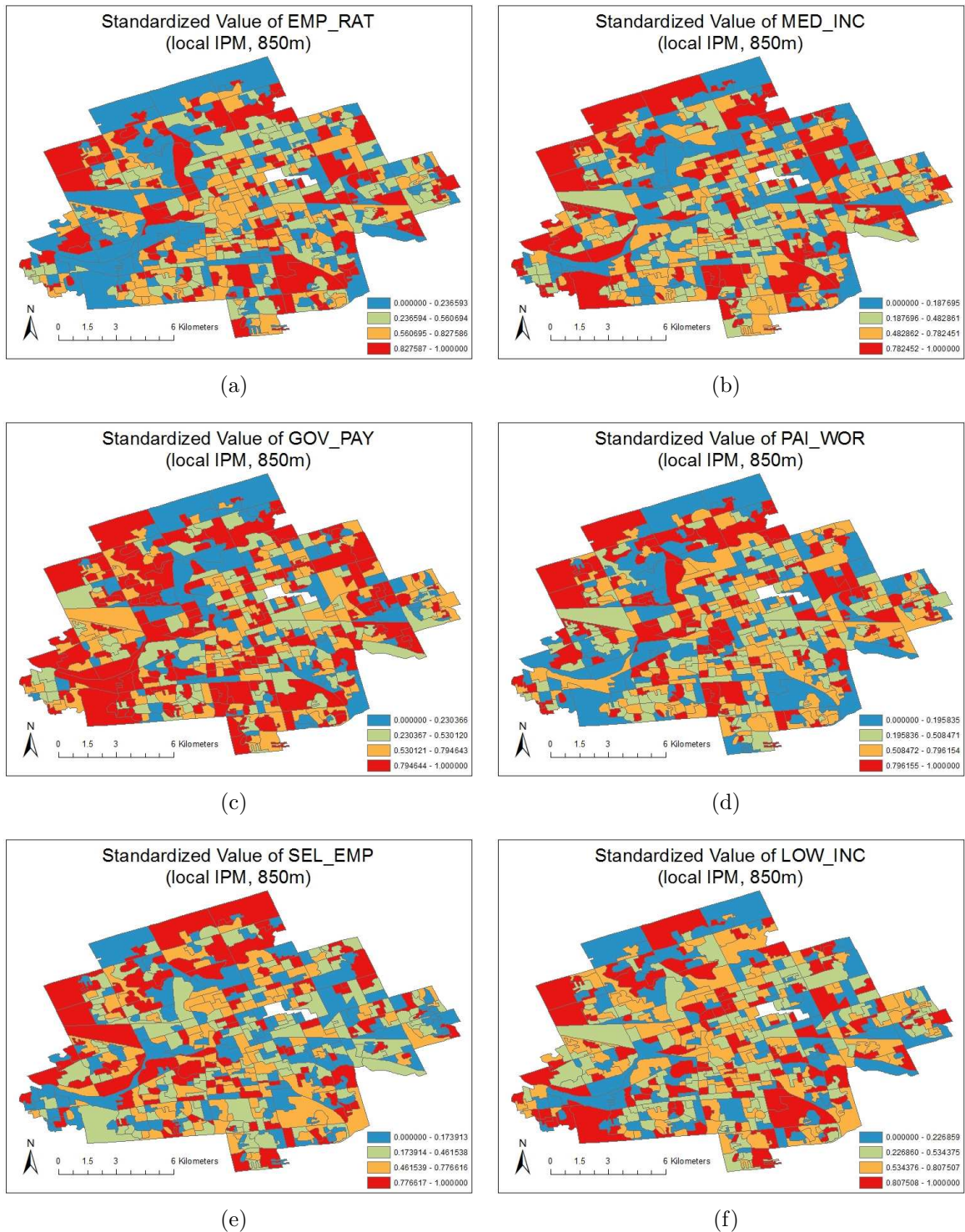


Figure 5.5: Local standardized criterion values based on neighborhoods defined by 850m for: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

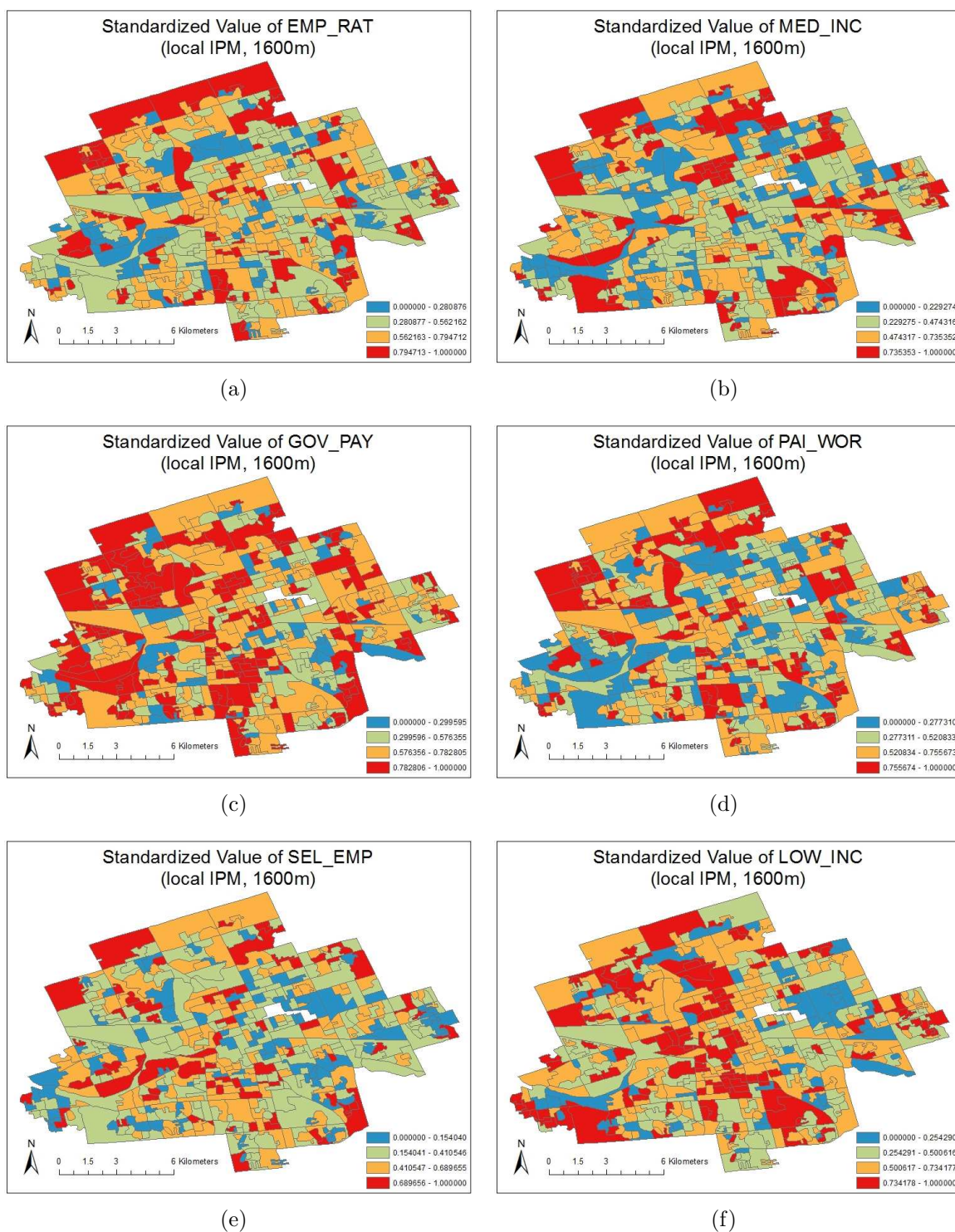


Figure 5.6: Local standardized criterion values based on neighborhoods defined by 1600m: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

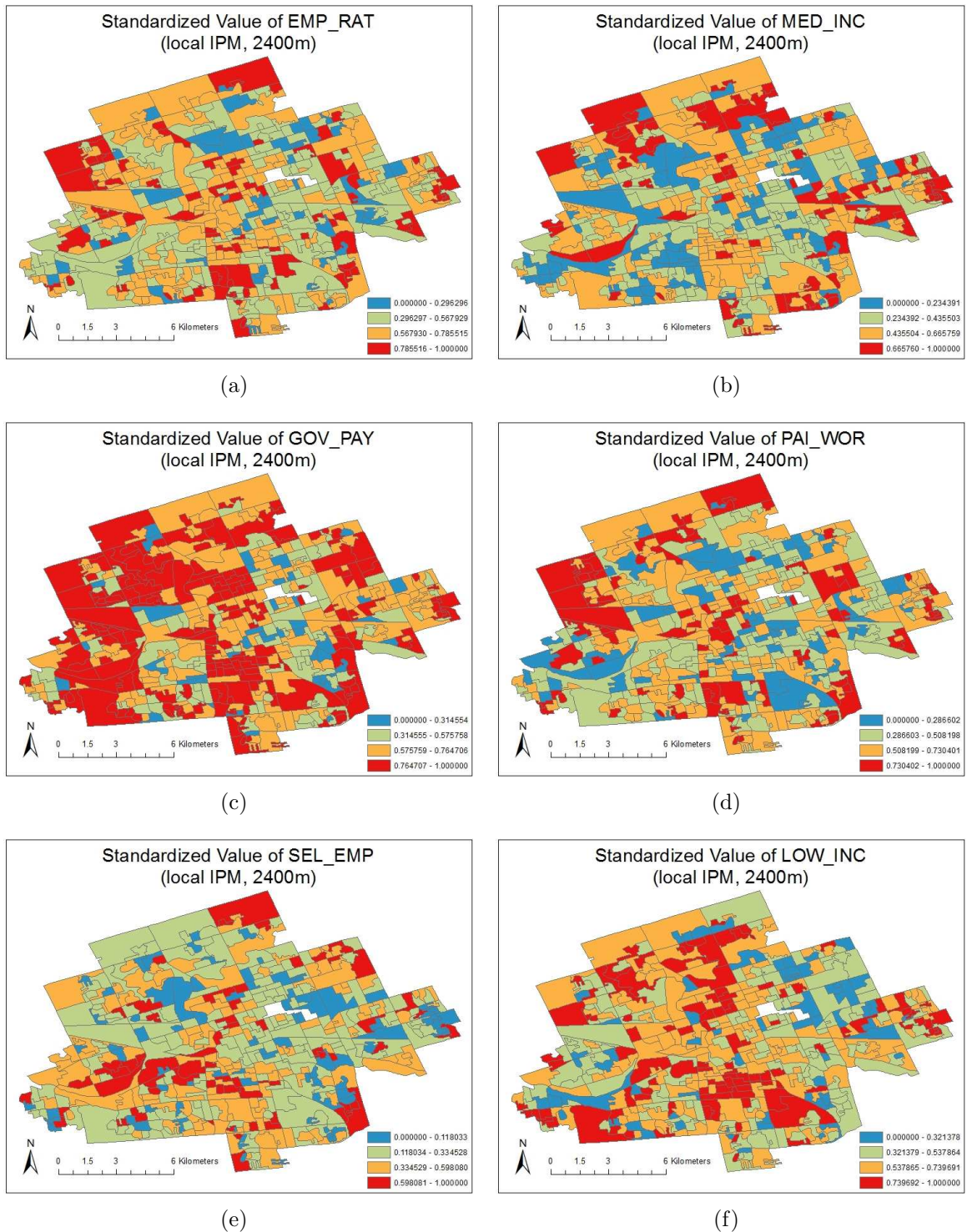


Figure 5.7: Local standardized criterion values based on neighborhoods defined by 2400m for: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

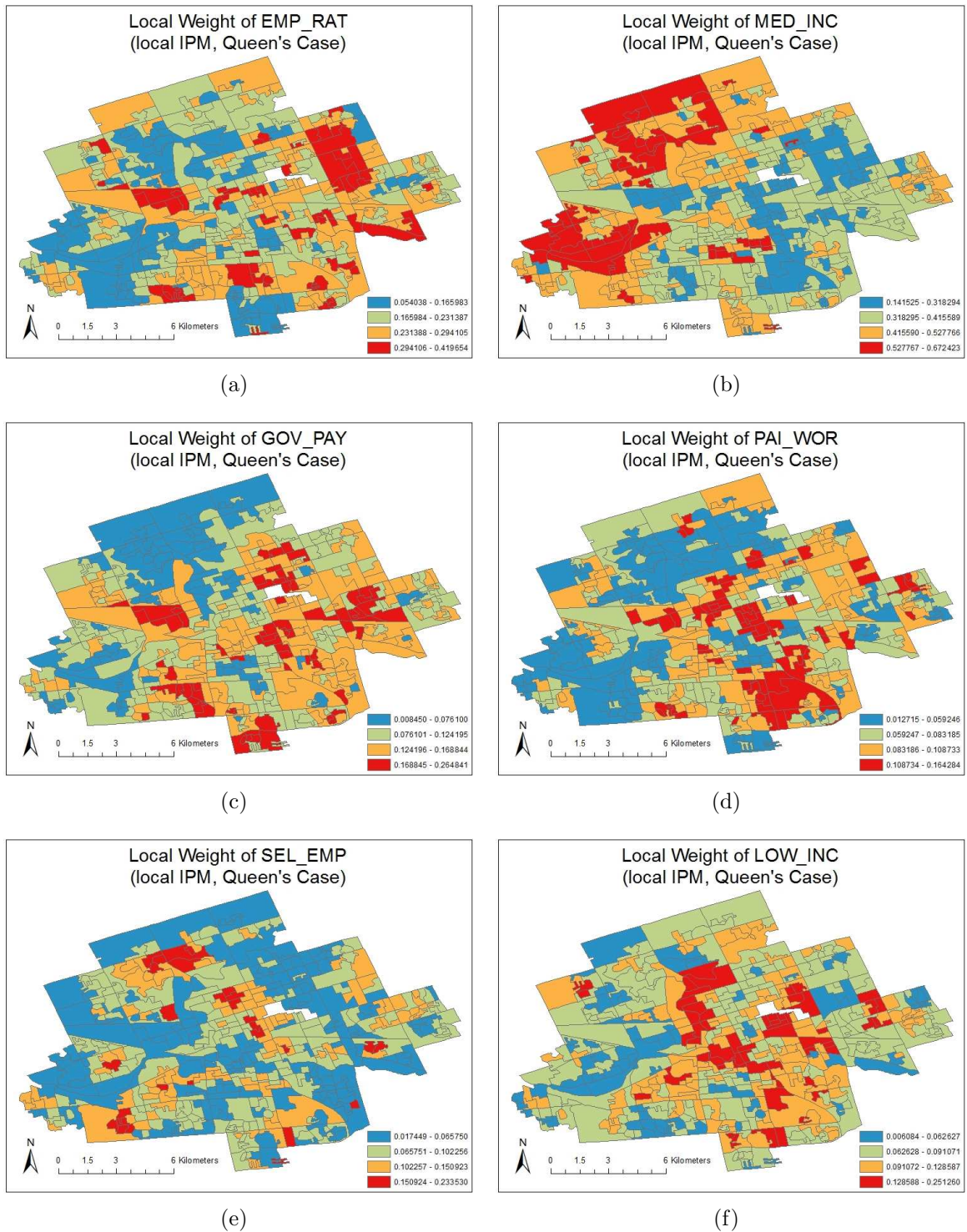


Figure 5.8: Local criterion weights based on Queen's case: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

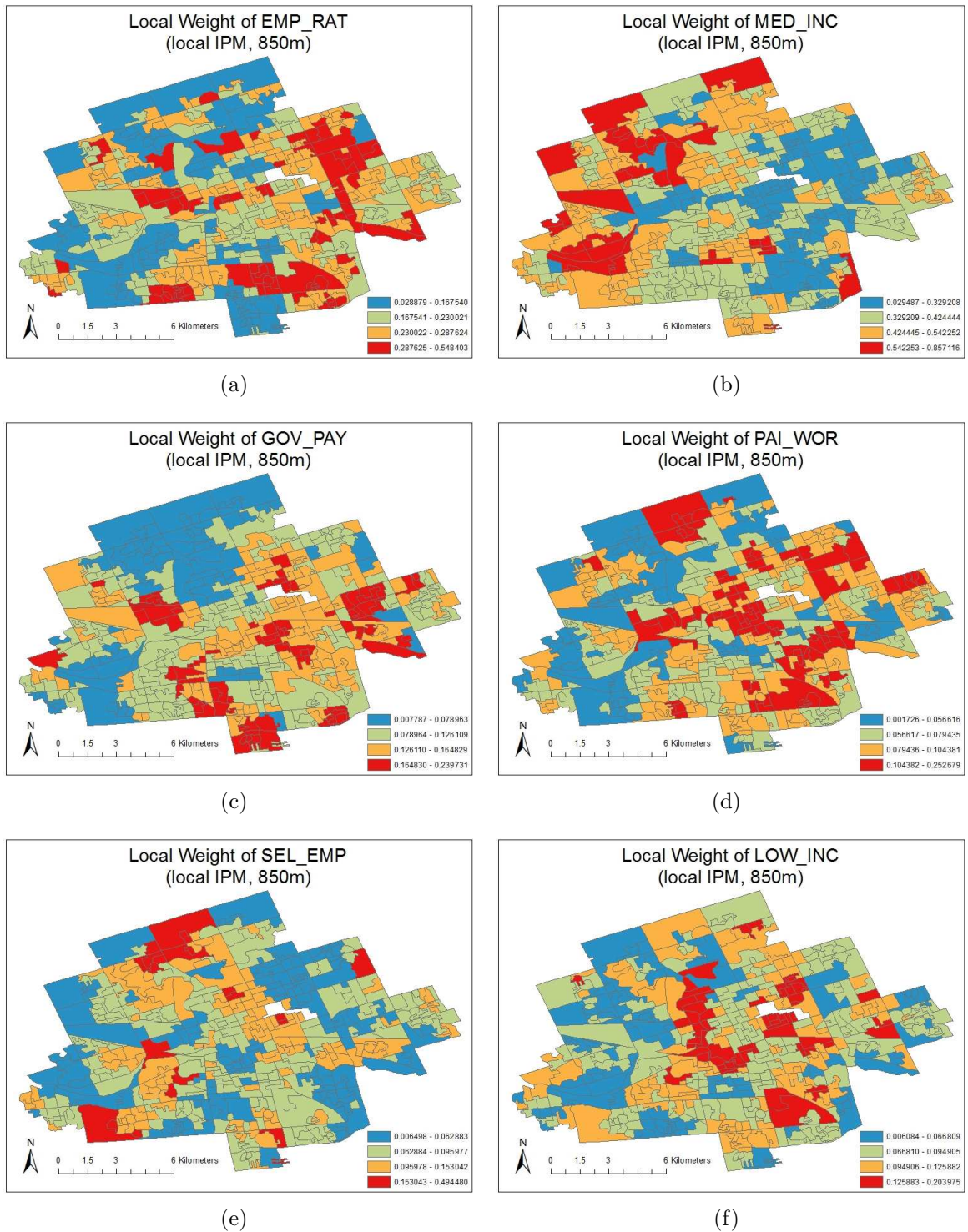


Figure 5.9: Local criterion weights based on neighborhoods defined by 850m: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

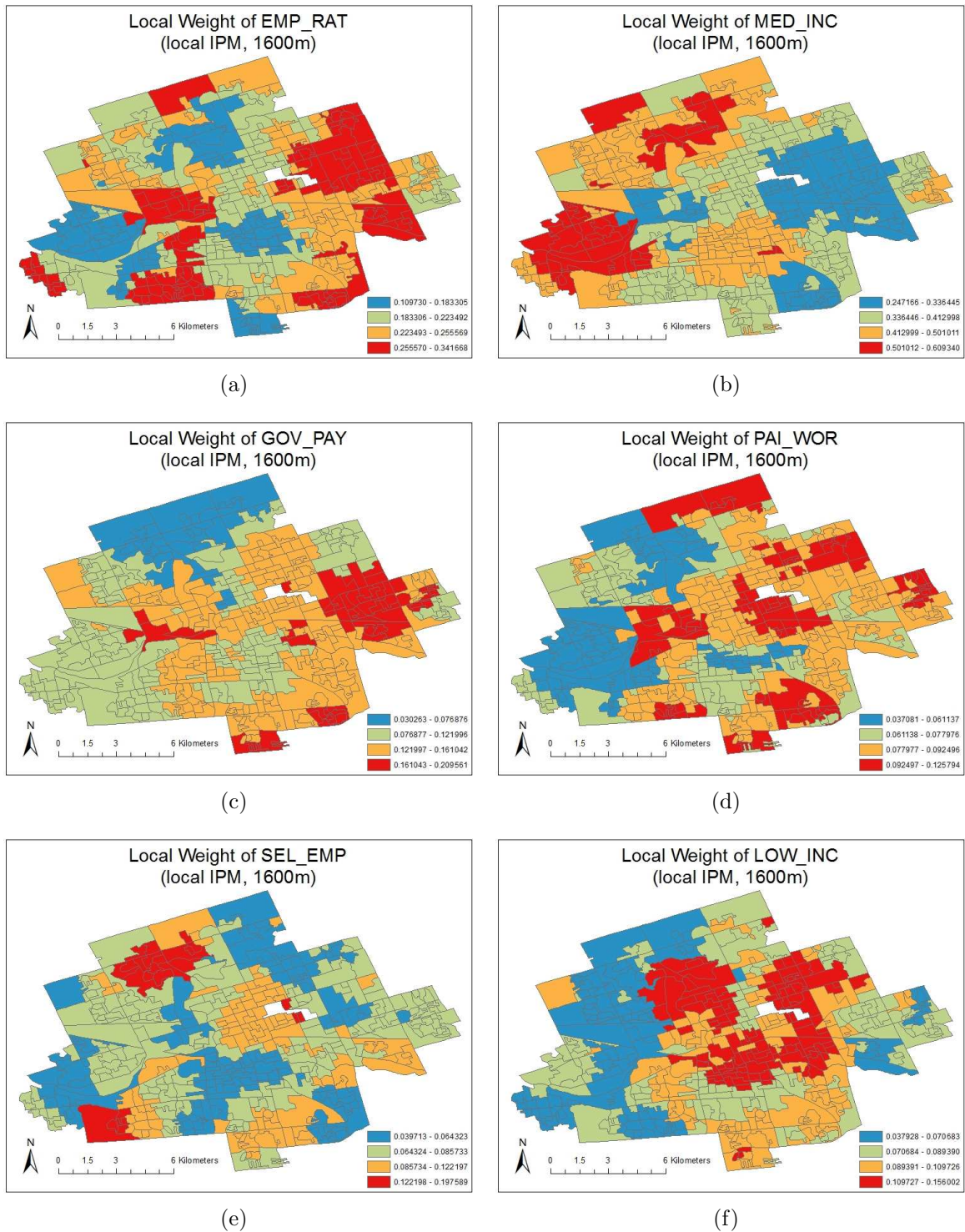


Figure 5.10: Local criterion weights based on neighborhoods defined by 1600m: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

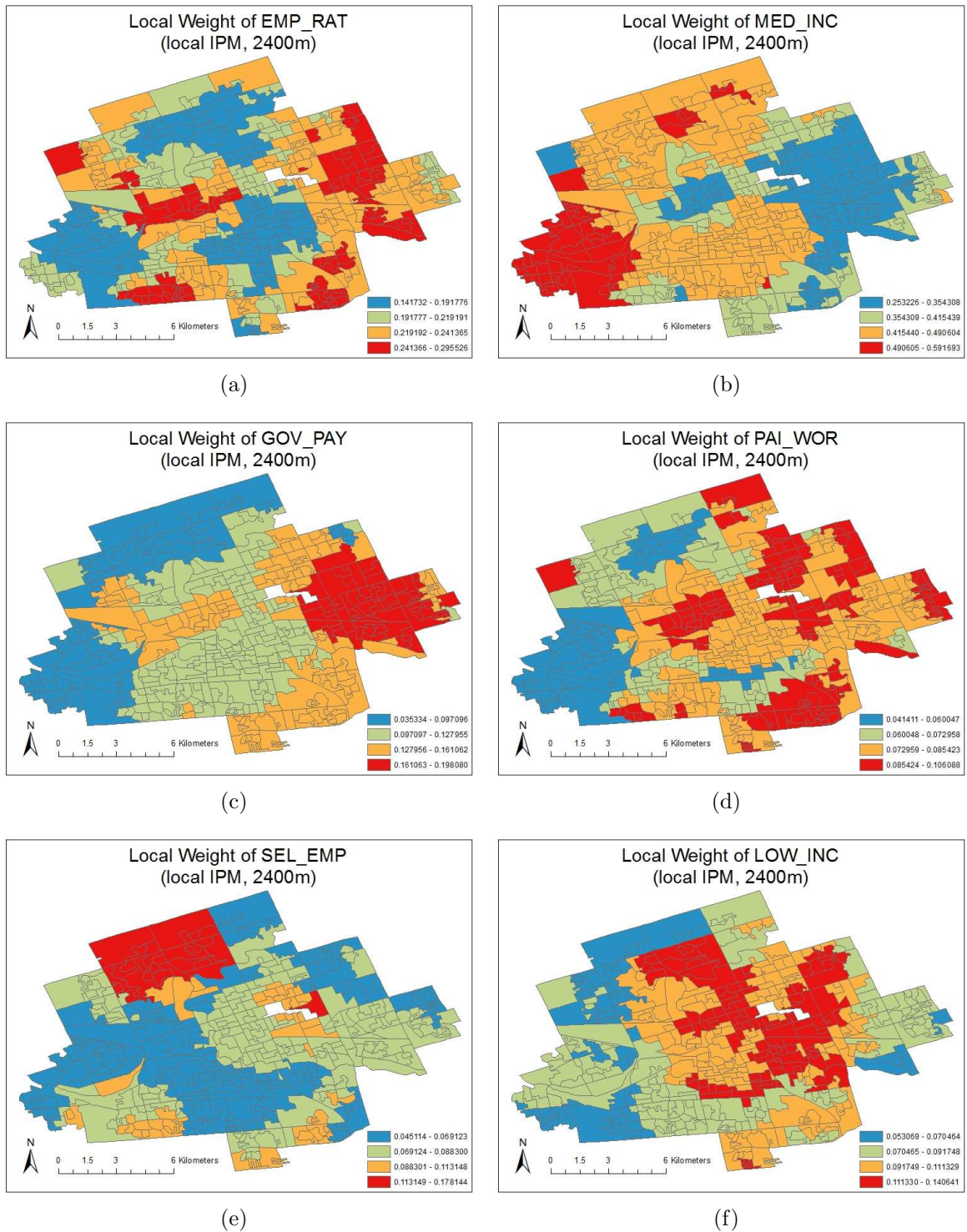


Figure 5.11: Local criterion weights based on neighborhoods defined by 2400m: (a) employment rate, (b) median income, (c) government transfer payment rate, (d) percentage of paid workers, (e) percentage of self-employed, and (f) incidence of low income.

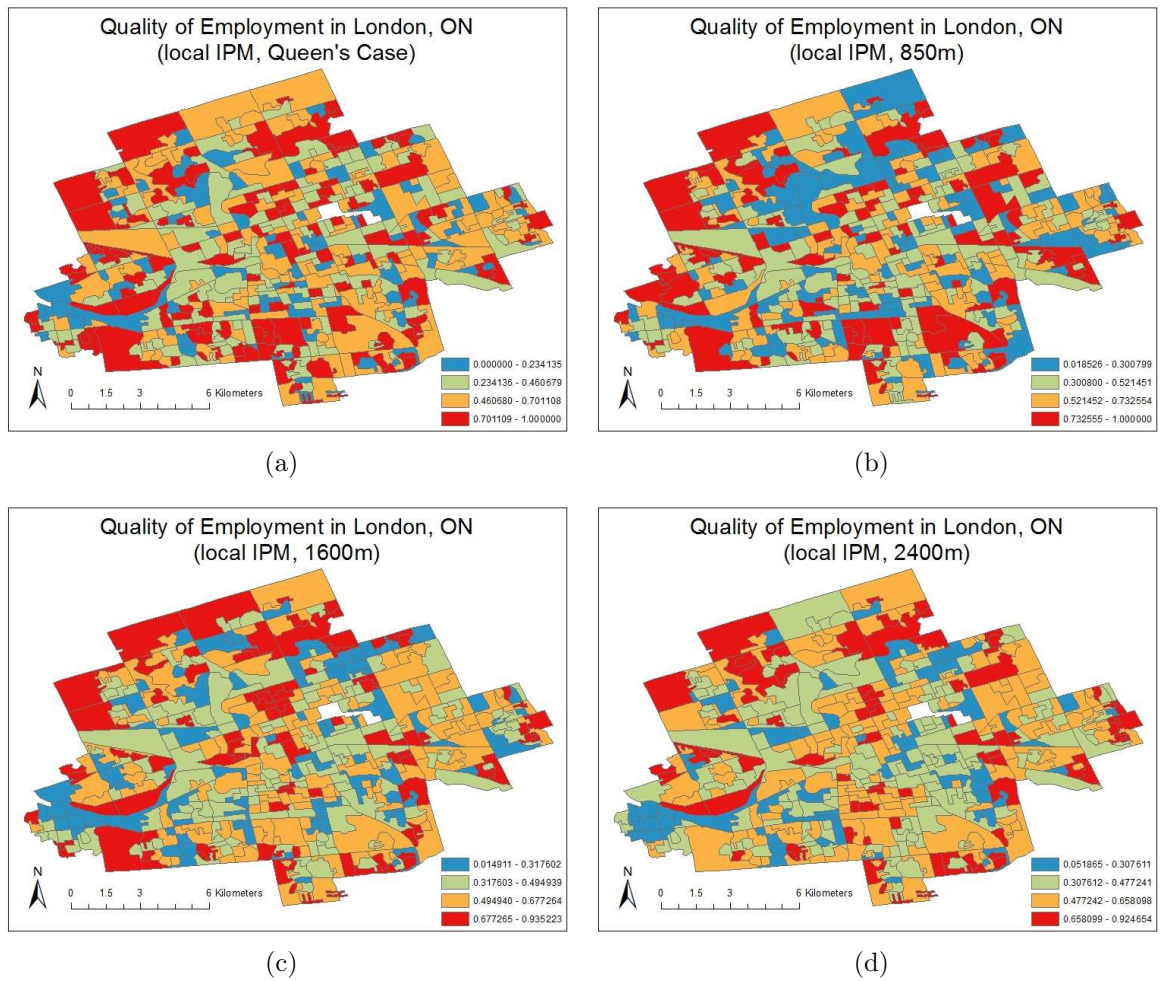


Figure 5.12: Overall scores of quality of employment generated by local IPM for neighborhoods defined based on: (a) Queen's case, (b) 850m, (c) 1600m, and (d) 2400m.

5.4 Discussion

This section compares the standardized values, criteria weights, and overall scores generated by the global and local IPM. For standardized values and criterion weights, the median income criterion is discussed as an example to demonstrate the differences between the two forms of IPM.

5.4.1 Global vs. Local Results

Global and local standardized criterion values

The comparative analysis of global and local criterion maps focuses on one given criterion (median income) as an example to show the differences between two forms of IPM. The spatial pattern of the standardized values of median income generated by the global IPM shows that the areas with high median income concentrate in the north, northwest, and southwest parts of London (see Figure 5.13a). Unlike the spatial pattern generated by the global IPM, the local model results in a dispersed spatial distribution. In other words, the results show local patterns at a neighborhood scale. One can point out the areas with high value within each neighborhood. The local IPM models based on the neighborhood defined by the Queen's case and distance of 850m generated similar spatial patterns of standardized values (see Figure 5.13b and 5.13c). Comparing Figures 5.13c, 5.13 and 5.13e, one can conclude that the local standardization which defines neighborhoods with relative small distance shows more peak values, both high and low. The smaller the neighborhood is, the more detailed information about the local pattern can be captured. Also, the local IPM patterns become more similar to the spatial pattern generated by the global IPM along with increasing the distance parameter used for defining neighborhoods.

Global and local criterion weights

Figure 5.14 shows the spatial patterns of local weights assigned to the criterion of median income. The global weight of median income is 0.44, which means all the polygons have the same weight value. In contrast, the local weights are spatially distributed (see Figures 5.8, 5.9, 5.10, and 5.11). The spatial pattern of local weight for the median income criterion indicates that the high values tend to be located

in the northeast part of London, while areas characterized by low values cluster in the central and southeast sections of the study area. In Figures 5.14a and 5.14b the distributions of the polygons with high local weight for median income are more dispersed compared with Figure 5.14c and 5.14d. This may be attributed to the size of the neighborhoods. When the size of neighborhood is small, local criteria ranges of neighborhoods are more likely to be different. This will also result in a greater variation of local criteria weight. Therefore, Figure 5.14 shows that criteria weights do vary over geographical space, and the local weights reflect the changes in the local condition.

Global and local overall scores

Figure 5.15 shows the spatial pattern of the quality of employment in London. A spatial global trend can be observed. Figure 5.15a shows that the neighborhoods with high quality of employment tend to be located in the north and west sections of London; while the low quality of employment areas are mostly found in the east and southeast parts of the study area. On the other hand, the high score areas spread more evenly according to the local IPM (see Figures 5.15b and 5.15c). One can argue that the results generated by the local IPM show more detail information about quality of employment. One can identify the peak overall scores of certain neighborhoods by using local IPM. For example, it is impossible to pick the polygon with relatively high quality of employment from the large areas of high quality of employment displayed in Figure 5.15a. However, based on the same way of classification for the four groups (see the map legend), one can easily distinguish the polygons with high overall scores in the same area.

A comparison of the spatial patterns generated by the local IPM suggests that the results are sensitive to the method of defining neighborhoods (see Figure 5.15b, 5.15c, 5.15d, and 5.15e). The neighborhoods defined by Queen's case and 850m are smaller than the ones determined by 1600m and 2400m; consequently, the polygons with highest values in each neighborhood are more likely to be different. The Queen's case considers the polygons around the focal unit as its neighbors. In the local IPM based on neighborhoods defined by 850m, the value of the distance parameter is just large enough to ensure that each focal unit has at least one neighbor.

The peak values, both high and low, tend to decrease with the increasing distance

used for defining neighborhoods (see Figures 5.15c, 5.15d, and 5.15e). The general patterns tend to be more similar to the one generated by global IPM along with increasing the distance parameter of the local IPM model. One may conclude that local IPM focuses on capturing the peak values of each neighborhood. The smaller the neighborhood is, the more detailed local information or peak values can be obtained. In fact, the global IPM can be considered as an extreme case of the local IPM when the distance used to define neighborhoods is large enough to ensure that the neighborhoods of each polygons consists of all polygons within the study area. In such case, the local range (r_k^q) is equal to global range (r_k), and the local standardization is equivalent to the global standardization. Also, the local weights are equal to the global ones. In a nutshell, the spatial patterns generated by the global and local IPM provide us with different information about quality of employment. The global pattern displays the absolutely high or low values based on whole study area, while the local approach captures the relatively high and low values for each neighborhoods. The global IPM cannot generate the results of local IPM, but the global pattern can be generated by a suitable form of the local model.

The results of the global and local IPM can also be examined using scatter plots (see Figure 5.16). The y axis of these plots shows the global IPM values, while the x axis of the scatter shows the results generated by local model. The points represent all polygons within the study area. Two reference lines are added into these plots as well: the lines representing the mean values generated by the local and global IPM. They divide the chart into four quadrants (see Table 5.7). The points (polygons) in the first or third quadrant indicate that their ‘positions’ in global and local distributions are similar: they are all above/below the average values. However, those points that fall into the second or fourth quadrant represent opposite situations. For example, they can be higher than average values for the global IPM, but lower than average for the local IPM, and vice versa.

The highlighted polygons in Figure 5.17 fall into the second quadrant of each scatter plot. These polygons are above the global mean value, but below the local average. The base map shows the overall scores of quality of employment in London generated by the global IPM. As discussed, the local IPM aims at capturing the relatively high and low value in each neighborhood. Therefore, the spatial configuration of highlighted polygons varies along with changing size of neighborhood (see Figure 5.17). However, the spatial patterns do share some common characteristics. First, the highlighted polygons tend to be located in the north, southwest, and south of the

Table 5.7: Description of the scatter plot quadrants

Quadrant	Location	Description
1	Upper right corner	The global and local results are above their mean values.
2	Upper left corner	The global results are above the mean, while the local results are below the mean.
3	Lower left corner	The global and local results are below their mean values.
4	Lower right corner	The global results are below the mean, while the local results are above the mean.

core area of London. One can argue that there is significant difference in the quality of employment between polygons within those local areas. Second, most of the highlighted polygons are in the category of medium-to-high quality of employment but not in the group with highest quality of employment within the whole study area. They are more likely to be classified into the group with lower quality of employment in the local IPM, because, within the local area, they are considered as the ones with poor quality of employment compared to the polygons having higher values. According to Figures 5.17b, 5.17c, and 5.17d, the number of highlighted polygons decreases as the distance used for defining neighborhoods increases. Specifically, as the distance increases, the spatial patterns captured by the local IPM are becoming more similar to the spatial patterns generated by the global model.

Figure 5.18 shows those polygons that fall into the fourth quadrant of the scatter plots. The overall scores of the polygons are below the global mean and above the local average value. These polygons tend to cluster in the east and southwest portions of London. Some of them locate in the core area of the City. In general, they are characterized by a poor quality of employment. Moreover, the number of this type of polygons decreases along with increasing value of the distance for neighborhoods.

5.4.2 Statistical Analysis of the Results

This section aims at analysing the results generated by the local and global IPM using the Moran's I coefficient and t -statistic. The Moran's I coefficient is used for analyzing the spatial autocorrelation of the results. Spatial autocorrelation indicates a dependency "between values of a variable in neighboring or proximal locations, or

a systematic pattern in values of a variable across the locations on a map” (Griffith, 2009). Moran’s I is one of the most often used methods for measuring the spatial autocorrelation (de Smith et al., 2013). It tests the global spatial autocorrelation for continuous data to determine whether the spatial pattern shown by the data is clustered, random, or dispersed. The value of Moran’s I ranges from -1 to +1. For Moran’s I close to +1, it represents a positive spatial autocorrelation; that is, the similar alternatives tend to cluster. When the value of Moran’s I near -1, there is a negative spatial autocorrelation which means dissimilar alternatives tend to cluster. The spatial pattern is random when the Moran’s I is around 0. The Moran’s I test is analyzed within ArcGIS 10.

The Table 5.8 shows the summary of the Moran’s I tests for the results of global and local IPM. The spatial pattern generated by global IPM has the highest value of Moran’s I , which means it has the highest level of positive spatial autocorrelation among the results. The results of local IPM (Queen’s case) and local IPM (850m) are characterized by the negative spatial autocorrelation. In addition, the value of Moran’s I increases along with increasing distance of the neighborhood scheme. Based on the p -value and z -value, the spatial patterns shown by results of global IPM, local IPM (1600m), and local IPM (2400m) are clustered, while the spatial patterns generated by the local IPM (Queen’s case) and local IPM (850m) are dispersed. These results of Moran’s I test support the conclusions made in Subsection 5.4.1: the global IPM results show a spatial trend of the quality of employment in London, while peak values are spread ‘evenly’ in the spatial patterns obtained by the local IPM.

Table 5.8: Summary of Moran’s I for Global and Local IPM Results

Method	Moran’s I	p -value	z -value	Spatial Pattern
Global IPM	0.271	0.000	9.956	Clustered
Local IPM (Queen’s case)	-0.136	0.000	-4.877	Dispersed
Local IPM (850m)	-0.125	0.000	-4.471	Dispersed
Local IPM (1600m)	0.082	0.002	3.068	Clustered
Local IPM (2400m)	0.180	0.000	6.630	Clustered

A pairwise t -statistic is used for testing the differences between the mean values of overall scores generated by the global and local models. SPSS software is used to run the t -tests. The null hypothesis for the t -test is that there is no significant difference between the mean values obtained by the local and global IPM. Table 5.9 gives a summary of the statistical testing. The results of the t -tests suggest that there are

statistically significant differences between the mean overall values generated by the two methods. This conclusion is applicable to all pairwise comparisons between the global IPM and each of the four local models.

Table 5.9: Summary of pairwise *t*-test for Global and Local IPM Results

	Paired Differences		Correlation
	Mean difference	<i>t</i> statistic	
Global IPM and Local IPM Queen's case	-0.071	-8.143*	0.643
Global IPM and Local IPM 850m	-0.076	-9.220*	0.660
Global IPM and Local IPM 1600m	-0.063	-11.107*	0.772
Global IPM and Local IPM 2400m	-0.051	-10.137*	0.778

* Significant at 0.01

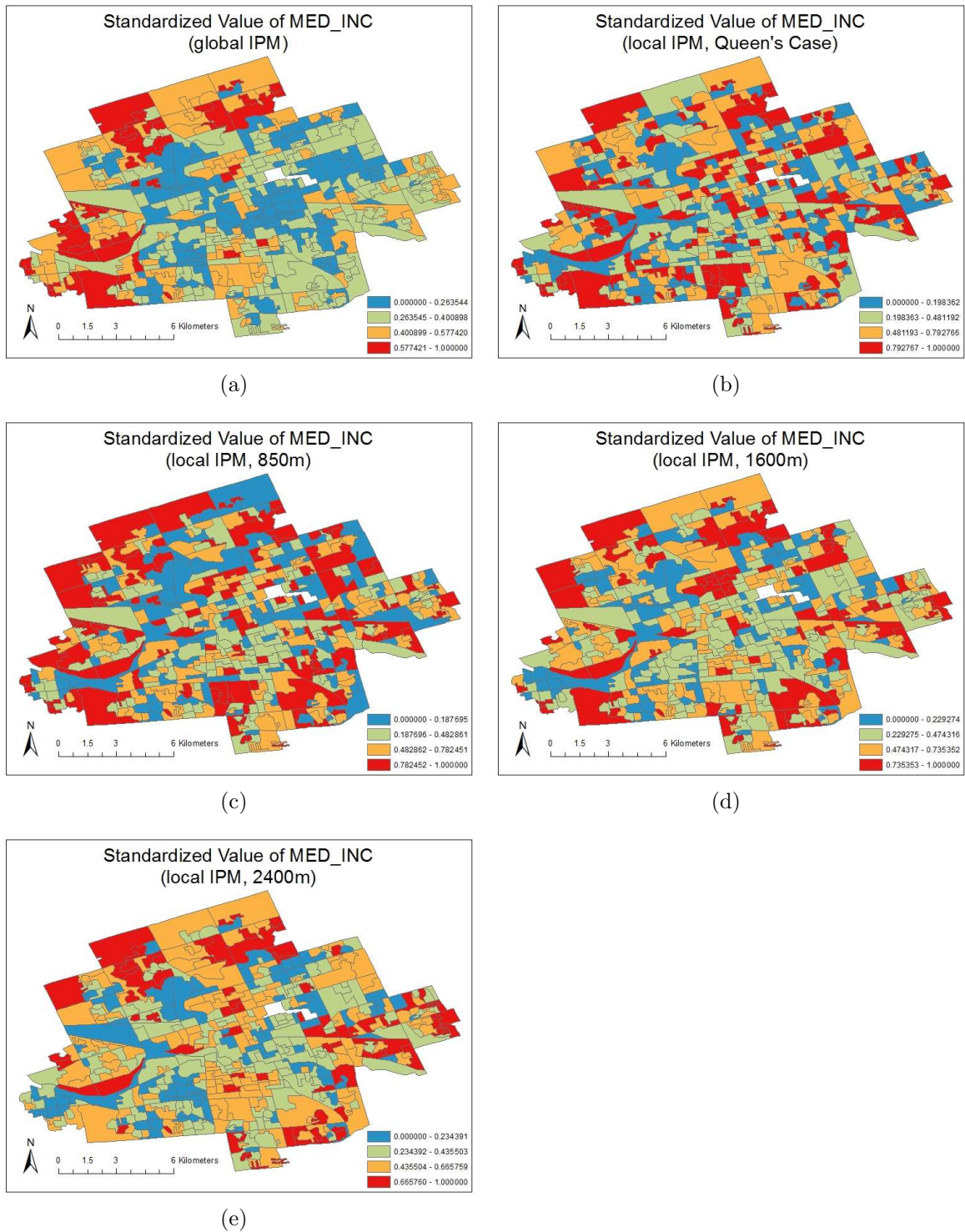


Figure 5.13: Standardized value of median income generated by: (a) global IPM, (b) local IPM based on neighborhood defined by Queen's case, (c) local IPM based on neighborhoods defined by 850m, (d) local IPM based on neighborhoods defined by 1600m, and (e) local IPM based on neighborhoods defined by 2400m.

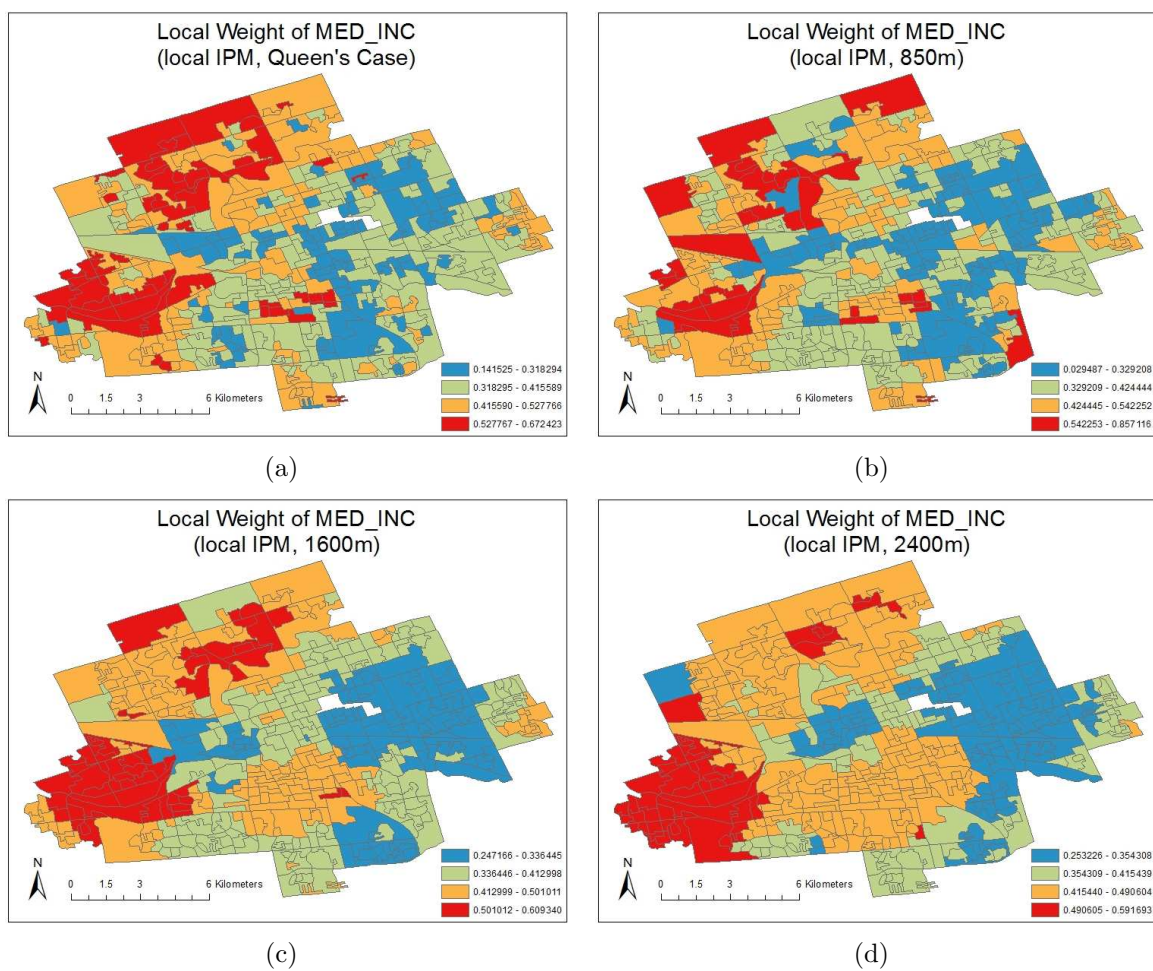


Figure 5.14: Local weights of the median income criterion in London generated by local IPM based on neighborhood defined by: (a) Queen's case, (b) 850m, (c) 1600m, and (d) 2400m.

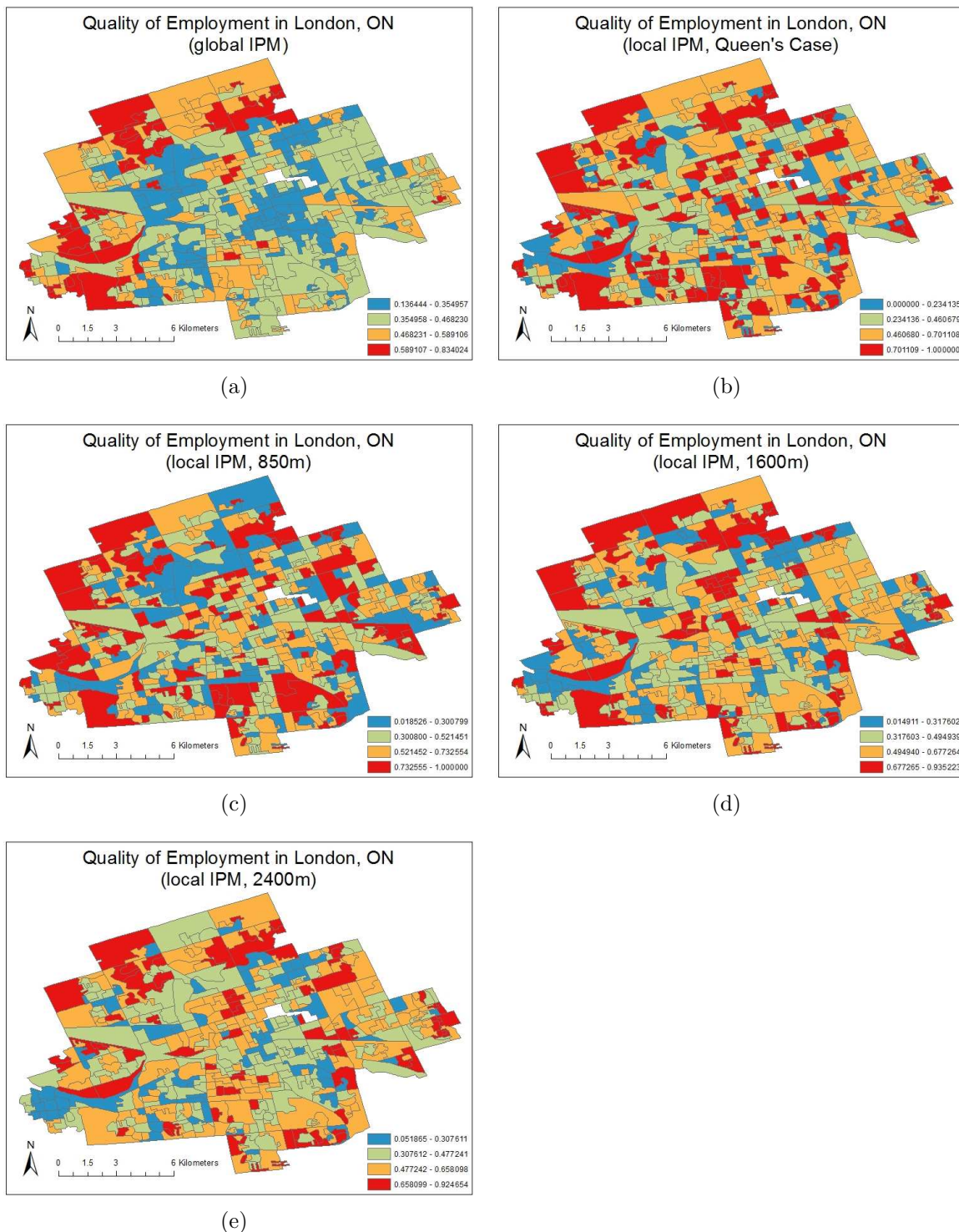


Figure 5.15: Overall scores for quality of employment generated by: (a) global IPM, (b) local IPM based on neighborhoods defined by Queen's case, (c) local IPM based on neighborhoods defined by 850m, (d) local IPM based on neighborhoods defined by 1600m, and (e) local IPM based on neighborhoods defined by 2400m.

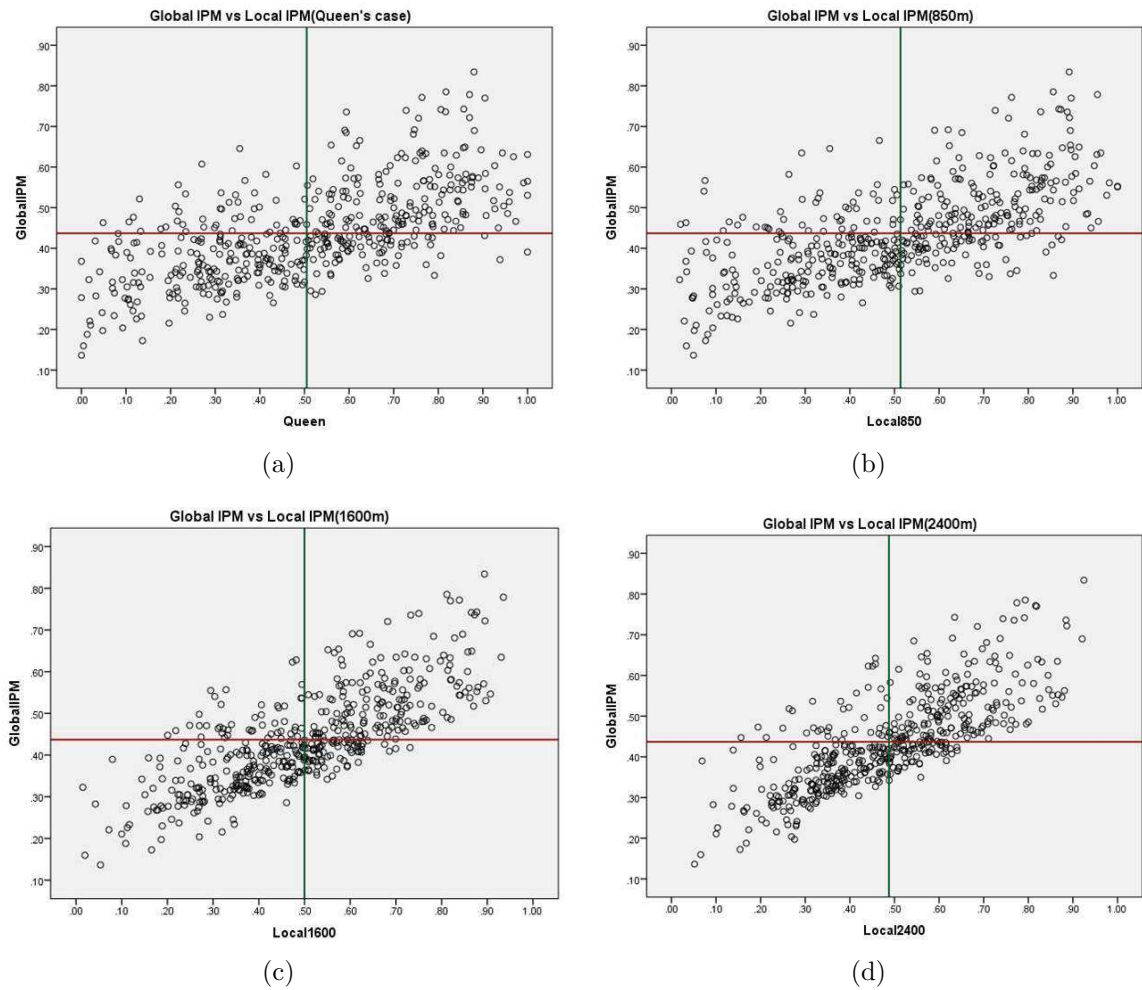
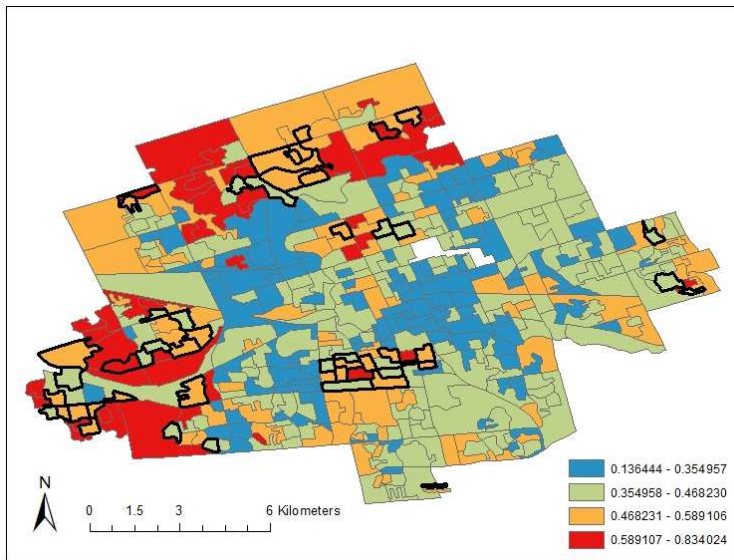
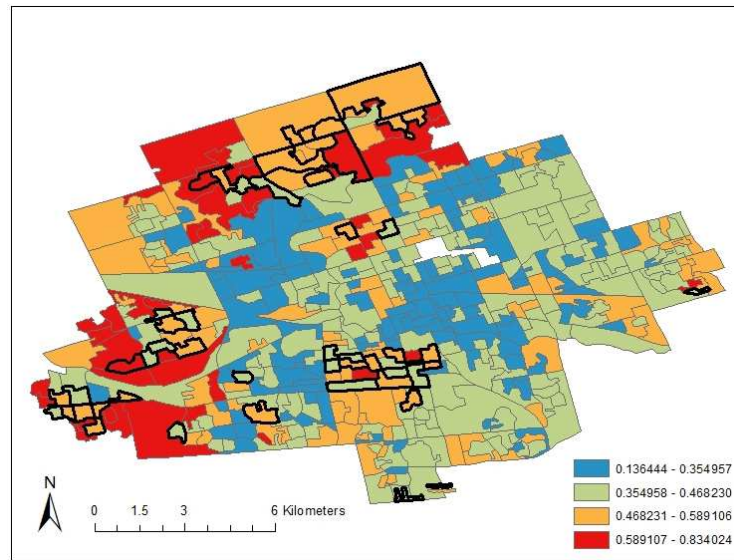


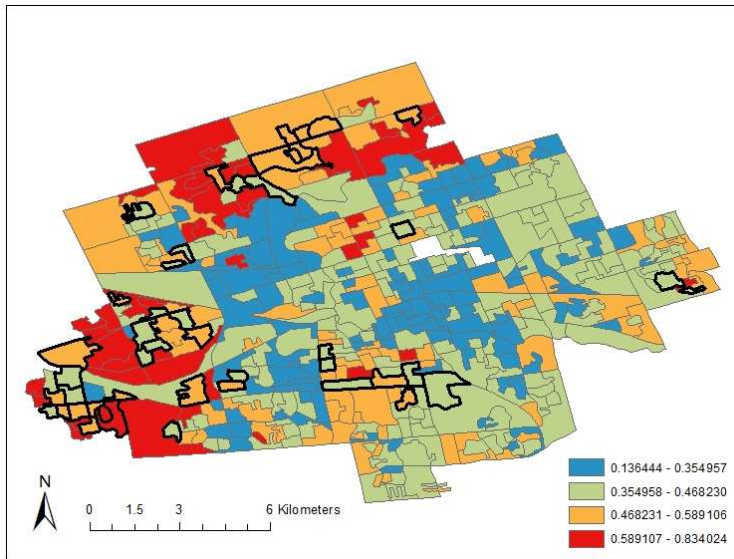
Figure 5.16: Scatter plots of the results of global and local IPM with neighborhoods defined by: (a) Queen's case, (b) 850m, (c) 1600m, and (d) 2400m.



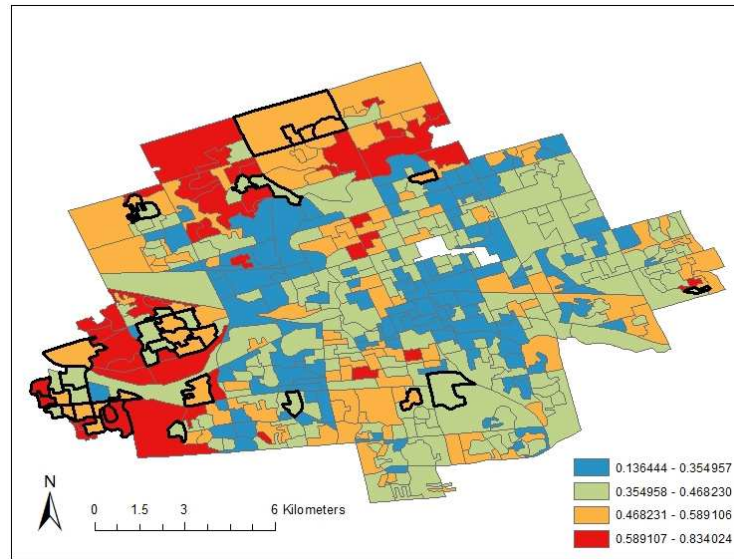
(a)



(b)

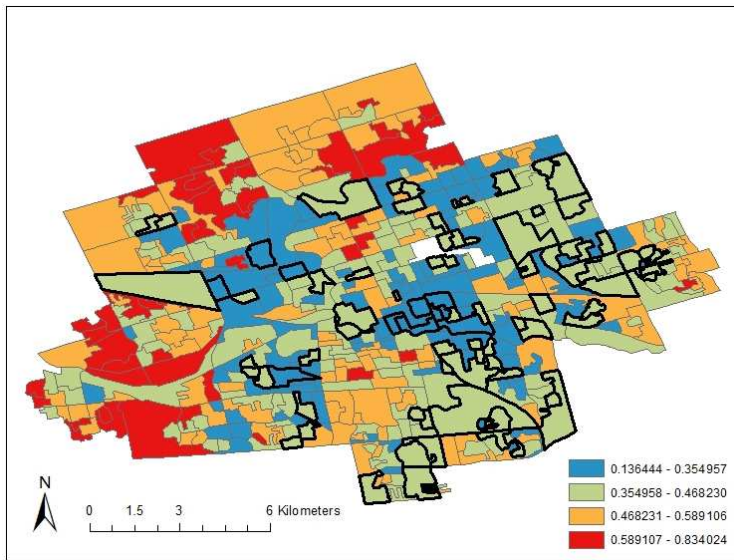


(c)

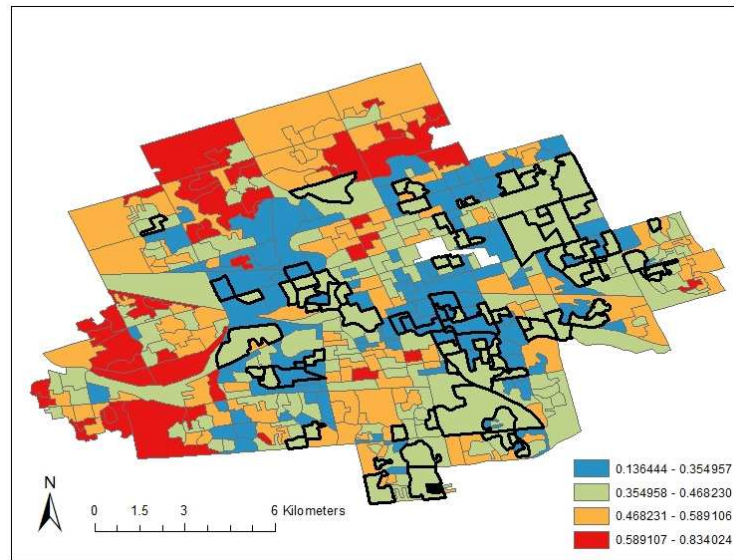


(d)

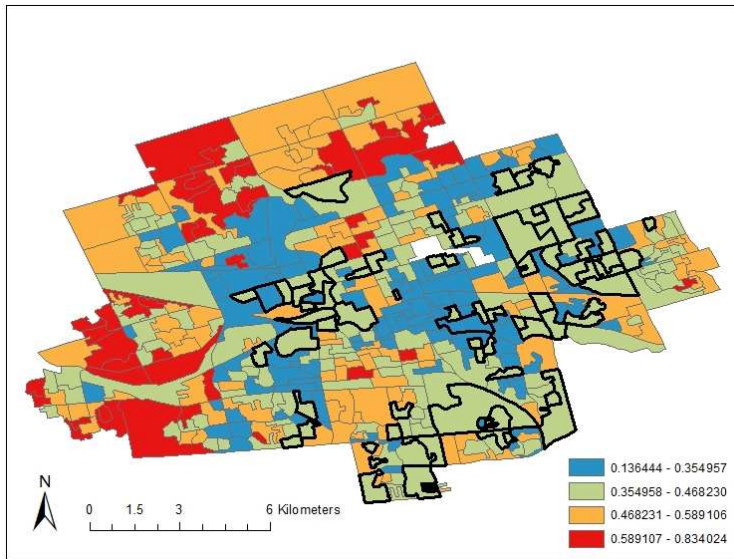
Figure 5.17: Polygons in the second quadrant of scatter plots of the results of global and local IPM with neighborhoods by: (a) Queen's case, (b) 850m, (c) 1600m, and (d) 2400m.



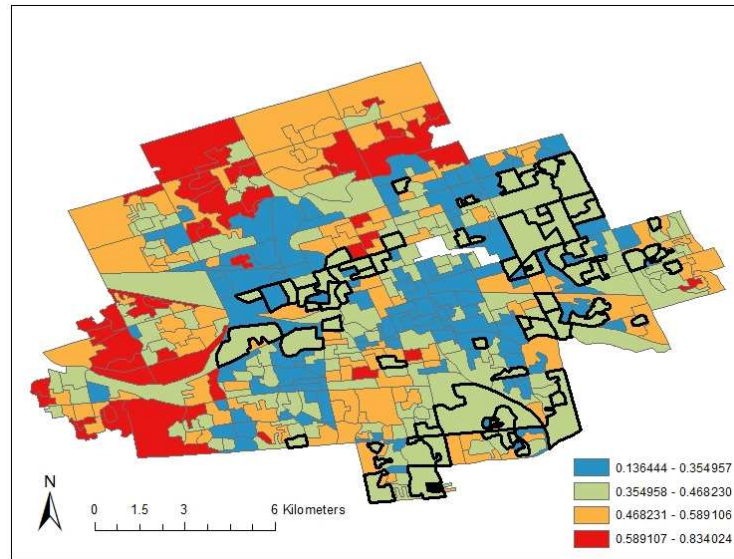
(a)



(b)



(c)



(d)

Figure 5.18: Polygons in the fourth quadrant of scatter plots of the results of global and local IPM with neighborhoods by: (a) Queen's case, (b) 850m, (c) 1600m, and (d) 2400m.

5.5 Summary

This chapter aimed at demonstrating the differences between the global and local IPM using a case study of evaluating the quality of employment in London, Ontario. For the local IPM, four different methods of defining neighborhood were used: Queen's case and the distance based method with the threshold parameter of 850m, 1600m, and 2400m. The result of the global IPM shows spatial trend of the quality of employment in London. The areas with high quality of employment tend to be located in the north and southwest parts of London. The results generated by the local IPM display significantly different spatial patterns. The local analysis identifies local disparities between high and poor quality of employment. It indicates areas with relatively high overall values within each neighborhood. In addition, the differences between the global and local pattern diminish with increasing size of neighborhood. The scatter plots of the results obtained by the global and local IPM support the above conclusions. Also, the statistical testing indicates that there is significant difference between the results generated by the two IPM modes.

Chapter 6

Conclusion

This study focused on developing a local form of IPM model in order to overcome the limitation of global IPM. The global model makes an implicit assumption about spatial homogeneity of its parameters. The range sensitivity principle was used as a central concept for developing the local form of IPM. In addition, a case study of evaluating the quality of employment in London, Ontario, was presented to demonstrate the differences between the two IPM models. The global IPM generates a spatial pattern of overall values for the whole study area ignoring the local context of each location (area); that is, the overall values can only be interpreted in an absolute term (e.g., the model identifies the location of the maximum overall value irrespectively of the criterion values of the neighbouring areas). The local IPM captures the local context of overall value for each location. Those values have relative connotation (e.g., the high and low values distributed across the study area have a meaningful interpretation in the context of their locations within neighborhoods). Moreover, the local form of IPM provides a tool for place-based analysis. The elements of the local model, such as the standardized criterion values, criterion weights, are localized that provide detailed information about neighborhoods. The results generated by local IPM open up new opportunities for spatial analysis. They are potentially useful in targeting priority areas for informing local planning and socio-economic policies development such as the quality of employment related policies. They suggest that the policies regarding quality of employment should be informed by an understanding of contextual factors of the employment quality of employment. In particular, these factors should be examined locally, and different policies should be applied in different neighborhoods of the city.

When local IPM is applied, key decisions concern the choice of (i) the neighborhood scheme, and (ii) the value of the p parameter (the measure of distance or separation between the actual criterion values and the ideal/nadir values). The choice of these elements of local IPM modelling may have considerable effect on the results. While a sensitivity analysis can be performed regarding the p parameter by systematically changing its value, a method for selecting an ‘optimal’ neighborhood scheme does not exist. This is one of the main limitations of the proposed approach to the local IPM modelling. This limitation is reflected in the process of criteria selection. The local IPM sets an implicit requirement on the raw data for the evaluation criteria; that is, there must be sufficient variability of the data so that the local range is greater than 0. For the distance based neighborhood scheme this means that a minimum distance for defining a neighborhood can be identified so that for every neighborhood the maximum criterion value is greater than the minimum value of that criterion. However, this does not provide a method for identifying the best neighborhood scheme for a given study area. One of the main challenges of future studies involving local IPM is to develop a procedure for identifying the best neighborhood scheme.

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Appendix A

Local MCA Calculator

The computation of local range r_k^q , local standardized value v_k^q , local weight w_k^q , and distance (separation) between each alternatives and the ideal/nadir point of their neighborhoods are calculated using Local MCA Calculator developed in JAVA. Figure A.1 shows the interface of the calculator.



Figure A.1: Interface of computation in JAVA

A.1 Input

- **Criteria File:** the raw data for evaluation criteria.
- **Neighborhoods File:** the neighbors of each polygon.
- **Global Weight File:** the global weights for all criteria.
- **Indicator File:** the type (MAX/MIN) of each criterion.

A.2 Output Data

- **Criteria Range** calculates the local criterion ranges for each neighborhood.
- **Standardization** computes the local standardized criterion values for each neighborhood.
- **Local Weight** calculates the local weights for each polygon.
- **IPM Distance** outputs the distance between the actual criterion value and the ideal/nadir points for each neighborhood.

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