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GIS-Based Local Ordered Weighted Averaging: A Case Study in London, Ontario

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(Thesis format: Monograph)

by

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Abstract

GIS-based multicriteria analysis is a procedure for combining a set of criterion maps and associated criterion weights to obtain an overall value for each spatial unit (location) in the study area. Ordered Weighted Averaging (OWA) is a generic algorithm of multicriteria analysis. It has been integrated into GIS and applied for tackling a wide range of spatial problems. However, the conventional OWA method is based on an assumption of spatial homogeneity of its parameters. Therefore, it is referred to as a global model. This thesis proposes a local form of OWA. The local model is based on the range sensitivity principle. A case study of examining spatial patterns of socioeconomic status in London, Ontario is presented. The results show that there are substantial differences between the spatial patterns generated by the global and local OWA methods.

Keywords

Multicriteria analysis, local ordered weighted averaging (OWA), geographic information system (GIS), socioeconomic status, London Ontario.

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Preface

Chapter 1

1 Introduction

Multicriteria Analysis (MCA) is a systematic procedure for evaluating a set of decision alternatives based on multiple criteria. It has emerged as an area of research within the field of environmental economics and regional planning in the early 1970s (Carver, 1991). Over the last two decades there has been substantial growth of MCA applications (Wallenius et al., 2008). Decision or evaluation problems that involve geographical (spatial) data are referred to as spatial decision problems. This type of problems is typically tackled with the use of Geographic Information Systems (GIS). However, GIS has limited capability for handling preferential information (such as preferences with respect to relative importance of evaluation criteria). This limitation can be addressed by integrating GIS and MCA (Malczewski, 1999; Chakhar and Mousseau, 2008).

A number of GIS-based MCA (GIS-MCA) methods have been developed over the last two decades or so. These include weighted linear combination (WLC) (Eastman et al., 1993; Malczewski, 2000; Mahini and Gholamalifard, 2006), ideal point methods (Carver, 1991; Jankowski, 1995), analytical hierarchy process (Banai 1993; Rinner and Taranu, 2006) and outranking analysis (Joerin et al., 2001; Chakhar and Mousseau, 2008). Among these procedures, WLC and Boolean overlay approaches are considered as the most straightforward and are most often employed (Malczewski, 1999). Boolean overlay approaches apply the logical operators such as intersection (AND) and union (OR) on Boolean maps to assess criteria (Jiang and Eastman, 2000). Yager (1988) generalized these approaches and introduced a MCA method based on the ordered weighted averaging (OWA) concept.

1.1 The Significance of GIS-based OWA

The main rationale for integrating GIS and OWA is that the two sets of methods have unique and complementary capabilities for tackling spatial decision problems. On one hand, GIS is efficient at storing and managing data, analyzing spatial information and visualizing outcomes. On the other hand, OWA is a generic MCA procedure that provides a platform for analyzing, evaluating, and prioritizing decision (or evaluation) strategies (Malczewski, 1999; Rinner and Malczewski, 2002).

GIS-based OWA provides a tool for generating and visualizing a wide range of multicriteria evaluation strategies by applying different operators and associated set of ordered weights. The strength of OWA is that it can efficiently generate a set of diverse solutions by changing the set of ordered weights. The OWA method not only provides a single "optimal" solution, but can also generate a combination of solutions that can be further examined for developing decision or evaluation scenarios.

1.2 The Limitation of Conventional OWA

In the last two decades, GIS-based OWA has been widely applied for solving a variety of spatial problems including: use-land suitability problems (Eastman 1997; Malczewski, 2006b; Chen, et al., 2009), site-selection problems (Rinner and Raubal, 2004; Valente, 2008; Ekmekçioĝlu, et al., 2010), heat vulnerability assessment (Rinner, et al., 2010), urban water management (Makropoulos et al., 2003), natural hazards (Gorsevski, et al., 2010), and personal route planning (Nadi and Delavar, 2011). However, the limitation of previous researches should be noted. The conventional OWA approach applied in previous studies is regarded as "**global OWA**" because of the underlying assumption about spatial homogeneity of the OWA parameters. The procedures of GIS-MCA, including GIS-OWA, have mostly been derived from the general theory of decision analysis (Malczewski, 1999) rather than from spatial theories. Consequently, the conventional GIS-OWA approach fails to adequately represent spatial variability. The method is based on an assumption that there is spatial homogeneity within the study area. For instance, in the conventional GIS-OWA procedure, every alternative (location) is assigned the same criterion weight. The conventional procedure uses a single value function for the whole study area ignoring the fact that the form of the function may depend on the local context (Malczewski, 2011). Therefore, all the previous studies are based on the global OWA method and do not involve an explicit spatial representation of local contexts.

Both Feick and Hall (2004) and Malczewski (2011) have addressed this limitation of global GIS-MCA. Feick and Hall (2004) adopt an easy-to-use procedure to examine weight sensitivity in both criteria and geographic space. They demonstrate a method for visualizing the spatial dimension of criteria weight sensitivity by mapping the weight sensitivity in order to detect localized variations of outcomes. Malczewski (2011) introduces the concept of local weighted linear combination (WLC) to advance the global WLC method, using the range sensitive principle as a core concept for developing the local form of WLC model. However, there has been no attempt to develop the local OWA method. This research is designed to fill this gap in the GIS-OWA studies.

In sum, OWA method is a generic GIS-MCA procedure. The conventional OWA method is based on an assumption of spatial homogeneity. Consequentially, the conventional OWA is referred to as the global OWA method. This research aims at advancing the global OWA approach by developing a new OWA method to take into account the spatial homogeneity. This new method is called local OWA.

1.3 Research Objectives

There are two main objectives of this research:

(1) To develop a local form of the OWA method. This objective will be achieved by developing a new algorithm for transforming the global OWA to local OWA using the range sensitivity principle.

(2) To examine the results of the local and global OWA using a case study of socioeconomic status of neighborhoods in London, Ontario, Canada.

Chapter 2

2 Theoretic Background

This chapter provides a theoretical background of GIS-MCA methods. It includes the concept of MCA and spatial MCA.

2.1 Multicriteria Analysis

Multicriteria analysis (MCA) is a set of methods and procedures for evaluating decision alternatives on the basis of multiple, conflicting criteria and selecting the best alternative(s) (Voogd, 1983; Janssen and Rietveld, 1990). Criterion is a generic term that includes both the concept of attributes and objectives (Malczewski, 1999). Hence multicriteria analysis can be classified into two types: multiobjective and multiattribute analysis.

Objective is a statement about the desired state of the system under consideration (e.g., land-use pattern, spatial pattern of transport facilities, location of public services, spatial pattern of socioeconomic status, etc.). Objectives are functionally related to, or derived from a set of attributes, indicating the direction towards which the attributes should be optimized. Each objective represents one aspect of the desired state of the system. A set of objectives should summarize all relevant concerns for achieving an overall goal of the decision or evaluation problem. The multiobjective analysis is a model-oriented, where the alternatives must be designed using the methods of mathematical programming (Janssen and Rietveld, 1990; Malczewski, 1999).

Attribute is a measurable characteristic of an object (decision alternative, location, area, etc.). It is a descriptive value (Drobne and Lisec, 2009). It aims at assessing the degree to which a given objective might be achieved (Pitz and McKillip, 1984). Attributes are used as the measurements of preference related to objectives. They can be regarded as the means or information sources available to the decision maker for formulating and achieving the decision maker's (or expert's) objectives (Starr and Zeleny, 1977). Multiattribute analysis is based on the assumption that the set of alternatives are known. The core of solving multiattribute decision problems is the evolution of (and choice among) alternatives described by their attributes. For the most part, GIS-MCA belongs to the multiattribute analysis (Malczewski, 2006). This research is concerned with multiattribute analysis. Hereafter, the terms multiattribute analysis and multicriteria analysis will be used interchangeably.

2.2 Spatial Multicriteria Analysis

Spatial MCA focuses on geographically defined decision alternatives which are evaluated by a set of criteria (Carver, 1991; Jankowski, 1995; Malczewski, 1999). The kernel of spatial MCA is the integration of MCA and GIS methods. Conventional MCA can be used to deal with the complexity of the real world problems that may involve a large number of alternatives and multiple and conflicting evaluation criteria. Nevertheless, to solve spatial decision problems, MCA also requires spatial analytical functions and the capacity of processing geographic data. This calls for the integration MCA and GIS.

In spatial multicriteria analysis or GIS-MCA, attributes, represented as map layers, are the properties of geographical entities; hence attributes can be interpreted as criteria (criterion maps). The weight associated with a criterion map represents the preference of decision makers (or experts). It indicates the relative importance of criteria. The spatial units (locations or areas) represent the decision (or evaluation) alternatives. In the raster data, each raster cell or a combination of cells is considered as an alternative. In the vector data, alternatives are represented by points, lines, polygons or a combination of these three spatial objects.

An evaluation matrix can be formed to represent the relationships between alternatives and criteria (see Table 2-1). The matrix contains criterion values, b_{ik}, i= 1, 2, …m; and k

= 1,2,…, n; where m and n are the number of alternatives and criteria, respectively. The criterion weights (w_k) are shown in the last row. In the spatial MCA, the evaluation criteria are associated with geographical entities therefore can be represented in the forms of maps (see Figure 2-1).

Table 2-1 Example of Evaluation Matrix

	Criterion 1	**Criterion 2**	**…**	**Criterion n**
Alternative 1	b_{11}	b_{12}	…	b_{1n}
Alternative 2	b_{21}	b_{22}	…	b_{2n}
…	…	…	…	…
Alternative m	b_{m1}	b_{m2}	…	b_{mn}
Weights	w_1	w_2	…	w_n

A criterion map consists of a set of polygons. Each polygon stands for an alternative in the evaluation matrix and is described by a set of criterion values (that is, the i-th alternative or polygon is described by b_{ik} for k = 1,2,…, n). Criterion weights are assigned to each criterion maps. Given the set of criterion maps and associated criterion weights, the input data can be processed by GIS techniques and MCA methods to obtain the decision (evaluation) outcome map.

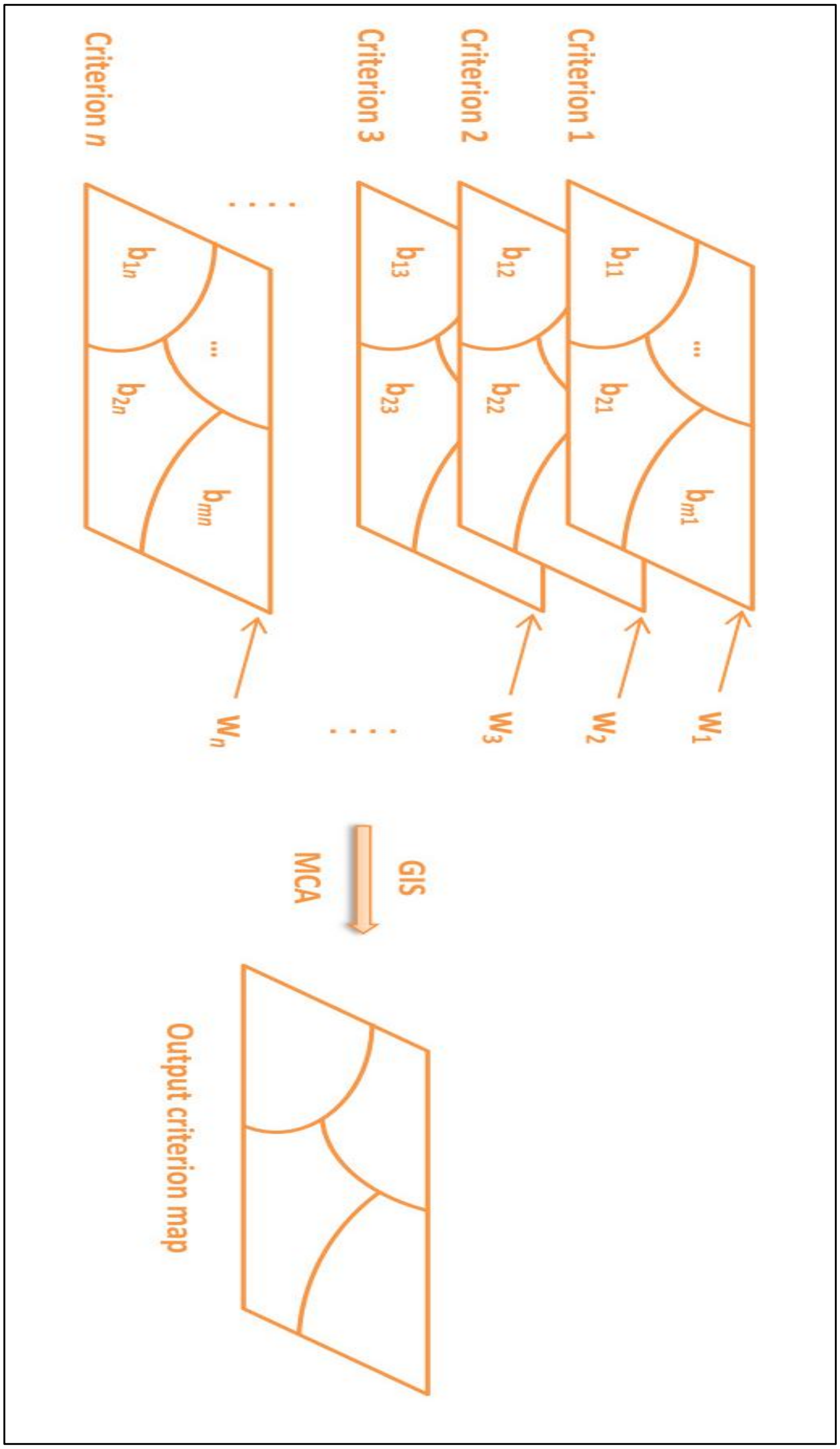


Figure 2-1 Example of Spatial MCA

2.3 GIS-based OWA Method

GIS-based OWA method is the combination of GIS techniques and OWA method. Eastman (1997) first extended the concept of OWA to GIS application to establish the decision support model in Idrisi-GIS. In the recent decade, many researches focus on integrating OWA concept and GIS application to practical problems (Jiang and Eastman, 2000; Malczewski, 2000; Rasmussen et al., 2002; Araújo and Macedo, 2002; Chen et al., 2009; Charabi and Gastili, 2011; Feizizadeh and Blaschke, 2012).

Criterion values, criterion weights and order weights are three important elements of OWA. Criterion values are the presentation of attributes. The criterion weights indicate the importance of each criterion. The order weights are assigned to each reordered criterion after the reordering process. The determination of order weights is critical on integrating GIS and OWA (Malczewski, 2006c). Jiang and Eastman (2000) demonstrated the Idrisi-OWA procedure but failed to provide a method for obtaining the order weights. Consequently, several researches proposed methods for generating the optimal order weights: based on the degree of ORness and *trade-off* (Asproth et al., 1999; Mendes and Motizuki, 2001; Rasmussen et al., 2002), based on the principles of maximum dispersion or the maximum *trade-off* (Rinner and Malczewski, 2002; Malczewski et al., 2003; Malczewski, 2006c). The approach of maximum *trade-off* can be implemented by parameterized OWA. This research applied a linguistic quantifier by using the α parameter to determine the order weights (see Section 3.1.5). The generality of OWA is related to its capability to implement different OWA operators by selecting appropriate order weights (Malczewski, 2006c).

Chapter 3

3 Methods

This chapter consists of two sections: the implementation of global OWA method and the development of local OWA approach.

3.1 Global OWA Method

3.1.1 Global OWA Procedure

The global or conventional OWA method applies a weighted sum of ordered evaluation criteria including a set of alternatives (or locations) and a set of evaluation criteria. Each alternative, i, is described by a set of standardized criterion (or attribute) values (a_{ik}), for i= 1, 2, … , m, and k = 1, 2, … , n. The OWA is composed of two types of weights: criterion weights (w_k) and ordered weights (v_k). The global criterion weights: $\mathrm{w}_1, w_2, \dots, w_n$ ($w_k \in [0, 1]$, $\sum_{k=1}^{n} w_k$= 1) are applied to specific criteria. They represent the preferences (of the decision maker or expert), with respect to each criterion to indicate its relative importance. On the other hand, order weights, $v_1, v_2, \dots, v_k$ ($v_k \in [0, 1]$; $\sum_{\mathrm{k}=1}^{\mathrm{n}} v_k = 1$), are assigned to ordered criteria associated with criterion values on location-by-location basis (see Section 3.1.5).

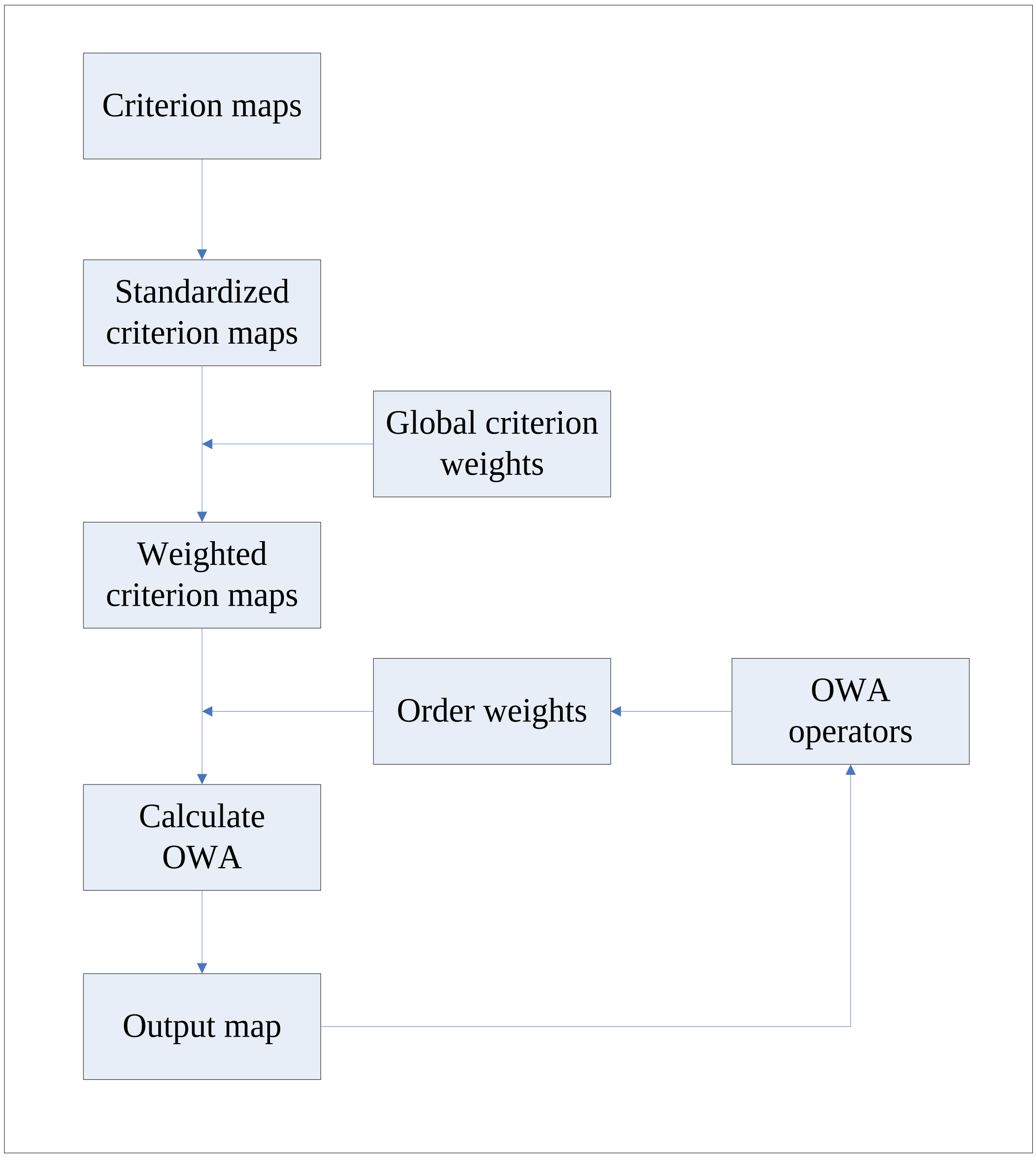


Figure 3-1 Global OWA Procedure

The procedure of global OWA involves the following steps (see Figure 3-1):

(1) standardize criterion values of each criterion maps;

(2) define the global criterion weights according to the preferences of experts;

(3) sort weighted standardized criterion values of each location in descending order;

(4) order global criterion weights according to the ordered criterion values for each location;

(5) select appropriate ordered weights by adopting different OWA operators;

(6) multiply the weighted standardized values by corresponding order weights;

(7) sum up the products to obtain an overall OWA score for each location.

3.1.2 Standardizing Criterion Maps

The first step of any MCA is to collect relevant data and information about the decision or evaluation problem. In GIS-MCA, the input data is typically represented in the form of criterion maps. Since the various criteria are likely to be measured in different system, the criterion maps must be transformed into a standardized scale (Carver, 1991). The method for transforming criterion maps into standardized forms is defined as follows:

$$r_k = max_i\{ b_{ik}\} - min_i \{ b_{ik}\}, \quad (3\text{-}1)$$

$$a_{ik} = \frac{max_i\{ b_{ik}\} - b_{ik}}{r_k}, \text{ for } k\text{-th criterion to be minimized;} \quad (3\text{-}2)$$

$$a_{ik} = \frac{b_{ik} - min_i\{ b_{ik}\}}{r_k}, \text{ for } k\text{-th criterion to be maximized} \quad (3\text{-}3)$$

where, b_{ik} refers to the raw (unstandardized) criterion value; $max_i\{ b_{ik}\}$ and $min_i\{ b_{ik}\}$ indicate the maximum and minimum criterion value of the k-th criterion, respectively; r_k is the global range of the k-th criterion; a_{ik} is the standardized criterion value, ranging from 0 to 1, where 0 is the least-desired value, while 1 indicates the most-desired value. If a criterion is to be maximized, then Equation 3-2 should be used to perform the criterion standardization (e.g., a benefit criterion). Equation 3-3 should be applied for criterion to be minimized (e.g., a cost criterion).

3.1.3 Deriving Criterion Weights using Pairwise Comparisons

Some criteria are more important than the others. The criterion weights estimate the perceived importance of individual criterion relative to the other criteria (Carver, 1991). The pairwise comparison method is applied to estimate criterion weights (see Table 3-1).

Table 3-1 Pairwise Comparison Matrix

	Criterion 1	**Criterion 2**	**…**	**Criterion *n***
Criterion 1	1	p_{12}	…	p_{1n}
Criterion 2	$p_{21} = 1/p_{12}$	1	…	p_{2n}
…	…	…	…	…
Criterion *n*	$p_{n1} = 1/p_{1n}$	$p_{n2}=1/p_{2n}$	…	1

In the pairwise comparison method, the pairwise comparison matrix should be developed first (Table 3-1). Comparing each pair of criteria, decision maker (or expert) evaluates the relative importance of criteria using the scale shown in Table 3-2. For instance, if criterion 1 is moderately more important than criterion 2, then $p_{12} = 4$; the comparison value of p_{21} is calculated using the reciprocal principle (that is, $p_{21} = 1/p_{12} = 0.25$). Note that the cells on the diagonal in the pairwise comparison matrix have the same values of 1 because pairwise comparisons represented of those cells are between a given criterion and itself. Given the pairwise comparison matrix, the pairwise comparisons are normalized; that is, each value is divided by the sum of its column and then the criterion weight is calculated as an average value of the normalized pairwise comparisons (see Section 4.3.2).

Table 3-2 Scale for Pairwise Comparison (Source: 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

3.1.4 Sorting Weighted Criteria

The next step is to generate ordered criteria (z_{ik}). This is achieved by sorting the weighted standardized criterion values ($a_{ik}w_k$) for each alternative or location in a descending order (Yager, 1988; Malczewski and Rinner, 2005). Table 3-3 illustrates the procedure using a set of four alternatives (locations), three standardized criterion ($a_{ik}, i \in [1, 4], k \in [1,3]$), and associated criterion weights (w_1 = 0.2, w_2 =0.5, w_3= 0.3). The standardized criteria are weighted by multiplying the associated criterion weights. Further, the weighted criterion values ($a_{ik}w_k$) are sorted in a descending order. The ordered weighted criterion values (z_{ik}) are obtained as the results. For instance, the set of weighted criterion values ($a_{11}w_1$= 0.0, $a_{12}w_2$ = 0.45, $a_{13}w_3$ = 0.18) associated with i = 1 is arranged in the descending order as follows: z_{11} = 0.45, z_{12} = 0.18, z_{13} = 0.0.

Since the criterion values are shuffled, the corresponding criterion weights are also rearranged in the sorting process. These rearranged criterion weights form a new matrix, the ordered criterion weight (u_{ik}). The ordered criterion weights are used to determinate the ordered weights (see Section 3.1.5). The procedures of sorting criterion values and generating ordered criterion weights have been implemented in a Local MCA Calculator (see Appendix).

Table 3-3 Illustrative Example: calculating ordered criterion (z_{ik})

Criteria	a_{ik}	w_k	$a_{ik}w_k$
c_1	{0.0, 0.7, 1.0 ,0.4}	0.2	{0.0, 0.14, 0.2, 0.08}
c_2	{0.9, 0.3, 0.2, 0.6}	0.5	{0.45, 0.13, 0.01, 0.3}
c_3	{0.6, 0.8, 0.1, 0.3}	0.3	{0.18, 0.24, 0.03, 0.09}

Criteria	u_{ik}	z_{ik}
c_1	{0.5, 0.3, 0.2, 0.5}	{0.45, 0.24, 0.2, 0.3}
c_2	{0.3, 0.2, 0.3, 0.3}	{0.18, 0.14, 0.03, 0.09}
c_3	{0.2, 0.5, 0.5, 0.2}	{0.0, 0.13, 0.01, 0.08}

3.1.5 Determining Order Weights

3.1.5.1 Fuzzy linguistic quantifiers

The order weights can be estimated using a number of methods (Yager, 1996). The linguistic quantifier-based method is one of the most often used in OWA applications. Linguistic quantifiers can be represented as a fuzzy set (Zadeh, 1983). Consequently, the term linguistic and fuzzy quantifiers can be used interchangeable. Translating natural language specifications into mathematics formulas is the core purpose of fuzzy quantifiers. Yager (1996) proposed a procedure for quantifier-guided MCA that fuzzy linguistic quantifiers were used to specify the statement about the number (proportion) of criteria to be satisfied by applying OWA operators (e.g., *all* criteria must be satisfied, *most* of the criteria should be satisfied or *at least half* of criteria should be satisfied).

To determine the values of order weights, the associated quantifier Q needs to be specified first. There are two generic classes of linguistic quantifiers: absolute and relative quantifiers (Zadeh 1983; Yager 1996). The statements such as "about five" or "more than ten" belong to the class of absolute quantifiers; they are defined as fuzzy subsets of [0, $+\infty$]. The relative quantifiers are closely related to imprecise proportions. They are defined as fuzzy subset of [0, 1] with proportional terms such as "a few", "half", "many", "most". Therefore, the relative quantifier can be identified by one of the simplest and the most often used method to parameterize subset on the unit interval as following (Yager, 1996):

$$Q(p) = p^{\alpha}, \alpha > 0 \tag{3-4}$$

The $Q(p)$ represents a fuzzy set in interval [0, 1], including monotonically increasing proportions of elements. Hence the whole family of regular increasing monotone (RIM) quantifier can be generated from this quantifier $Q(p)$. Consequently, by changing the value of parameter α, one can obtain a wide range of aggregation operators. Specifically, one can also generate different types of quantifiers and associated order weights between the two extreme cases of the "*at least one*" and "*all*" quantifiers (see Table 3-4) (Malczewski and Rinner, 2005). For instance, when the value of parameter α tends to be zero, the quantifier $Q(p)$ approaches its extreme case of "*at least one*". When the value of parameter α approaches infinity, the quantifier $Q(p)$ approaches its extreme case of "all". Using the parameter α, the order weights can be defined as follows (Yager, 1996; Malczewski, 2006b):

$$v_{ik} = \left(\sum_{j=1}^{k} u_{ij}\right)^{\alpha} - \left(\sum_{j=1}^{k-1} u_{ij}\right)^{\alpha}, \ \alpha > 0 \qquad (3\text{-}5)$$

where v_{ik} is the order weight for the k-th criterion associated with the i-th location; u_{ij} is the ordered criterion weights; α is the parameter associated with the fuzzy quantifier.

Table 3-4 Properties of Regular Increasing Monotone Quantifiers with selected values of Parameter α (source: Malczewski, 2006b)

Parameter α	**Quantifier (Q)**	**Order Weights (v_{ik})**	**GIS Combination Procedure**	***ORness***	***Trade-off***
$\alpha \to 0$	*At least one*	v_{i1} = 1; v_{ik} = 0, $(1 < k \le n)$	OWA (OR)	1.0	0
$\alpha \to 0.1$	*At least a few*	*	OWA	*	*
$\alpha \to 0.5$	*A few*	*	OWA	*	*
$\alpha \to 1$	*Half (identity)*	$v_{ik} = 1/n$, $(1 \le k \le n)$	OWA (WLC)	0.5	1
$\alpha \to 2$	*Most*	*	OWA	*	*
$\alpha \to 10$	*Almost all*	*	OWA	*	*
$\alpha \to \infty$	*All*	v_{in} = 1; v_{ik} = 0, $(1 \le k < n)$	OWA (AND)	0	0.0

Note: * the set of order weights depends on values of sorted criterion weights and parameter α according to Equation 3-5.

3.1.5.2 OWA operators

The generality of OWA method is related to its ability of implementing a wide range of combination operators by selecting an appropriate set of order weights (Yager 1988). The combination operators are called OWA operators. They include the weighted linear combination (WLC) and Boolean overlay operations such as intersection (AND) and union (OR) (Yager 1988; Jiang and Eastman, 2000). The AND and OR operators are the most often used GIS combination procedures.

In fact, the set of order weights determinates the type of the OWA operator. In the practical application, the AND and OR operators represent the two extreme situations. For example, when parameter $\alpha = 1000$ ($\alpha \rightarrow \infty$), the order weights are generated as $[v_1, v_2, \ldots, v_n] = [1, 0, 0 \ldots, 0]$. This extreme case represents the Boolean OR combination (see Table 3-4). If parameter α = 0.001 ($\alpha \rightarrow 0$), only the lowest values are selected by the OWA operator because the order weights $[v_1, v_2, \ldots, v_n] = [0, 0, 0 \ldots, 1]$; this is an equivalent of the AND type of Boolean combination (see Table 3-4).

Moreover, the WLC operator is determined by a set of equal order weights ($[v_1, v_2, \ldots, v_n] = [\frac{1}{n}, \frac{1}{n}, \frac{1}{n} \ldots, \frac{1}{n}]$); that is, the identity quantifier or parameter α = 1 is applied. Hence, the WLC operator does not change in the re-order weighted criterion value because equal ordered weights are assigned to each ordered weighted criterion. The AND, OR and WLC operators are only three 'special' cases. One can generate a large number of OWA operators by changing the value of parameter α or the quantifiers ranging from "*all*" to "at *least*".

One can use the measurements *ORness* and *trade-off* to classify the OWA operators with respect to their positions between the AND and OR operators (Yager, 1988; Eastman, 1997; Jiang and Eastman, 2000):

$$ORness_i = \sum_{k=1}^{n} \frac{(n-k)}{n-1} v_{ik}, \quad 0 \leq ORness \leq 1 \tag{3-6}$$

$$trade\text{-}off_i = 1 - \sqrt{n \sum_{k=1}^{n} \frac{(v_{ik} - \frac{1}{n})^2}{n-1}},\ 0 \leq trade\text{-}off \leq 1 \quad (3\text{-}7)$$

ORness measures the degree similarity of an OWA operator to the logical OR in terms of its combination behavior (Malczewski et al., 2003). The *trade-off* is a measurement for the substitutability (or compensation) of low values on one criterion by high values on other criterion (Jiang and Eastman, 2000). It indicates the degree of how a good performance on one criterion under consideration compensates a poor performance on other criterion (Malczewski et al., 2003). The value of zero conveys no *trade-off* among criteria and the value of one indicates a full *trade-off*.

3.1.5.3 Evaluation strategy space

Evaluation (or decision) strategy space can be formed by two measurements: *ORness* and *trade-off* (Jiang and Eastman, 2000; Rinner and Malczewski, 2002). Figure 3-2 shows the relationship between *ORness* and *trade-off*. The shape of evaluation strategy space depends on the number of criteria (n). When two criteria are involved in the evaluating process, the strategy space has a triangle shape (Figure 3-2). The three vertices of the triangle represent the three extreme cases of the OWA operators: AND, OR and WLC (see Figure 3-2). For instance, the top vertex represents the WLC operator (α = 1), characterized by an intermediate degree of *ORness* and full *trade-off.*

As the number of criteria increases from n = 2 to $n \rightarrow \infty$, the shape of decision strategy space changes to a rectangular form (Malczewski and Rinner, 2005). Specifically under a given degree of *ORness*, more criterion maps are involved in the procedure and this leads to the higher level of *trade-off*, except for the extreme cases of OWA operators (AND, OR and WLC operators). For AND, OR and WLC operators, the measures of *trade-off* and *ORness* are fixed irrespectively of the number of criterion maps (Malczewski and Rinner, 2005).

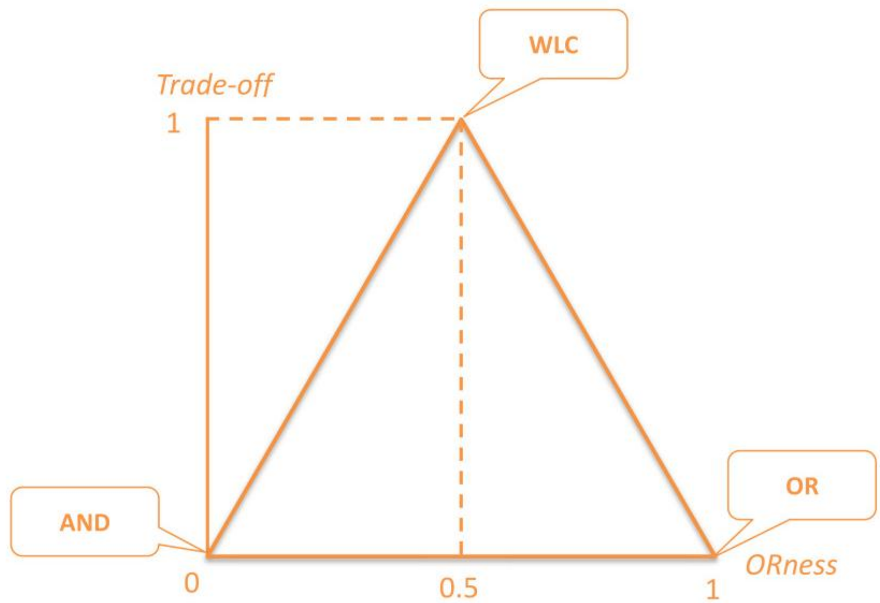


Figure 3-2 Evaluation Strategy Space: the relationship between the measures of *ORness* and *trade-off* (Source: Eastman, 1997)

3.1.6 Defining Global OWA

For a given set of criterion maps, the function of OWA scores is defined as follows (Yager, 1988):

$$\mathrm{OWA}_i = \sum_{k=1}^{n} v_{ik}\, z_{ik} \tag{3-8}$$

where OWA_i is the overall OWA score of the i-th location or alternative; v_{ik} is the ordered weight; z_{ik} is the ordered weighted criterion value. The spatial pattern of OWA scores can be displayed on a map. The location (alternative) with the highest overall score indicates the best alternative.

3.2 Local OWA Method

3.2.1 Local OWA Procedure

The local OWA procedure is illustrated in Figure 3-3. It starts with defining the set of evaluation criterion maps. Next, a neighborhood scheme is specified. Based on the neighborhood scheme, the range sensitivity principle is applied to obtain the local range for each location in the study area. This is followed by performing the local standardization for each criterion map. Then, the global criterion weights are estimated, providing the basis for calculating local criterion weights. Particularly, the local criterion weight associated with a given location is a function of the global weight and the local range. Given the local standardized criteria and local criterion weights, one can generate local weighted criterion maps. Further, a set of order weights is defined based on the specified value of parameter α. Finally, the local weighted criteria maps and order weights are combined to obtain the local OWA scores (output map).

The concept of the neighborhood, local range and local criterion weight are critical for conveying spatial heterogeneity and local context. Therefore, the rest of this chapter will focus on this concept. The order weights of the local OWA method are obtained in the same way as in the global OWA approach (see Section 3.1.5). Therefore, the process of selecting appropriate order weights by specifying different values of parameter α is not repeated here.

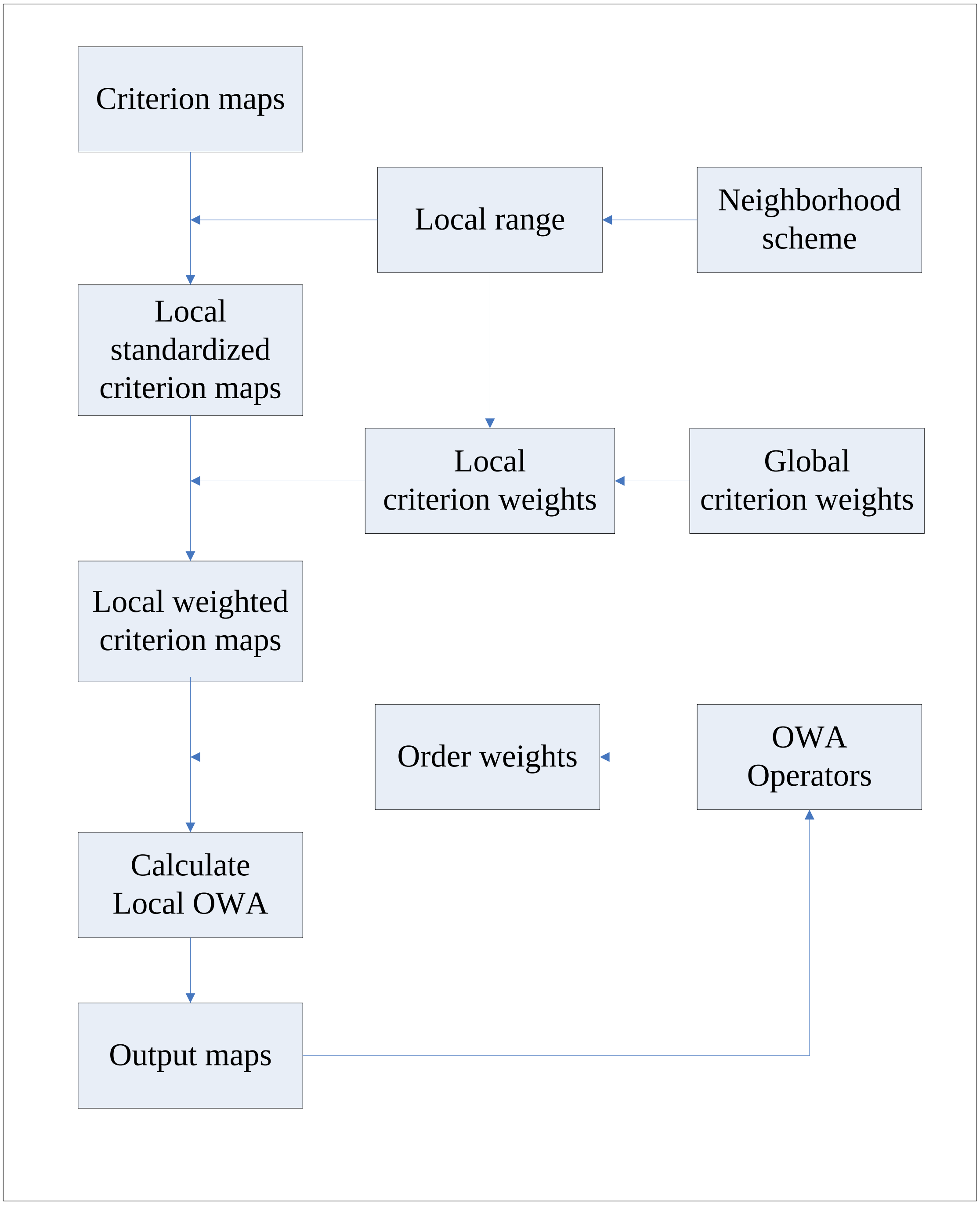


Figure 3-3 Local OWA Procedure

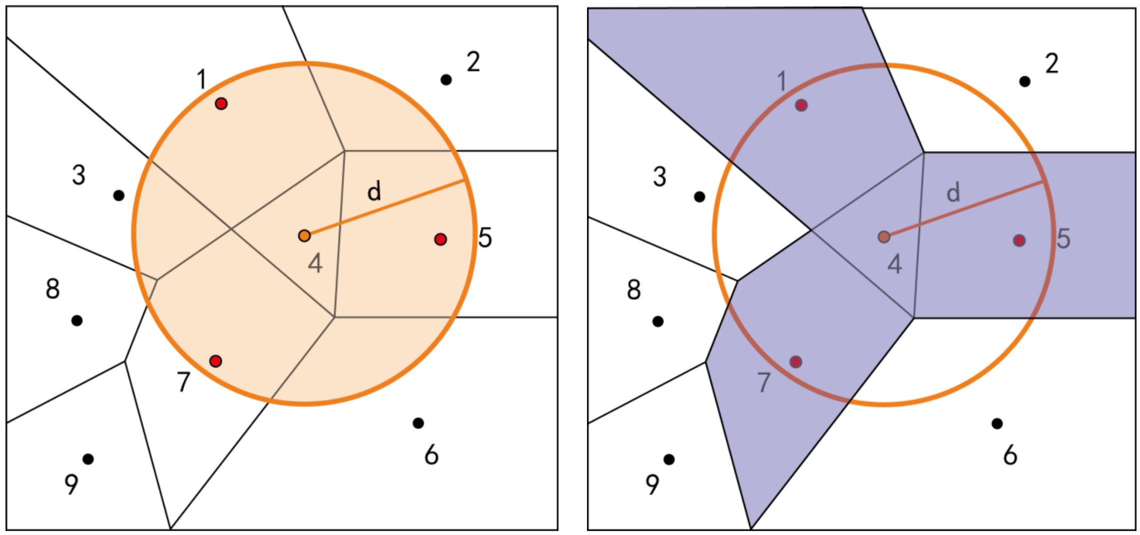
3.2.2 Defining Neighborhoods

One of the crucial differences between the local and global OWA methods is the utilization of the neighborhood scheme for localizing OWA method. In this research, an alternative is a polygon (or location). Two approaches are applied to identify neighborhoods: the distance-based method and the boundary-based method.

3.2.2.1 Distance-based neighborhood scheme

In the distance-based method, neighborhoods are generated based on the threshold distance (d). The centroid of each polygon must be found in order to measure the distance between polygons (locations). The threshold distance is assigned according to specific situation. Once the threshold distance is determined, one can compare the threshold distance with the distances between focal polygon and other polygons. If the distance between the focal location and its nearby polygon is smaller than the threshold distance, then the polygon is defined as a neighbor of the focal polygon. The neighborhood of focal location consists of the focal location and its neighbors. For the local OWA method, the value of threshold distance must be large enough to guarantee that each polygon has at least one polygon as its neighbor. This rule ensures that the denominator of Equations 3-10, 3-11 and 3-12 is greater than zero. Moreover, if the threshold distance is large enough to cover the whole study area, then the neighborhood of each location contains all other locations in the study area. In this case, the local and global OWA methods generate the same results.

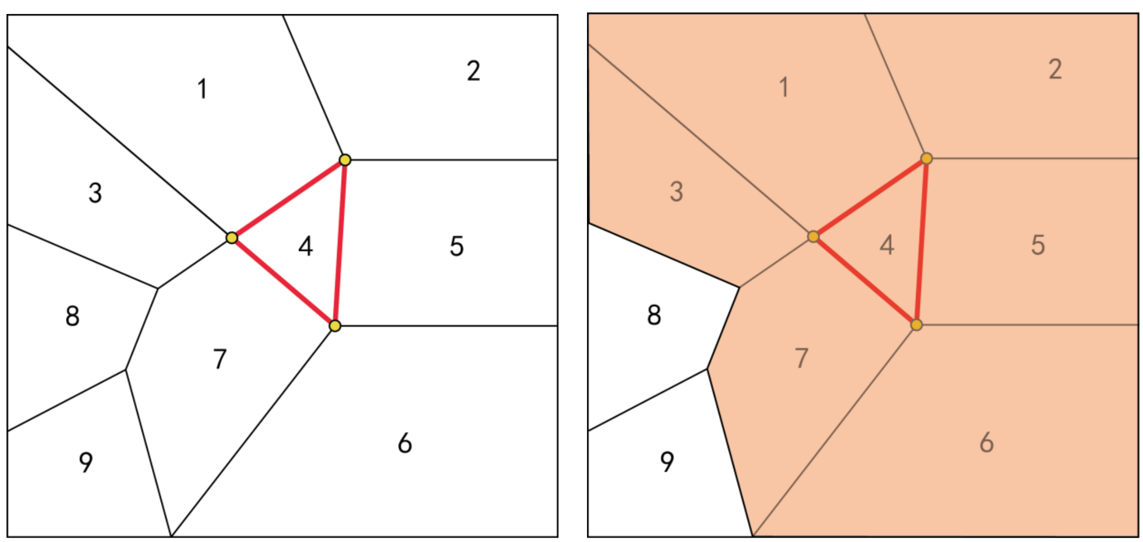
Figure 3-4 shows an example. The study area is represented in a vector format. Points from 1 to 9 represent the centroids of nine polygons. In Figure 3-4-A, d represents the threshold distance and polygon 4 is the focal polygon. Since the straight line distances between the centroid of polygon 4 and centroids of polygon 1, 5 and 7 are smaller than the threshold distance (d), polygons 1, 4, 5 and 7 form the neighborhood of the focal polygon (see Figure 3-4-B).



(A) (B)

Figure 3-4 Identifying Neighborhood Using the Distance Based Method

3.2.2.2 Boundary-based neighborhood scheme



(A) (B)

Figure 3-5 Identifying Neighborhood Using the Boundary Based Method

In the boundary-based method, neighborhoods are defined as areas which share their boundaries with the focal area. This research is based on the Queen's case. If two polygons share boundary, including any shared line or point, they are considered as neighbors. Any polygon sharing boundaries with a given focal polygon is defined as the neighbor of that area (see Figure 3-5). For example, the polygon 4 shares three points and three lines with surrounding polygons (see Figure 3-5-A), therefore polygon 1 to 7 form the neighborhood of polygon 4 (see Figure 3-5-B).

3.2.3 Range Sensitivity Principle and Local Range

The range sensitivity principle is used as a core concept for developing the local form of OWA method. The range sensitivity is a normative property with respect to the dependence of criterion weights on the ranges of criterion values (von Nitzsch and Weber 1993; Fischer, 1995; Malczewski, 2011). In the global OWA method, an assumption about uniformity of preferences over the whole study area is applied to global criterion weights. In the process of global standardization, the global standardized criterion value (a_{ik}) is the function of global range (r_k) (see Equation 3-2 and 3-3). The global range is the parameter that is defined for the whole study area. It implies that the spatial heterogeneity is ignored, irrespectively of the local context and factors that may affect the level of worth associated with a particular criterion value.

The range sensitivity principle assumes that for a given criterion the greater the range of the criterion values is, the greater the weight of importance assigned to the criterion should be (von Nitzsch and Weber 1993; Fischer, 1995). To convey local context in the specific neighborhood, the local range can be generated based on this principle. The **local range** (r_k^q) is defined as the difference between the maximum and minimum criterion values in the qq-th neighborhood for the k-th criterion. Formally:

$$r_k^q = max_{i,q}\{a_{ik}^q\} - min_{i,q}\{a_{ik}^q\} \quad (3\text{-}9)$$

where $max_{i,q}\{a_{ik}^q\}$ and $min_{i,q}\{a_{ik}^q\}$ are the minimum and maximum values of the k-th criterion in the q-th neighborhood; r_k^q is the local range of the k-th criterion in the q-th neighborhood.

3.2.4 Local Standardization

The values of each criterion are standardized locally as follows:

$$a_{ik}^{q} = \frac{max_{i,q}\ \{b_{ik}^{q}\} - b_{ik}^{q}}{r_{k}^{q}}\ \text{, for the } k\text{-th criterion to be minimize;} \qquad (3\text{-}10)$$

$$a_{ik}^{q} = \frac{b_{ik}^{q} - min_{i,q}\ \{b_{ik}^{q}\}}{r_{k}^{q}}\text{, for the } k\text{-th criterion to be maximize} \qquad (3\text{-}11)$$

where $max_{i,q}\{\,b_{ik}^{q}\}$ and $min_{i,q}\{\,b_{ik}^{q}\}$ are the minimum and maximum values of the q-th neighborhood for the k-th criterion; r_{k}^{q} is the local range; a_{ik}^{q} is the locally standardized criterion values, ranging from 0 to 1, where 0 is assigned as the least-desired criterion value and 1 is assigned as the most-desired value in the q-th neighborhood.

3.2.5 Local Criterion Weights

The value of local criterion weight depends on the scheme used for subdividing a study area into neighborhoods (zones or regions). Local criterion weight (ω_{k}^{q}) can be obtained as follows:

$$\omega_{k}^{q} = \frac{\frac{w_k r_k^q}{r_k}}{\sum_{k=1}^{n} \frac{w_k r_k^q}{r_k}}\ , 0 \leq\ \omega_{k}^{q} \leq 1 \text{ and } \sum_{k=1}^{n} \omega_{k}^{q} = 1 \qquad (3\text{-}12)$$

where ω_{k}^{q} is the local criterion weight associated with the q-th neighborhood for the k-th criterion; w_k is the global criterion weight of k-th criterion; r_k is the global range, which equals to the maximum minus the minimum criterion value in the k-th criterion; r_{k}^{q} is the local range. Since the value of local weight depends on the neighborhood scheme, it is also referred to the neighborhood-based criterion weights (Feick and Hall 2004).

3.2.6 Sorting Local Weighted Criteria

Unlike global criterion weights (w_k), which are presented as an array, the local weights (ω_k^q) form a matrix. It implies that each location (spatial unit) on the criterion map has assigned a corresponding value of the local weight. The calculation process of weighting local criterion maps involves the matrix multiplication of standardized criterion values and local criterion weights. The procedure for sorting (ordering) local weighted criteria is the same as the sorting method for the global OWA method (see Section 3.1.4). Thus, one can sort the weighted criterion values ($a_{ik}^q \omega_k^q$) to obtain the ordered weighted criterion values (z_k^q)

3.2.7 Generating Local Order Weights

In the local OWA method, the procedure of generating local order weights is the same as of determining order weights in the global OWA method (see Section 3.1.5). According to Equation 3-5, the order weights (v_{ik}) are derived from ordered criterion weights (u_{ik}). Although the local criterion weights (ω_k^q) are different from global criterion weights (w_k), both weights are formed as a matrix. In the local OWA method, the order weights are defined as follows:

$$v_k^q = \left(\sum_{j=1}^{k} u_j^q\right)^\alpha - \left(\sum_{j=1}^{k-1} u_j^q\right)^\alpha \ , \ \alpha > 0 \qquad (3\text{-}13)$$

where v_k^q is the local order weight; u_j^q is the ordered weighted local criterion values for the j-th criterion in the q-th neighborhood; α is the parameter associated with the fuzzy quantifier(see Section 3.1.5.1).

3.2.8 Calculating Local OWA

The calculation of local OWA scores is defined as follows:

$$\mathrm{OWA}^{q} = \sum_{k=1}^{n} v_k^q \, z_k^q \tag{3-14}$$

where OWA^{q} is the overall local OWA score for the q-th neighborhood; v_k^q is the local order weights (see Section 3.2.7); u_k^q is the ordered weighted local criterion values for the k-th criterion in the q-th neighborhood(see Section 3.2.7).

3.3 Comparing Local OWA methods and Global OWA methods

The most important difference between local and global OWA methods lies in applying different criterion weights. In the global OWA method, the relative importance of evaluation criterion is the only factor to determine the criterion weights, defined as the global weights. In the local OWA method, however, the local criterion weights are estimated on the basis of the preferences with respect to relative importance of criteria and the local context. In addition, the local weights can be considered as the adjusted global weights depending on the definition of neighborhoods. To be more specific, the local criterion weight is the function of the global criterion weight modified by the relationships between the local and global ranges. The ranges in turn depend on the configuration of neighborhoods and the size of study area.

Chapter 4

4 Case Study

The aim of the case study is to test the local OWA method and to compare the results of global and local OWA methods by evaluating the socioeconomic status of neighborhoods in London, Ontario.

4.1 The Study Area

The study area is the City of London, Ontario (see Figure 4.1). London is located in Southwestern Ontario. It is situated along the Quebec City - Windsor corridor. The city of London has a population of 366,151 (Statistics Canada, 2011).

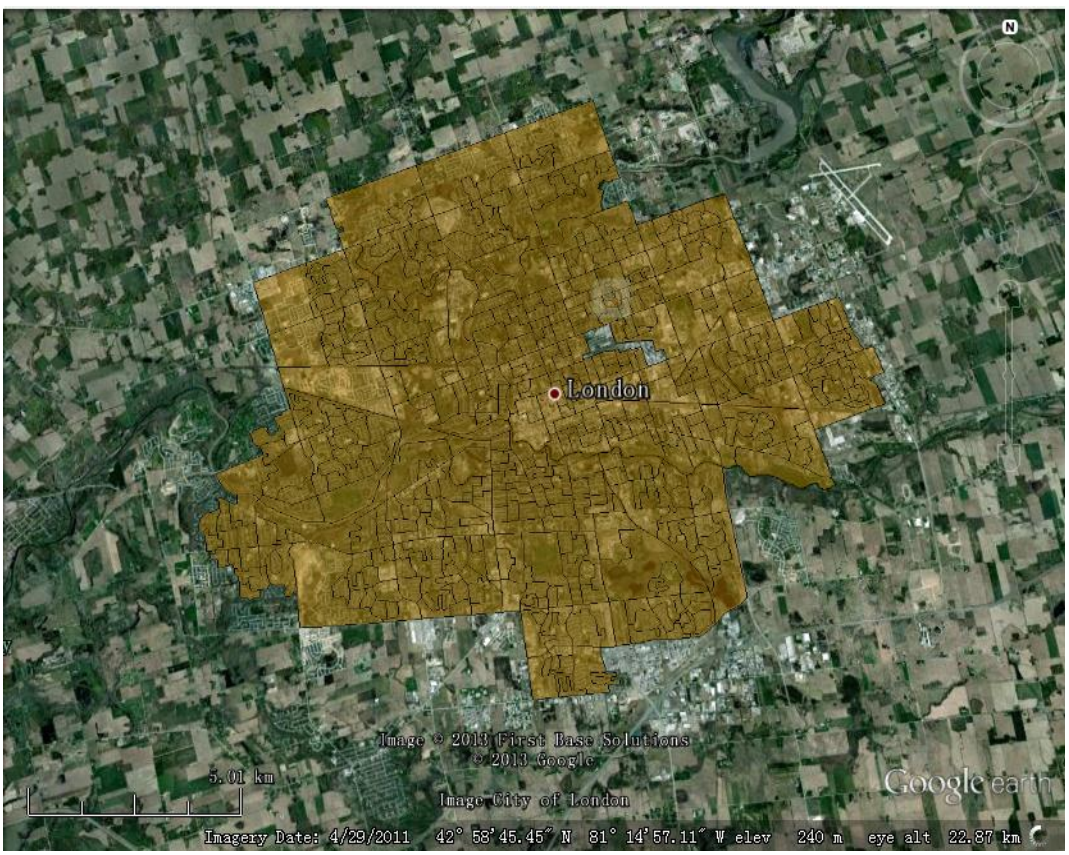


Figure 4-1 The Study Area: London, Ontario (Source: Google Earth)

4.2 Data Sources

The geographic data of the study area is obtained from a secure website database distributed through the university's library system (UWO, 2011). The geographic data are in the vector format; that is, the census dissemination area is represented by polygons. ArcMap 10.0 is applied to manipulate the spatial data.

The socioeconomic data for London was derived from the Population Census of 2006 (Statistics Canada, 2006). The census dissemination area is the basic unit of the analysis. The statistic data for the evaluation criteria is available for 494 dissemination areas in London, Ontario. The unpopulated Census Tract 0056 is excluded from the analysis.

4.3 The Application of OWA methods

4.3.1 Criteria Selection

The problem of evaluating socioeconomic conditions of residential neighborhoods (and related problem of measuring quality of life or residential quality) provides a good example of a situation in which one has to combine a number of evaluation criteria (indicators) to obtain a composite measure of socioeconomic status. Many studies rely on multivariate statistics and/or multicriteria evaluation procedures (Can, 1992; Raphael et al., 1996; CUISR, 2000). The weighted linear combination (WLC) is the most often used approach for obtaining a composite measure of quality of life (e.g. Raphael et al., 1996; CUISR, 2000; Massam, 2002). The Federation of Canadian Municipalities (FCM) provides a reporting system to monitor the quality of life in Canadian municipalities (FCM, 1999; FCM, 2001). The project is known as the quality of life reporting system (QOLRS). The selection of evaluation criteria for this case study of assessing the socioeconomic status in London is based on the QOLRS. The set of criteria includes: median incomes, incidence of low incomes, employment rate, average values per dwelling, university education and residential burglary (see Table 4-1). For the type of criterion, the maximum type indicates that the higher value is more desired. The minimum type means that the lower value of the criterion is more desired.

Table 4-1 Criteria for Evaluating Socioeconomic Status in London, Ontario

	Name	Description	Type
1	MED_INC*	Median incomes ($)	Maximum
2	LOW_INC*	Incidence of low income (%)	Minimum
3	EMP_RAT*	Employment rate (%)	Maximum
4	AVE_DWE*	Average value of dwelling ($)	Maximum
5	UNI_EDU*	University education (% population 15 years and over)	Maximum
6	RES_BUR**	Residential burglary (relative risk ratio)	Minimum

(Sources of data: * Statistics Canada, 2006 and ** Poetz, 2003)

4.3.2 Identify Global Criterion Weights

The global criterion weights represent the relative importance of criteria. To define the global criterion weights, several scenarios are developed by applying the pairwise comparison approach (see Section 3.1.3). For the purpose of demonstrating the OWA procedures, this case study focuses on one of the criterion weighting scenarios. Table 4-2 shows the pairwise comparison matrix. The meaning of scores in the pairwise comparison matrix is given in Table 3-2. The pairwise comparisons are normalized; that is, each cell of the matrix is divided by its column total (the results are shown in Table 4-3). Then the global criterion weights are obtained by computing the average value of the normalized pairwise comparisons (see Table 4-3).

Table 4-2 A Scenario for Global Criterion Weighting: Pairwise Comparison Matrix

	MED_INC	LOW_INC	EMP_RAT	AVE_DWE	UNI_EDU	RES_BUR
MED_INC	**1**	1	3	1	2	2
LOW_INC	1	**1**	1	2	1	1
EMP_RAT	0.33	1	**1**	1	2	1
AVE_DWE	1	0.5	1	**1**	1	1
UNI_EDU	0.5	1	0.5	1	**1**	1
RES_BUR	0.5	1	1	1	1	**1**

Table 4-3 Global Criterion Weights

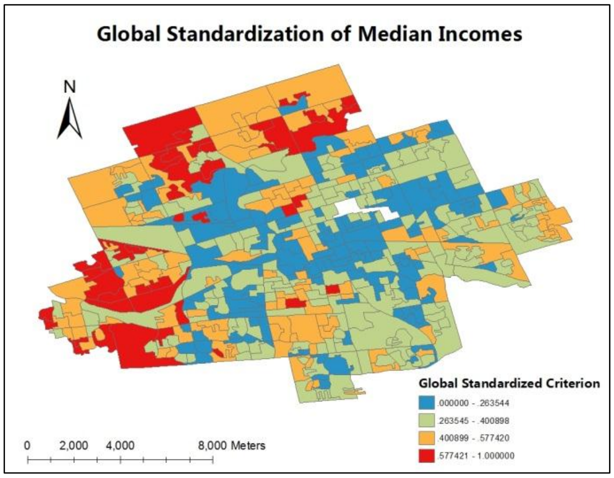
	MED_INC	LOW_INC	EMP_RAT	AVE_DWE	UNI_EDU	RES_BUR	**Weights**
MED_INC	0.23	0.18	0.40	0.14	0.25	0.29	**0.25**
LOW_INC	0.23	0.18	0.13	0.29	0.13	0.14	**0.18**
EMP_RAT	0.08	0.18	0.13	0.14	0.25	0.14	**0.15**
AVE_DWE	0.23	0.09	0.13	0.14	0.13	0.14	**0.14**
UNI_EDU	0.12	0.18	0.07	0.14	0.13	0.14	**0.13**
RES_BUR	0.12	0.18	0.13	0.14	0.13	0.14	**0.14**
Sum	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	***1.00***

Note: the consistency ratio CR = 0.06 < 0.1 indicates that the global criterion weights are based on a consistent set of pairwise comparisons (see Section 3.1.3).

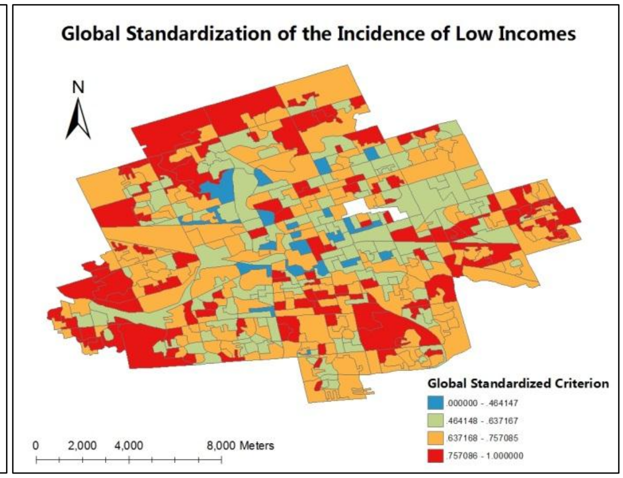
4.3.3 Global Standardization

The six standardized global criterion maps are generated according to Equations 3-1, 3-2, and 3-3 (see Figure 4-2). The Jenks natural breaks classification method is applied to display criterion maps, where classes are developed on natural groupings inherent in the data. The class breaks are statistically determined by best grouping similar values and maximizing the differences between classes in ArcGIS 10.0 (ESRI, 2010). Boundaries of divided classes are set according to the relatively 'big jumps' within data values. The Jenks natural breaks classification method is applied to all criterion maps in this study.

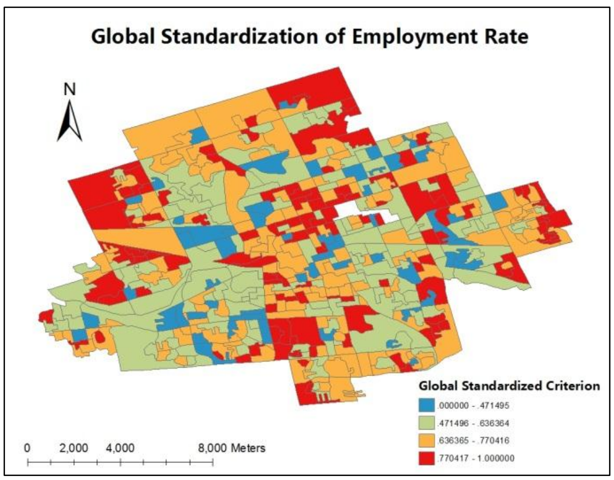
In the outcome of global standardization, the criterion map of median incomes shows that the northwestern of London has high values, while the central and southeastern of the city are characterized by low values of median incomes (see Figure 4-2-A). A similar spatial pattern can also be observed for criteria of average value per dwelling, university education and residential burglary (see Figures 4-2-D, 4-2-E and 4-2-F). One can conclude that the residential neighbourhoods in the northwest part of London are characterized by higher median incomes, higher average value of dwelling, higher level of education and lower residential burglary rates. Conversely, the central and southeast sectors of the city tend to have lower median incomes, lower average value of dwelling, lower level of education and higher residential burglary rates. For criterion maps of the incidence of low income and the employment rate (see Figures 4-2-B and 4-2-C), the spatial pattern is dispersed with a slight tendency of clustering higher values at the outskirts of the study area.



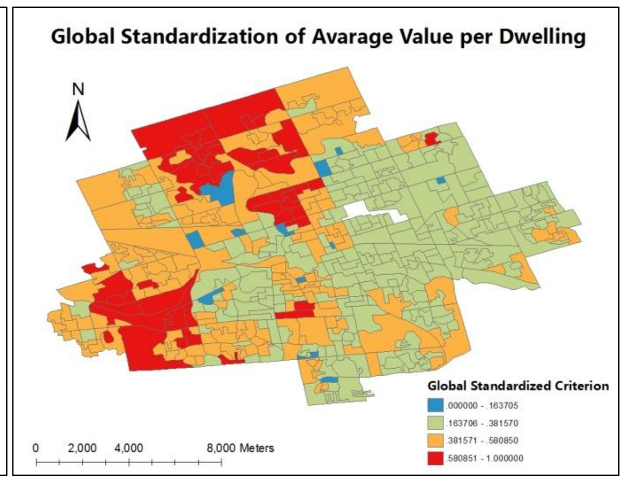
(A) MED_INC



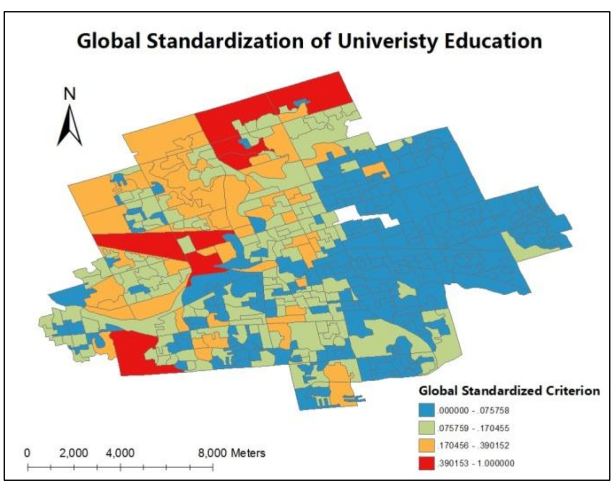
(B) LOW_INC



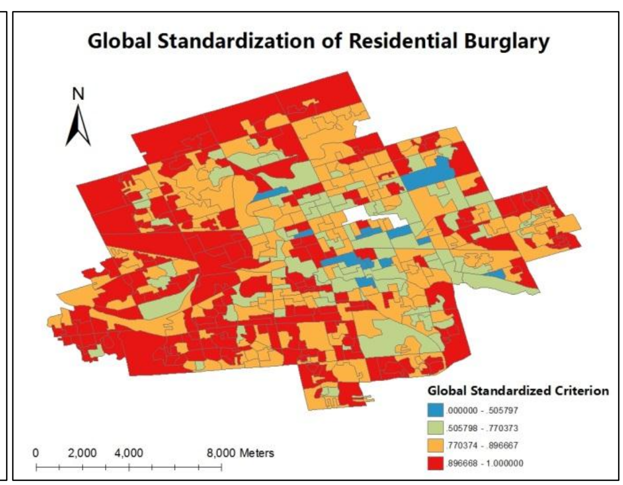
(C) EMP_RAT



(D) AVE_DWE



(E) UNI_EDU



(F) RES_BUR

Figure 4-2 Global OWA: Standardized Criterion Maps

4.3.4 Neighborhood Scheme

This research applies two methods of the neighborhood scheme: distance-based and boundary-based methods (see Section 3.2.2). ArcGIS 10.0 is used as the tool to establish the neighborhood scheme (ESRI, 2010). Table 4-5 lists the four specific neighborhood schemes applied in this case study.

Table 4-4 Neighborhood Scheme

Method	Descriptions
Based on the distance	*d* = 850 m
	d = 1600 m
	d = 2400 m
Based on the boundary	Queen's case

(Note: *d* = threshold distance)

Implementing the distance-based method in ArcGIS involves two steps: (1) the "Feature to Point" tool generates centroid points of polygons, and (2) the tool "Point Distance" is applied to find neighbors according to the threshold distance. The output is a table that contains the list of the focal polygons and information of about all near polygons (centroids) within the search radius or threshold distance. Three threshold distances are used: 850m, 1600m and 2400m (see Table 4-5). The threshold should be large enough to guarantee that each location (polygon) has at least one neighbor. The distance of 850m is the smallest threshold to meet this constrain, and the distance of 2400m is selected based on previous research (Malczewski and Poetz, 2005). The research findings suggest that the processes underlying the relationships between some socioeconomic variables in London, Ontario operate at a local (neighborhood) scale. Malczewski and Poetz (2005) demonstrated in the context of geographically weighted regression that the spatial variability in the relationships is significant at the spatial scale associated with kernel bandwidths less than 2400 m.

The boundary-based method is another way to identify the neighborhood scheme (see Section 3.2.2.2). Using the tool “Spatial Join” in ArcGIS 10.0 creates the neighborhood attribute table for identifying neighborhoods based on shared boundaries (ESRI, 2010). For instance, the neighborhood attribute table of the example showed in Figure 3-5 is given in Table 4-5. The Neighbor column of the table indicates the number of polygons which share the boundary with the target polygon.

Table 4-5 Neighborhood Attribute Table Based on Boundary Method

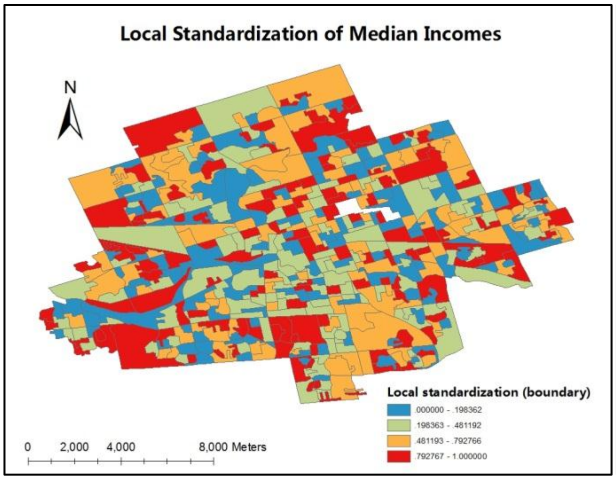
No.	Target	Neighbor	No.	Target	Neighbor	No.	Target	Neighbor
1	1	2	14	4	2	27	7	1
2	1	3	15	4	3	28	7	3
3	1	4	16	4	5	29	7	4
4	1	5	17	4	6	30	7	5
5	1	7	18	4	7	31	7	6
6	2	1	19	5	1	32	7	8
7	2	4	20	5	2	33	7	9
8	2	5	21	5	4	34	8	3
9	3	1	22	5	6	35	8	7
10	3	4	23	5	7	36	8	9
11	3	7	24	6	4	37	9	7
12	3	8	25	6	5	38	9	8
13	4	1	26	6	7			

Based on the table of neighborhoods, generated by both the distance-base method and the boundary-based method, one can compute the local range for each dissemination area (polygon) according to Equation 3-9 (see Section 3.2.3). Since the calculation of the local range cannot be accomplished in the ArcGIS, a calculator for computing the local ranges is developed (see Appendix).

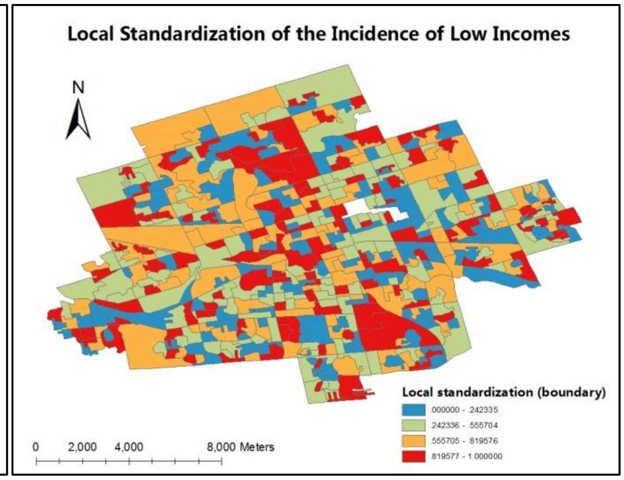
4.3.5 Local Standardization

Since four neighborhood schemes are applied in this case study, four sets of local standardized criterion maps are generated by using Equations 3-10 and 3-11. Figure 4-3 shows the results of local standardization for six criteria according to the boundary-based neighborhood scheme. The local standardized criterion maps based on distance-based neighborhood scheme with the threshold distance of 850m, 1600m and 2400m are showed in Figures 4-4, 4-5, and 4-6, respectively.

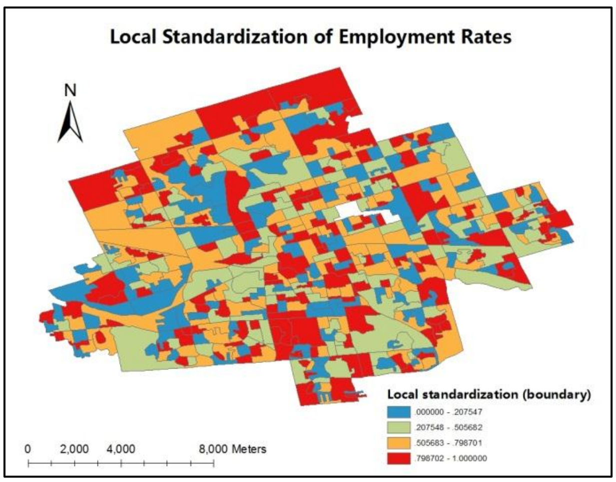
There are essential differences between the global standardized criterion map (Figure 4-2) and corresponding local criterion maps (Figures 4-3, 4-4, 4-5 and 4-6). As expected, spatial patterns of criterion values generated by the local OWA method are more localized than the global one. The AVE_DWE criterion (the average value per dwelling) is used to illustrate the differences between the global and local patterns (see Figure 4-7). This criterion has the distinct spatial pattern of the global standardization values (see Section 4.3.3). The spatial pattern with the higher values in the northwestern part of London can be observed for the global standardization (see Figure 4-7-A). However, the local standardized criterion maps are characterized by dispersed distribution of peaked values across the whole study area (see Figures 4-7-B, 4-7-C, 4-7-D, and 4-7-E). According to the global criterion standardization results, the spatial clustering of less expensive dwellings in central and southeastern London is greater than in the northwestern section of the city. On the other hand, in the local criterion results, peak



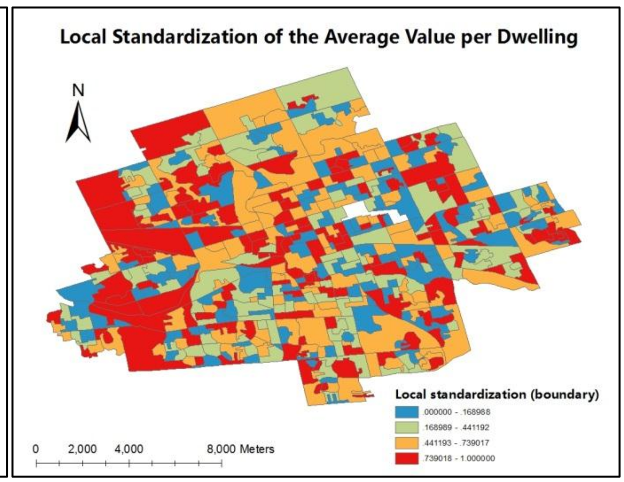
(A) MED_INC



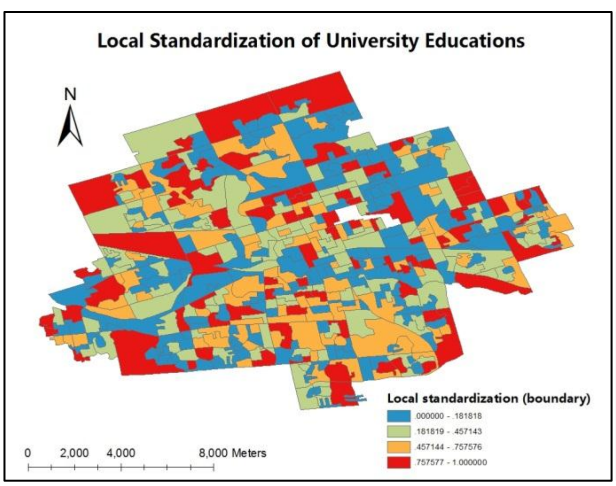
(B) LOW_INC



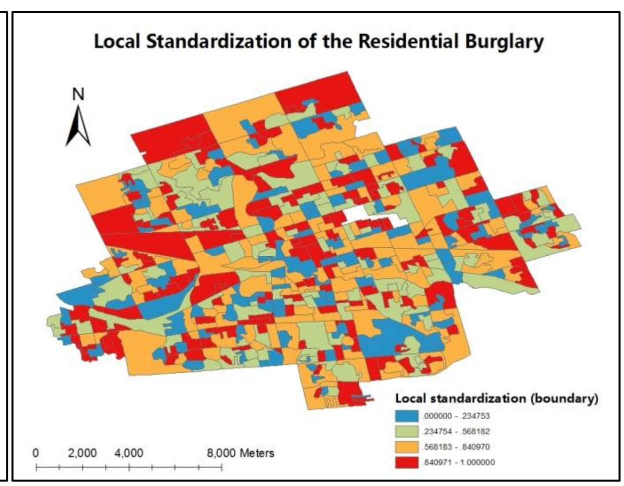
(C) EMP_RAT



(D) AVE_DWE

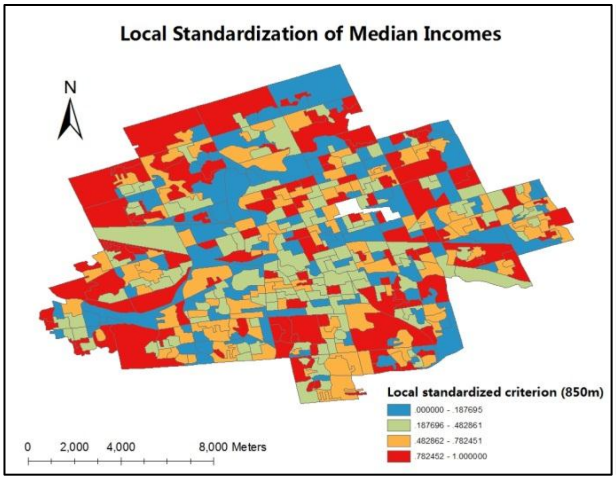


(E) UNI_EDU

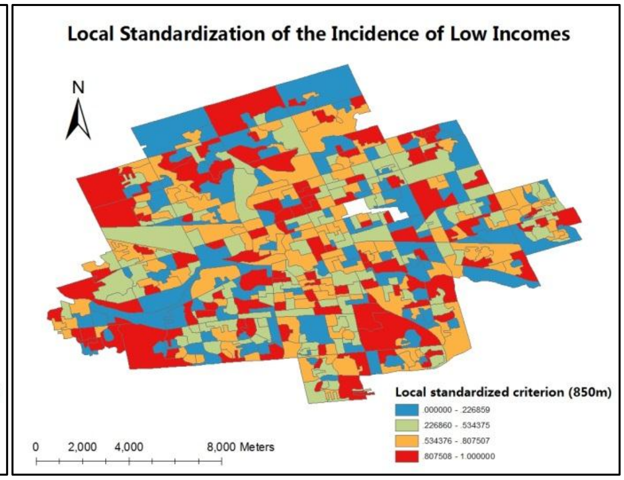


(F) RES_BUR

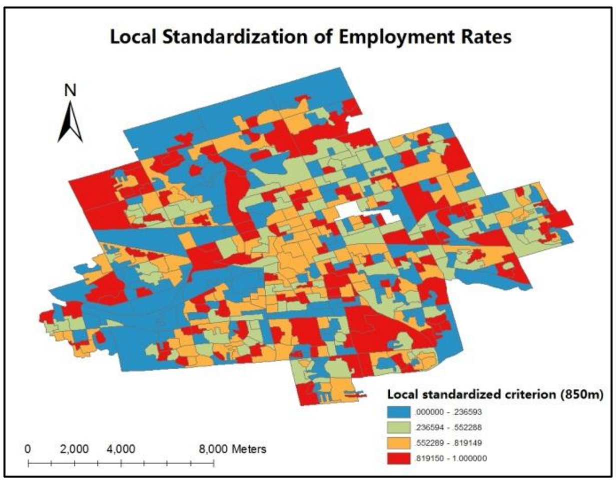
Figure 4-3 Local Standardized Criterion Maps Based on the Boundary



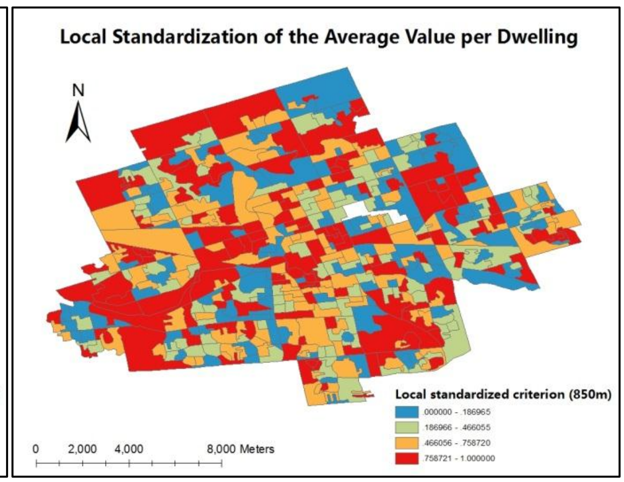
(A) MED_INC



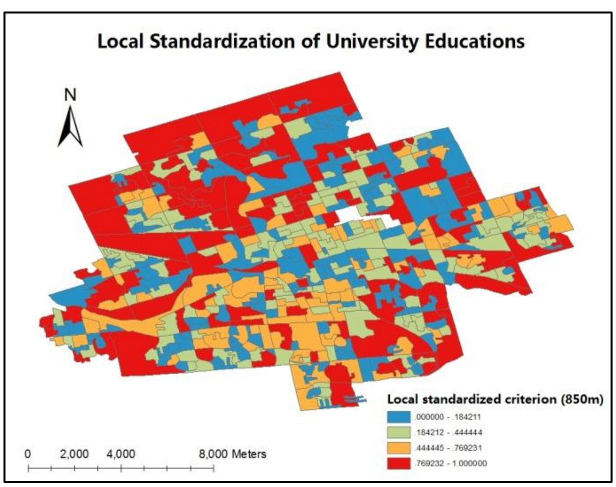
(B) LOW_INC



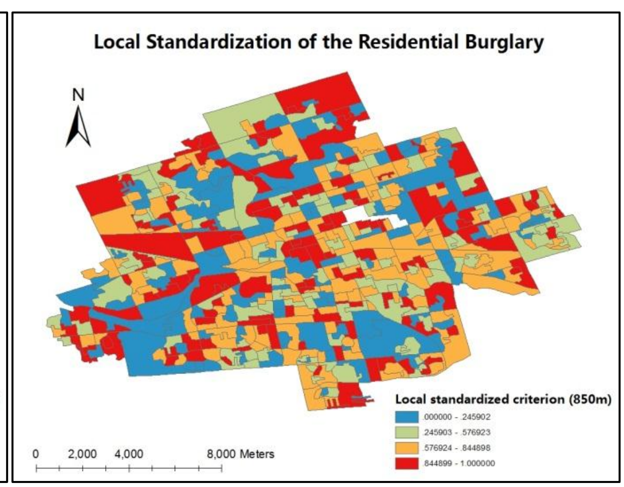
(C) EMP_RAT



(D) AVE_DWE

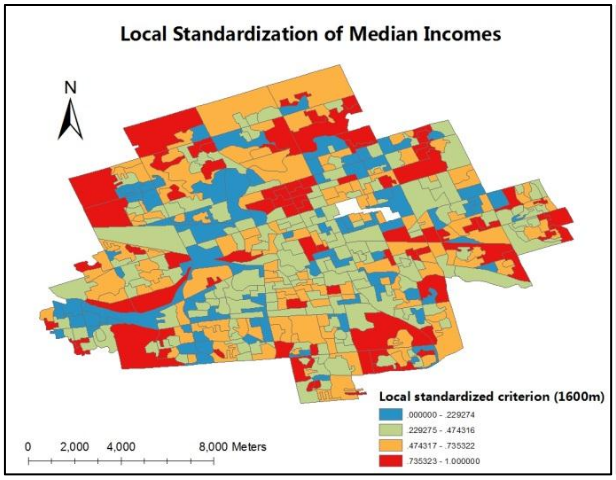


(E) UNI_EDU

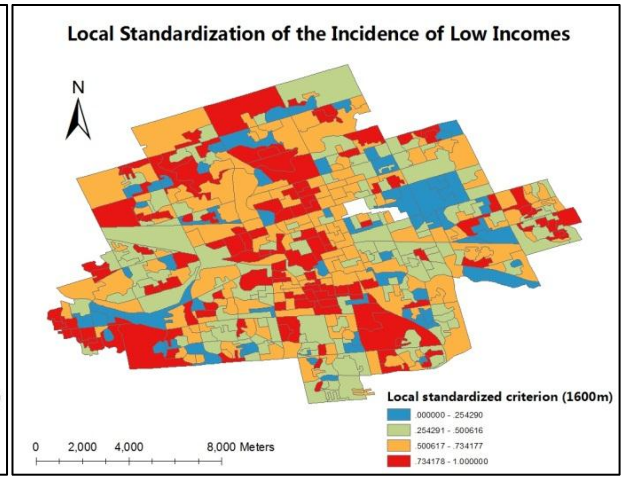


(F) RES_BUR

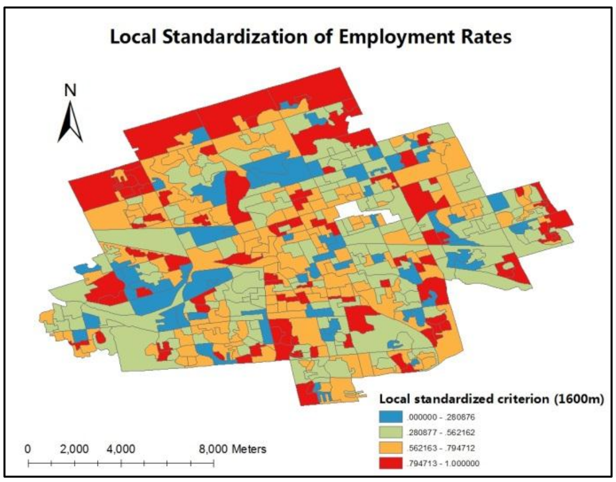
Figure 4-4 Local Standardized Criterion Maps Based on 850m Distance



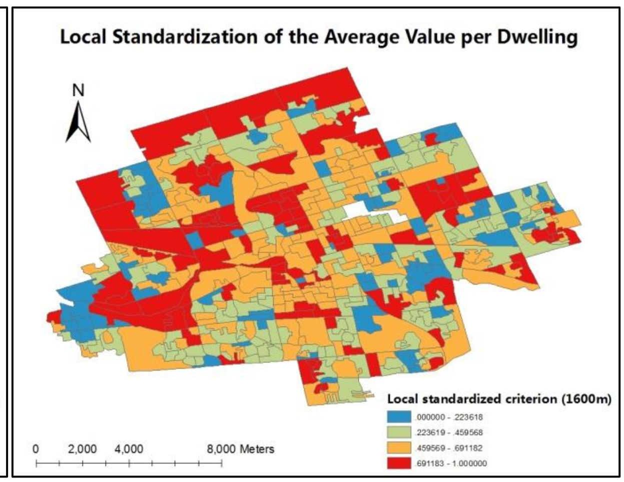
(A) MED_INC



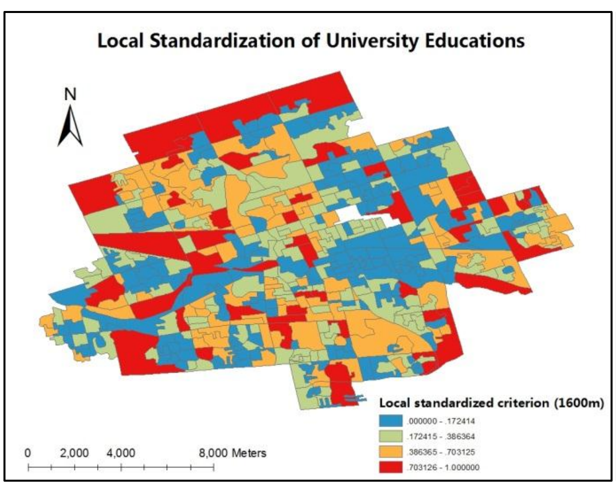
(B) LOW_INC



(C) EMP_RAT



(D) AVE_DWE



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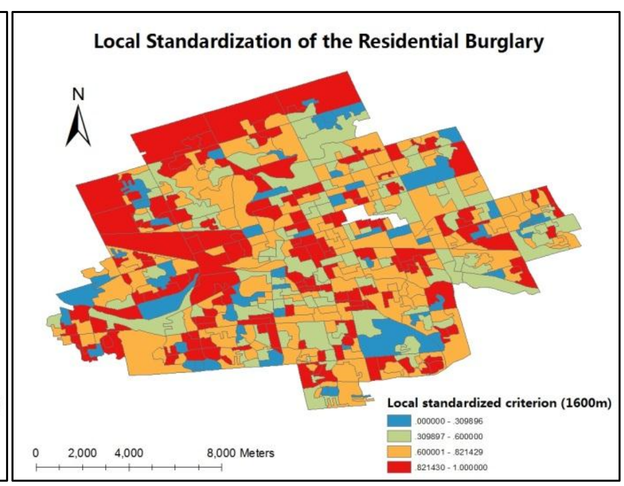
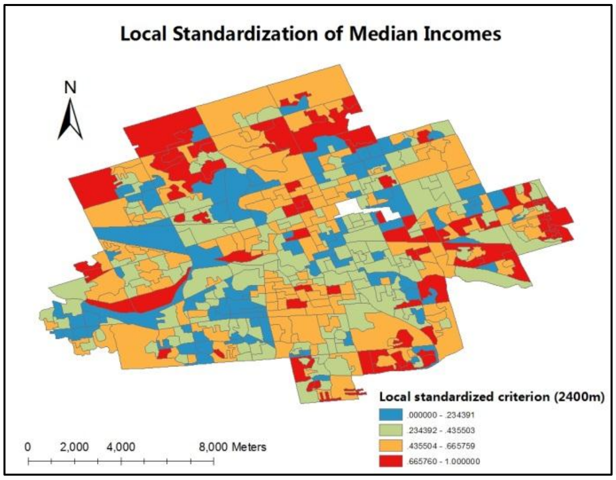
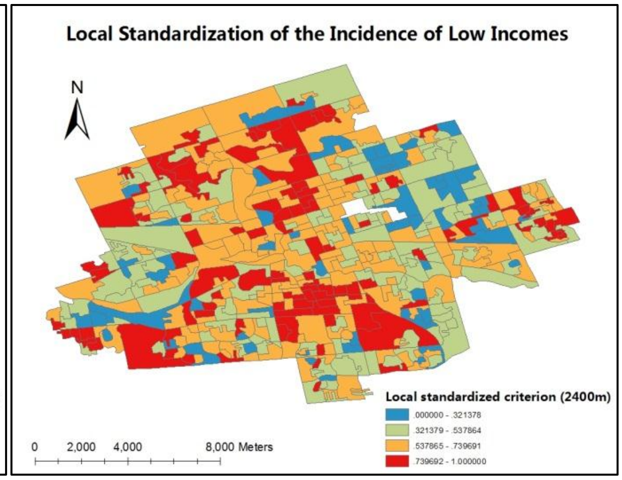


(F) RES_BUR

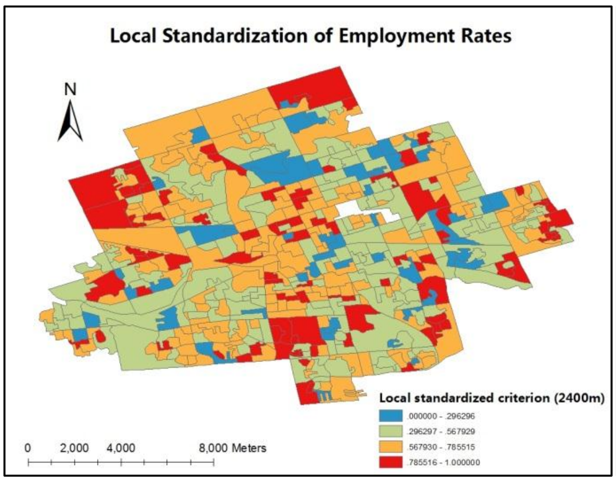
Figure 4-5 Local Standardized Criterion Maps Based on 1600m Distance



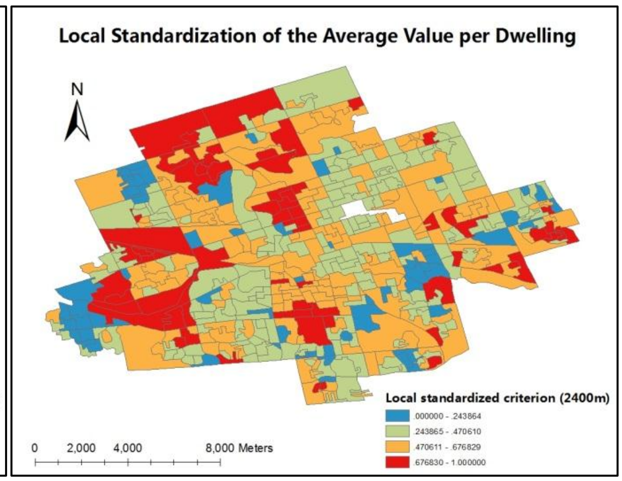
(A) MED_INC



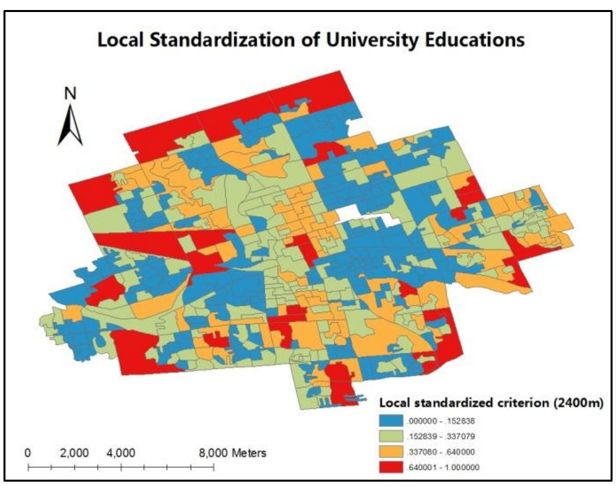
(B) LOW_INC



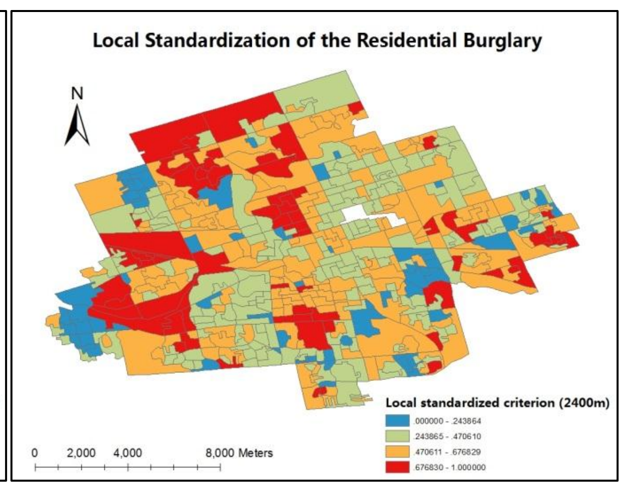
(C) EMP_RAT



(D) AVE_DWE



(E) UNI_EDU



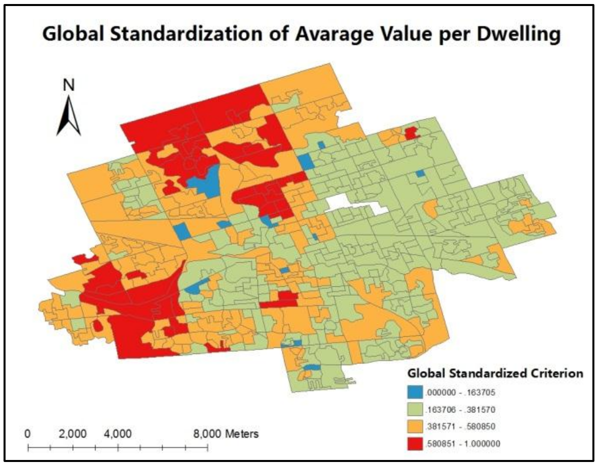
(F) RES_BUR

Figure 4-6 Local Standardized Criterion Maps Based on 2400m Distance

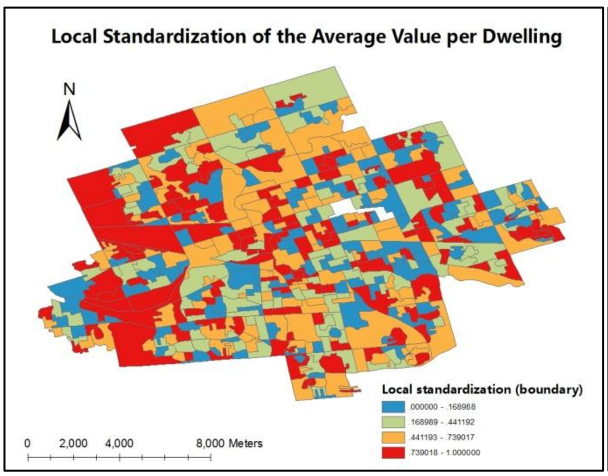
values can be observed in the central and southeastern parts of the city because local patterns underscore the relatively high values at the neighborhood scale.

Furthermore, four neighborhood schemes present difference outcomes. The results based on neighborhoods defined by shared boundaries and threshold distance of 850m show an ‘evenly’ dispersion of higher values (see Figures 4-7-B and 4-7-C). Comparing spatial patterns obtained with neighborhood schemes based on different threshold distances (see Figures 4-7-B, 4-7-C and 4-7-D), one can conclude that with increasing the threshold distance the number of areas with the highest criterion values decreases. This can be attributed to the increasing size of the neighborhood as a function of the increasing threshold distance. In general, the area having the highest value in every neighborhood is identified as a focal area of that neighborhood. When the size of the neighborhood increases, the number of peak values decreases.

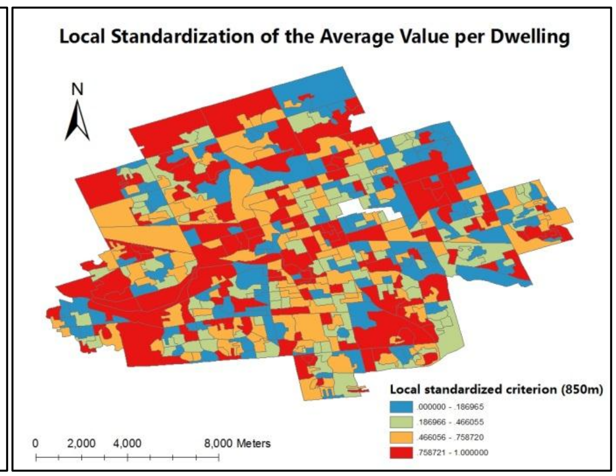
For the case of 2400m threshold distance (Figure 4-7-D), the high criterion values tend to cluster in the north and west sections of the study area. This makes the spatial pattern similar to that generated by the global standardization procedure (Figure 4-7-A). Note that when the value of threshold distance is sufficiently large, the outcomes of local and global standardization will be the same. Consequently, the global method can be deemed as the extreme case of the neighborhood scheme based on the threshold parameter.



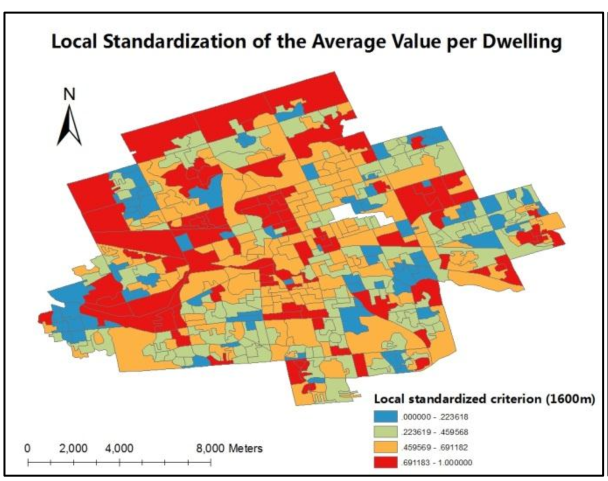
(A) global standardization



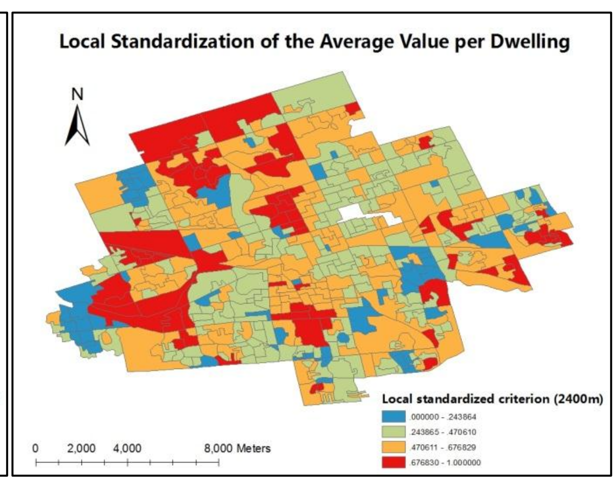
(B) local standardization on the boundary



(C) local standardization on 850m



(D) local standardization on 1600m



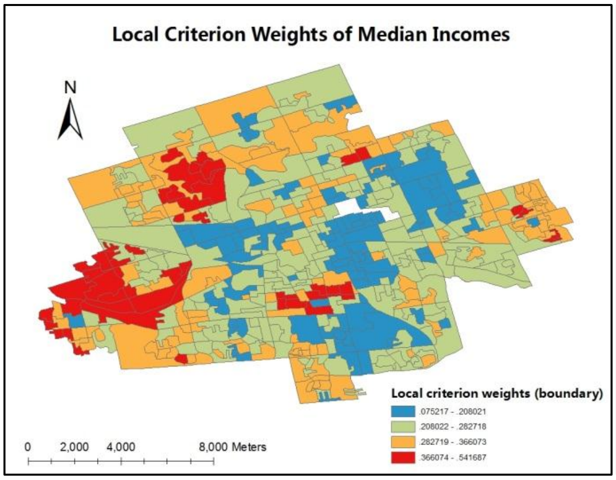
(E) local standardization on 2400m

Figure 4-7 The Comparison of Global and Local Standardized Criterion Maps for Average Dwelling Value Criterion

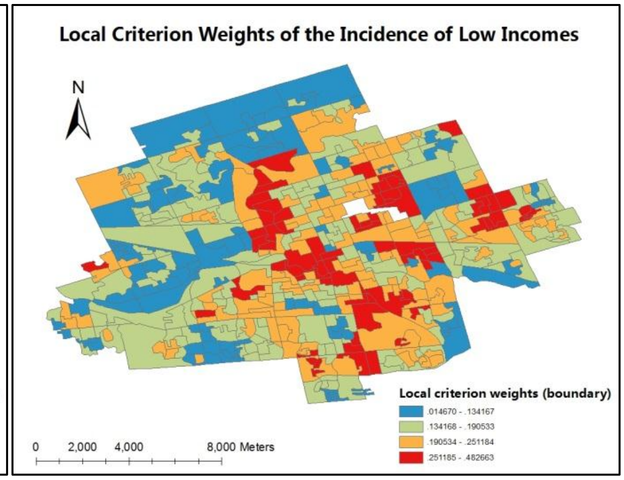
4.3.6 Local Criterion Weight

The local criterion weight is a function of global criterion weights, local range and global range (Equation 3-12). Given four neighborhood schemes, the results of the local criterion weighting have four sets of outcomes. Figures 4-8, 4-9, 4-10 and 4-11 show the spatial patterns of local criterion weights under different neighborhood schemes.

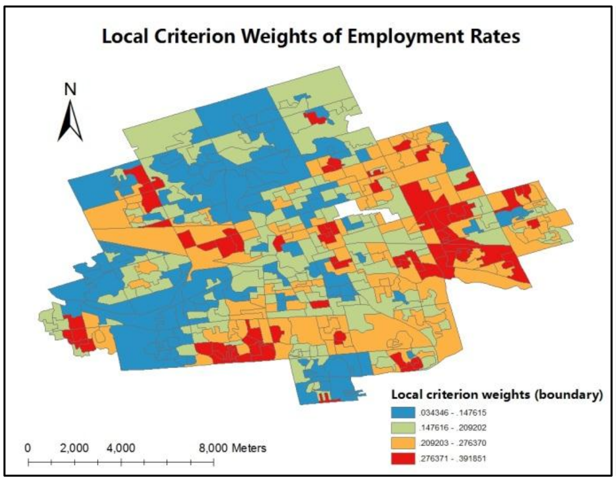
The local criterion weights are the kernel of the local OWA method. The local criterion weight contains the local context and supports spatial visualization. In the global OWA method, all locations (areas) are assigned by a single value as the global criterion weight. For example, the global criterion weight of median incomes is 0.25 (see Table 4-3). Since the local criterion weight depends on the local range, each location is assigned by a unique value of local criterion weight. This is because, for a given criterion, values of the global weight and the global range are constant, while the local criterion weight is a function of the local range which varies on the location basis (see Equation 3-12). The local ranges in turn depend on the neighborhood scheme. Therefore, the spatial pattern of local criterion weights can be considered as an important element of defining the character and the spatial arrangement of residential neighborhoods.



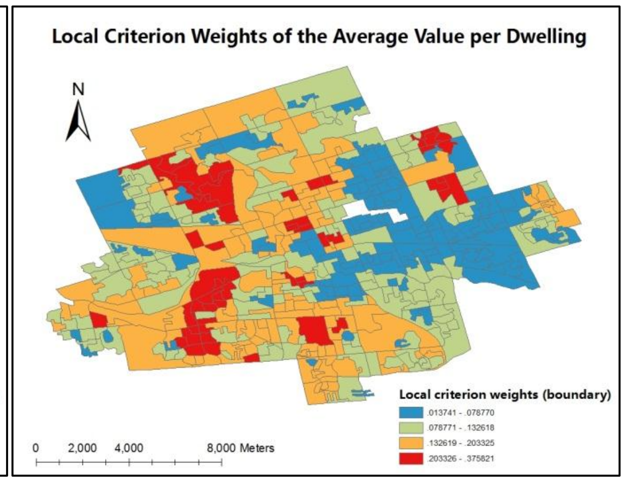
(A) MED_INC



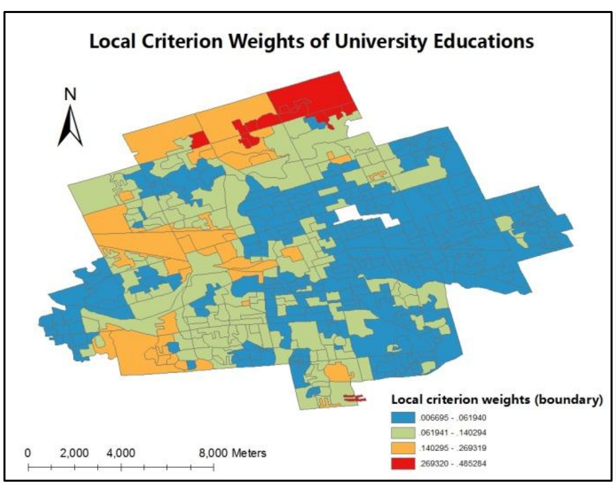
(B) LOW_INC



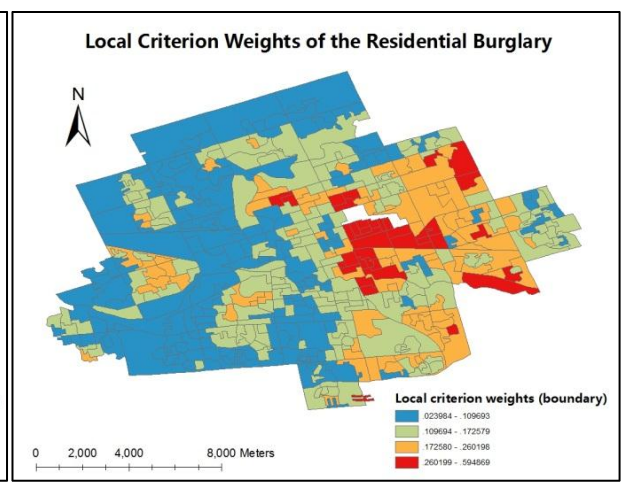
(C) EMP_RAT



(D) AVE_DWE

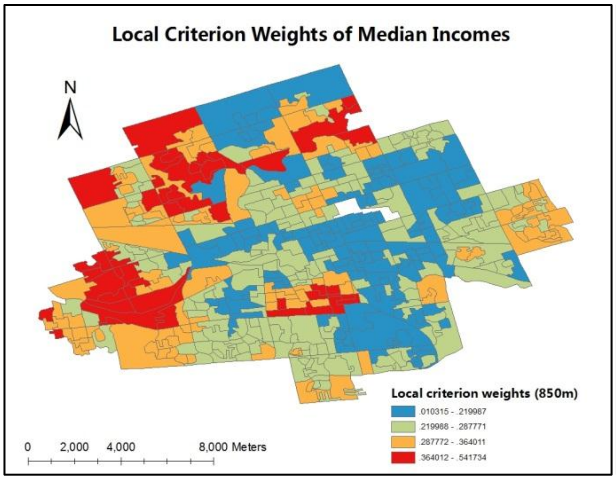


(E) UNI_EDU

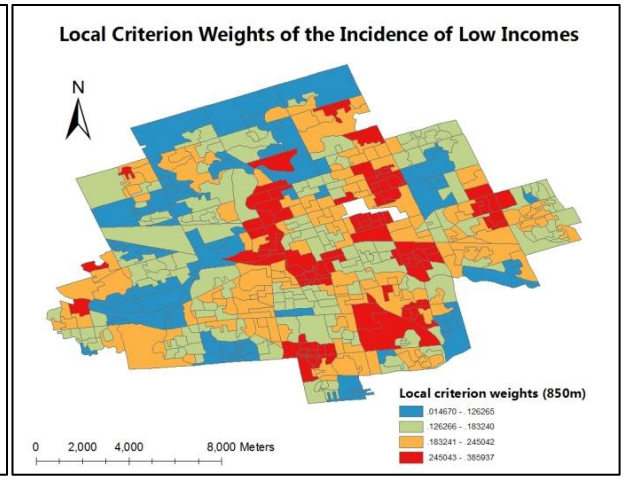


(F) RES_BUR

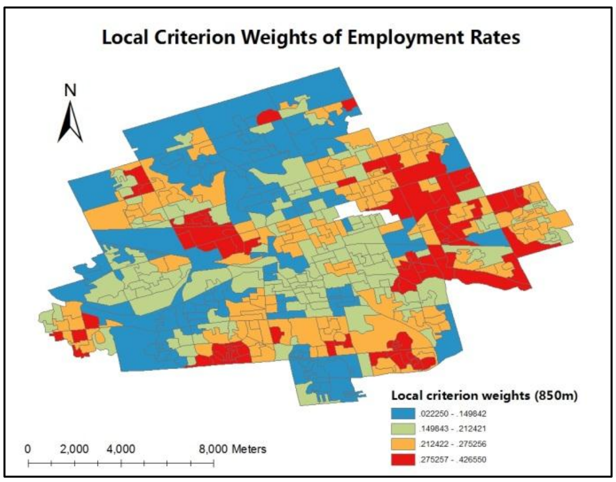
Figure 4-8 Local Weights Based on the Boundary



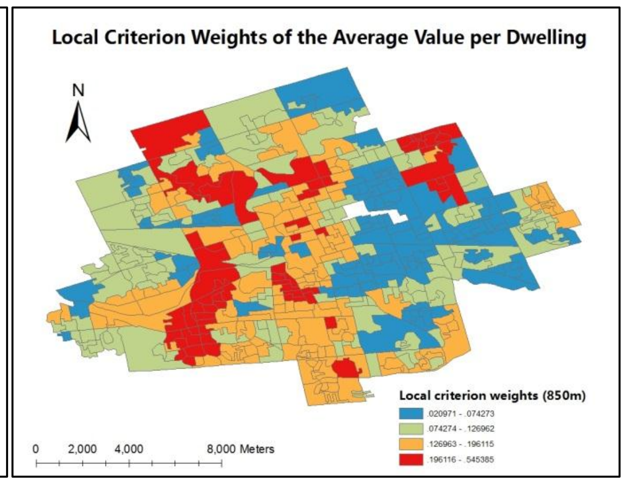
(A) MED_INC



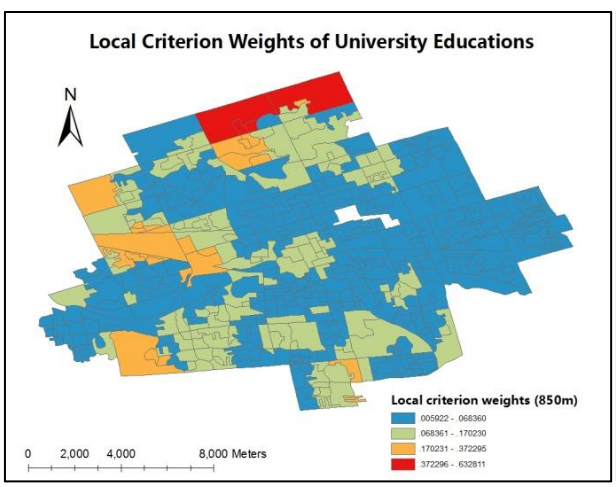
(B) LOW_INC



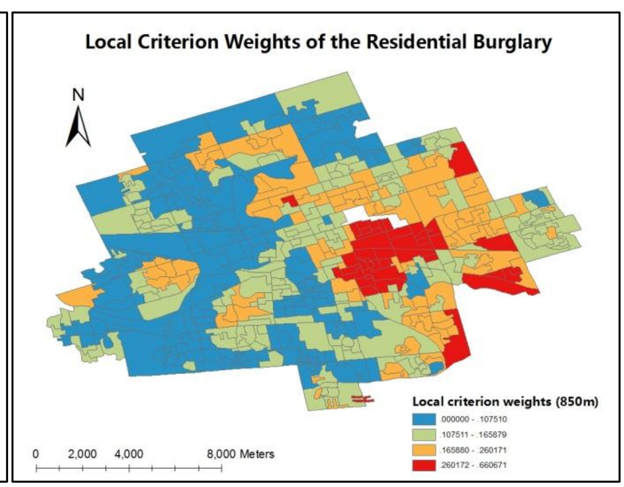
(C) EMP_RAT



(D) AVE_DWE

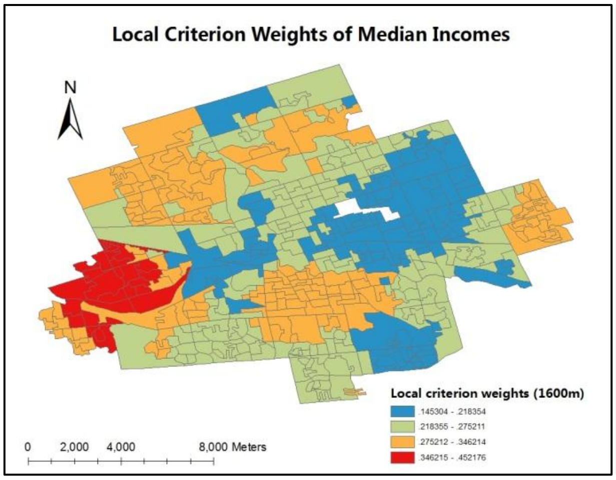


(E) UNI_EDU

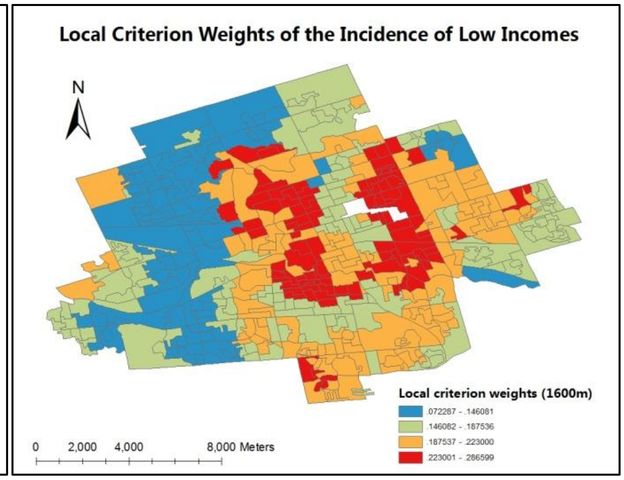


(F) RES_BUR

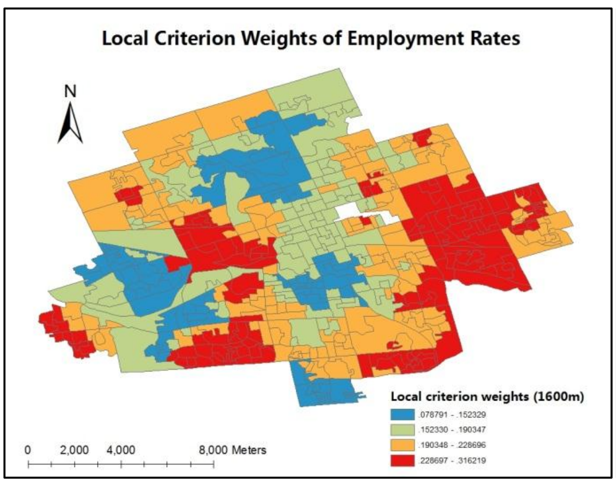
Figure 4-9 Local Weights Based on 850m Distance



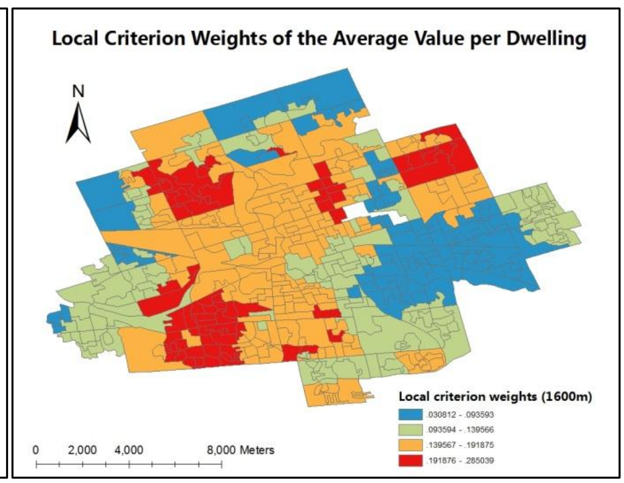
(A) MED_INC



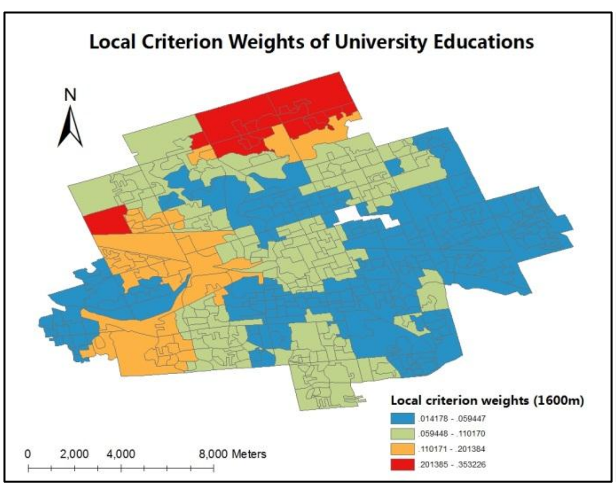
(B) LOW_INC



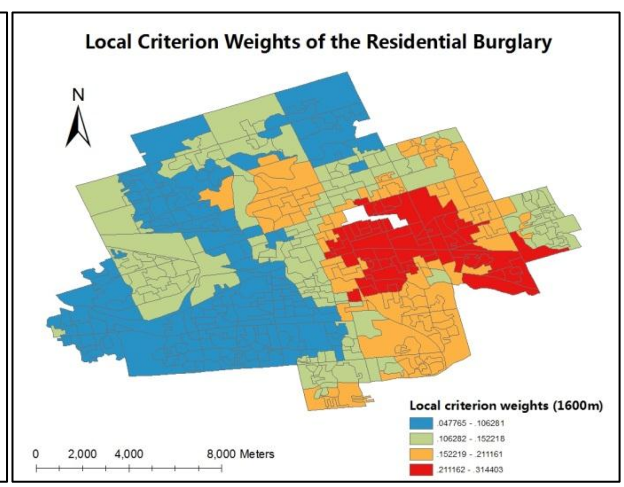
(C) EMP_RAT



(D) AVE_DWE

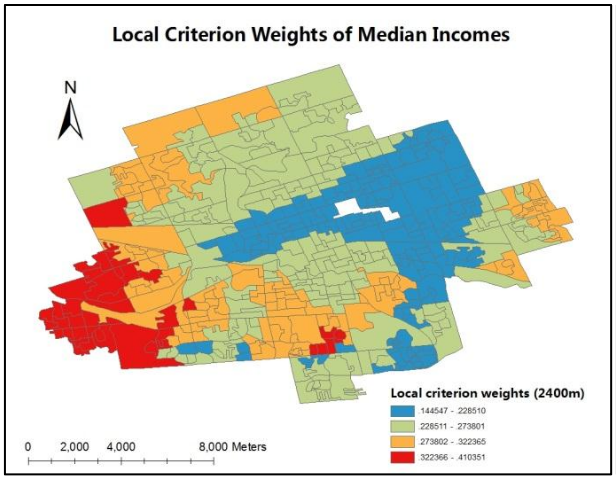


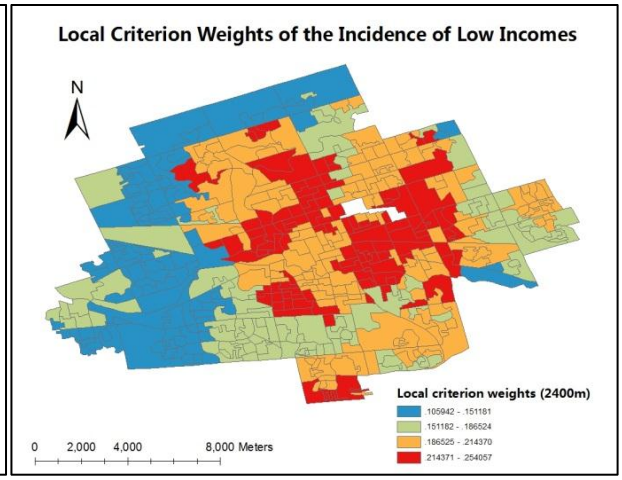
(E) UNI_EDU



(F) RES_BUR

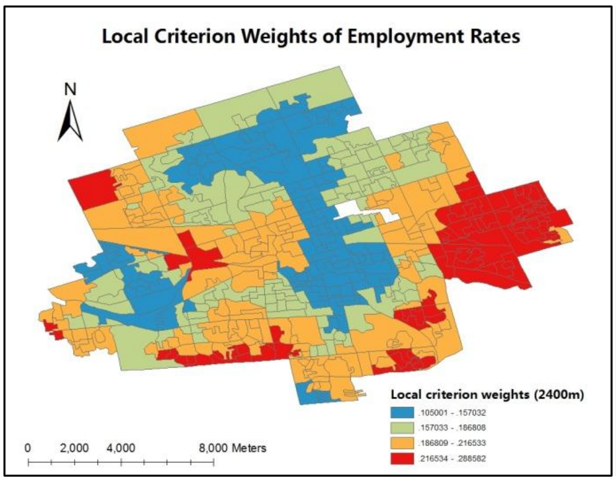
Figure 4-10 Local Weights Based on 1600m Distance

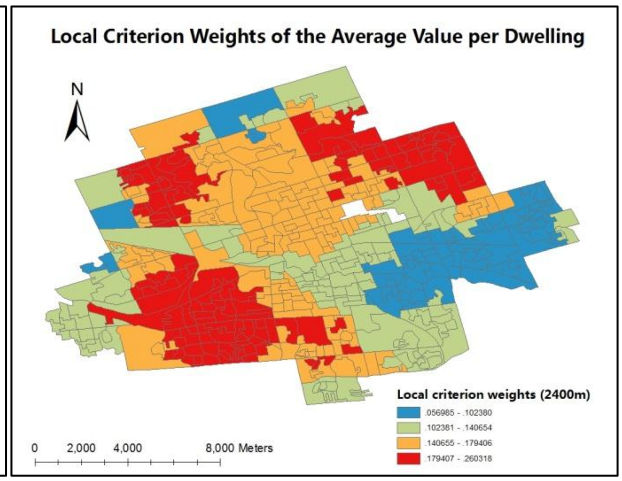




(A) MED_INC

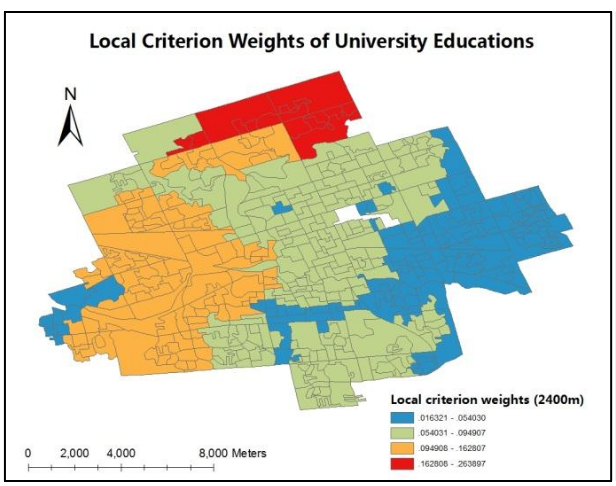
(B) LOW_INC

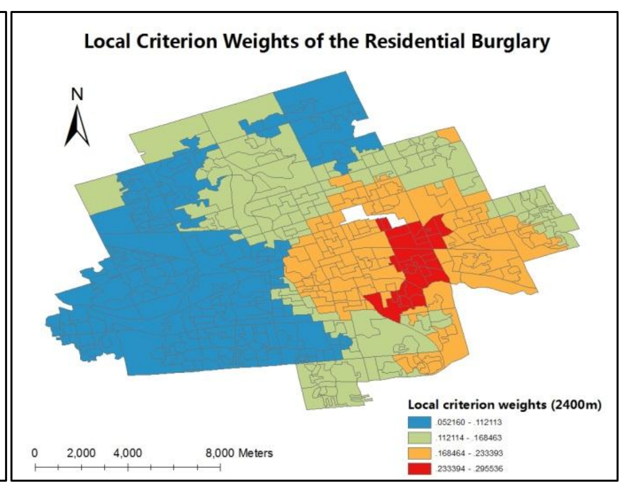




(C) EMP_RAT

(D) AVE_DWE





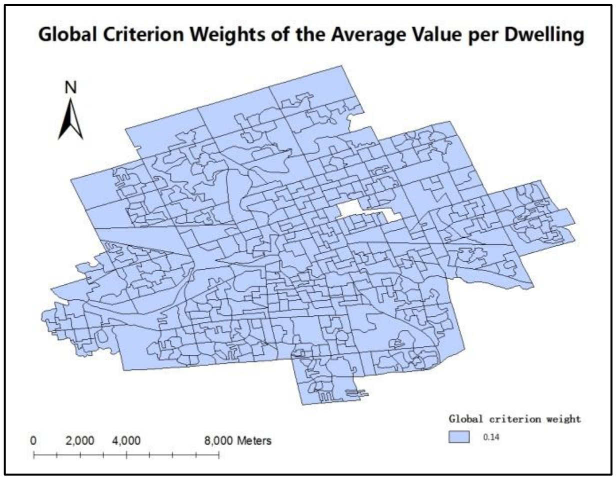
(E) UNI_EDU

(F) RES_BUR

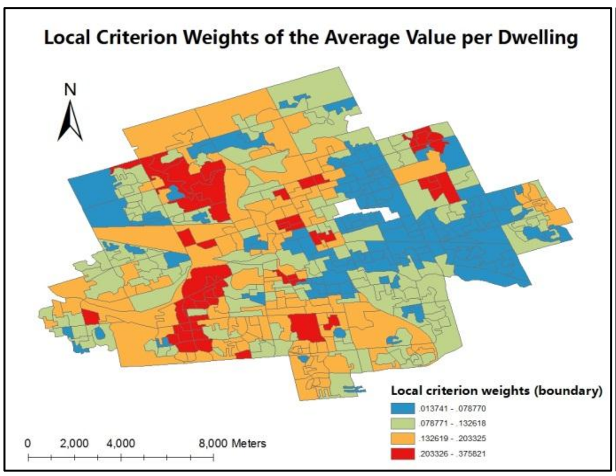
Figure 4-11 Local Weights Based on 2400m Distance

The criterion of the average value per dwelling (AVE_DWE) is selected to illustrate the impact of changing neighborhood schemes on the spatial patterns of local criterion weights (see Figures 4-8, 4-9, 4-10 and 4-11). The set of criterion maps also includes the global criterion weight of AVE_DWE criterion to show the difference between the spatial patterns of global and local criterion weights (see Figure 4-12).

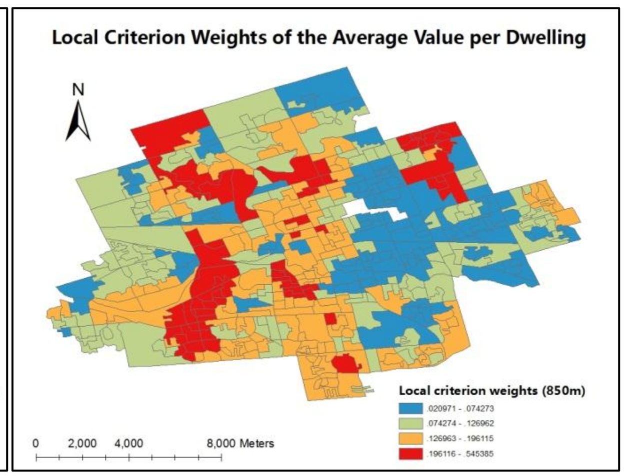
The global criterion weight is homogeneously applied to every location in the study area. In this example, each location is assigned the same value of 0.14 (see Figure 4-12-A). A comparison of spatial patterns of local criterion weights indicates that the neighborhood scheme has the considerable impact on the spatial distribution of local criterion weights. For the boundary-based neighborhood scheme, the size of neighborhoods tends to be smaller compared with the size of neighborhood generated by other neighborhood schemes. It results in a ‘patchy’ spatial pattern of local criterion weighs. The patches of local criterion weights become larger with the increasing threshold distance (see Figures 4-12-C, 4-12-D and 4-12-E).



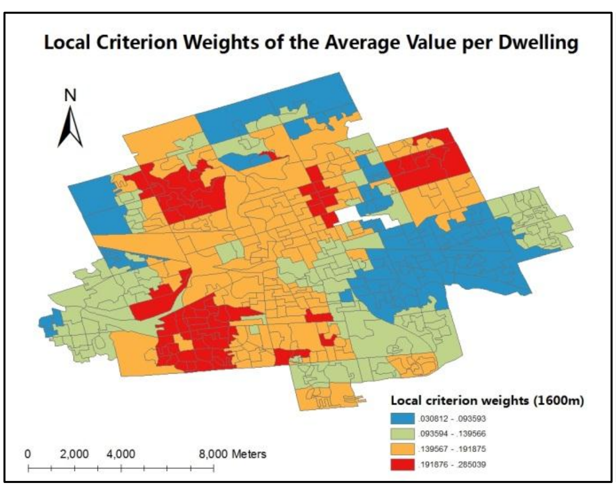
(A) global criterion weight



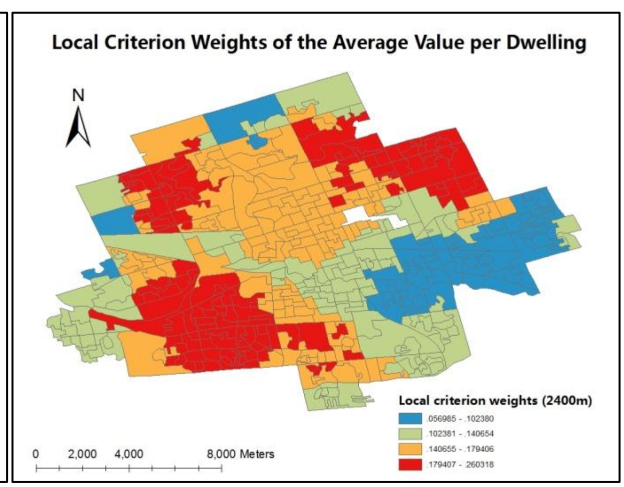
(B) local criterion weights on the boundary



(C) local criterion weights on 850m



(D) local criterion weights on 1600m



(E) local criterion weights on 2400m

Figure 4-12 The Comparison For Global and Local Criterion Weights of AVE_DWE

4.3.7 Measures of Order Weights

One can generate a wide range of OWA solutions (scenarios or spatial patterns) by changing the α parameter or the associated set of order weights (see Equation 3-5 and Equation 3-13). This case study explores five scenarios of order weights by applying different values of the parameter: α = 0.001, 0.5, 1, 2 and 1000 (see Section 3.1.5.2).

For the parameter of α = 0.001, the OWA model corresponds to the conventional OR operator. When parameter α = 1000, the OWA model is an equivalent of the conventional AND operator. These two operators are non-compensatory. Any value of parameter α between the two extreme cases results in a compensatory OWA method; that is, a relatively poor value of criterion can be compensated by a relatively high value for other criterion. The compensatory method is also referred to as the OWA *trade-off* method. Particularly, when parameter α = 1, then the OWA operator corresponds to the WLC operator, which is characterized by maximum value of the *trade-off* (see Equation 3-7).

The ORness and trade-off are the measures of OWA operators (see Section 3.1.5.2). Increasing the parameter α from 0 to 1 leads to different OWA operators, which are associated with the two measures. The types of OWA operators are defined by the values of order weights. For the AND, OR and WLC operators, the set of order weights remains the same values for both global and local OWA models (see Table 3-4), consequently, the *ORness* and t*rade-off* holds same value of these three OWA operators among different OWA models; while, other *trade-off* operators have different values of order weights according to Equation 3-5 for the global OWA method or Equation 3-13 for the local OWA method.

Table 4-6 The *ORness* and *trade-off* of different OWA operators for global and local order weights

OWA Operators:	OR (α = 0)	α = 0.5	WLC (α = 1)	α = 2	AND (α = 1000)
Global OWA					
ORness	1	0.676	0.5	0.311	0
Trade-off	0	0.729	1	0.738	0
Local OWA based on 850m neighborhood scheme					
ORness	1	0.682	0.5	0.332	0
Trade-off	0	0.724	1	0.777	0
Local OWA based on 1600m neighborhood scheme					
ORness	1	0.694	0.5	0.343	0
Trade-off	0	0.707	1	0.784	0
Local OWA based on 2400m neighborhood scheme					
ORness	1	0.694	0.5	0.343	0
Trade-off	0	0.708	1	0.774	0
Local OWA based on boundary-based neighborhood scheme					
ORness	1	0.676	0.5	0.324	0
Trade-off	0	0.732	1	0.769	0

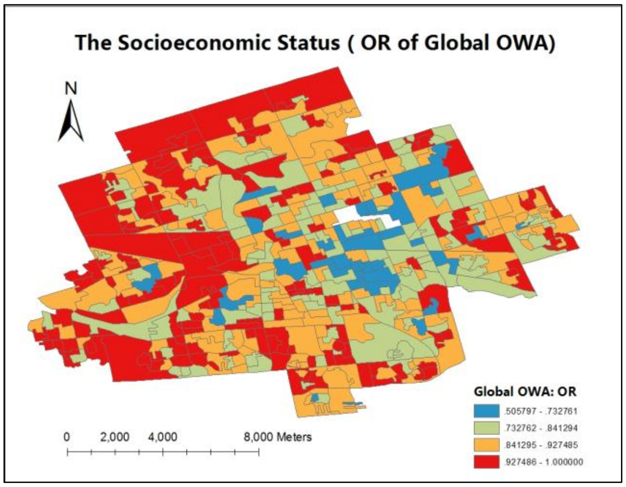
Table 4-6 shows the *ORness* and t*rade-off* of five OWA operators used in this case study for the global OWA method and four different neighborhood schemes of the local OWA. Particularly, given parameter α equals 0.5 and 2, the values of *ORness* and t*rade-off* shown in the Table 4-6 are the sum up value of the measurement of each location and divided by the total number of observations. With the increasing of parameter α that the OWA operator is changed from OR operator to AND operator, the value of *ORness* decreases from 1 to 0 (see Equation 3-6). This implies a decreased degree similarity of the OWA operators to the logical OR from OR operator to AND operator by increasing the value of parameter α. Moreover, for the OR operator and AND operator, the zero t*rade-off* values indicate no compensation among criteria; while WLC operator conveys a full t*rade-off.* The OWA operators of parameter α = 0.5 and α = 2 are in the similar medium degree of substitutability (or compensation) (see Section 3.1.5.2).

4.4 The Overall OWA Scores

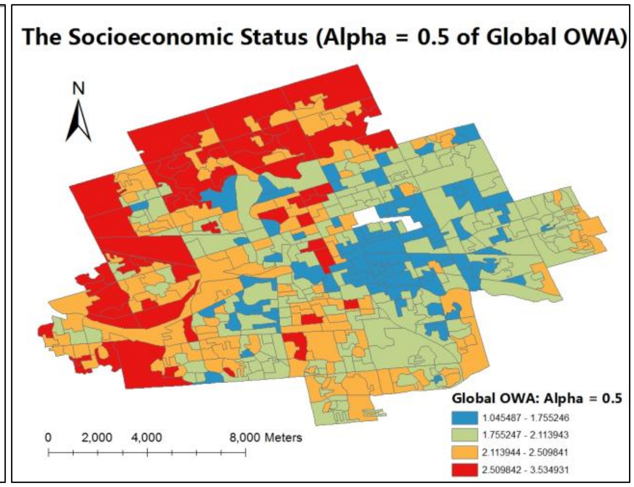
Changing the α parameter on the continuum ranging from 0 to 1 results in different OWA operators (including the conventional OR, AND and WLC operators). For each value of the α parameter, one output map can be obtained. In the local OWA method, varying neighborhood schemes also leads to different results. To explore the spatial pattern of socioeconomic status in London, five OWA operators are applied: OR, AND, and three *trade-off* operators. Furthermore, the local OWA method is used to generate the solutions in four different neighborhood schemes.

4.4.1 Overall Global OWA Scores

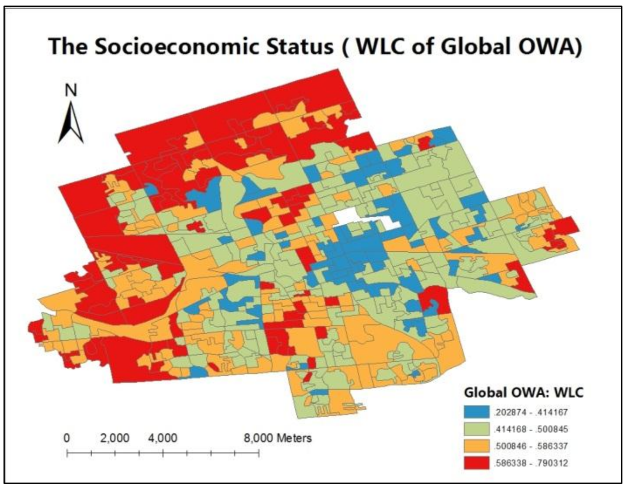
A set of output maps of the overall global OWA score is shown in Figure 4-13. In general, the northwestern sections of London have higher socioeconomic status than the central area and eastern part of the city. This spatial pattern can be observed from each of the five global OWA outcomes.



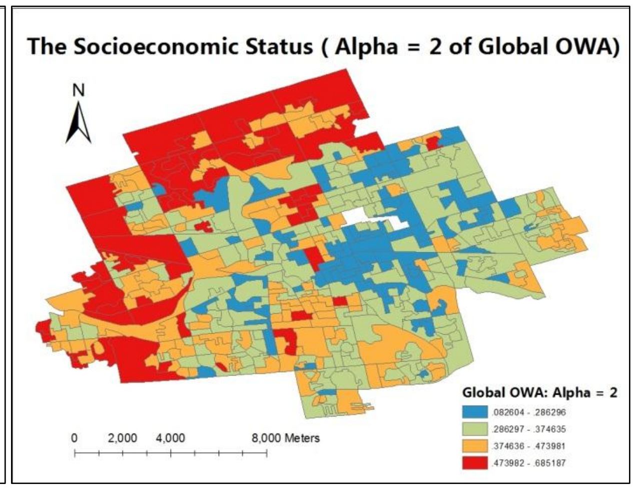
(A) OR



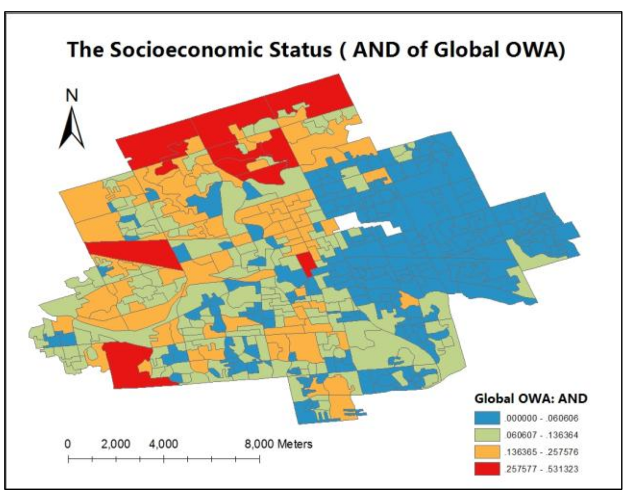
(B) Trade-off α = 0.5



(C) Trade-off α = 1 (WLC)



(D) Trade-off α = 2



(E) AND

Figure 4-13 Output Maps of Global OWA Method

The results of OR operator (see Figure 4-13-A) represent an ‘ideal’ situation of the socioeconomic status in London, Ontario. Specifically, the OR operator assigns the highest criterion values to each location. This type of spatial pattern can be referred to as an optimistic evaluation scenario (Yager, 1988; Malczewski, 2006). Figures 4-13-B, 4-13-C and 4-13-D show the results of three compensatory OWA operators (*trade-off* situations). In general, the spatial patterns of these three situations are similar to that generated by the OR operator; that is, the northwestern part of London has high socioeconomic status while the central and eastern areas of the city are characterized by low socioeconomic status. It is important to note that an increasing value of the α parameter corresponds to a decreasing degree of ORness (Malczewski, 2003). The maximum *trade-off* is achieved for the WLC model when $\alpha = 1.$ (see Table 4-6). The AND scenario represents an extremely pessimistic situation by assigning the lowest criterion value to each location (see Figure 4-13-E).

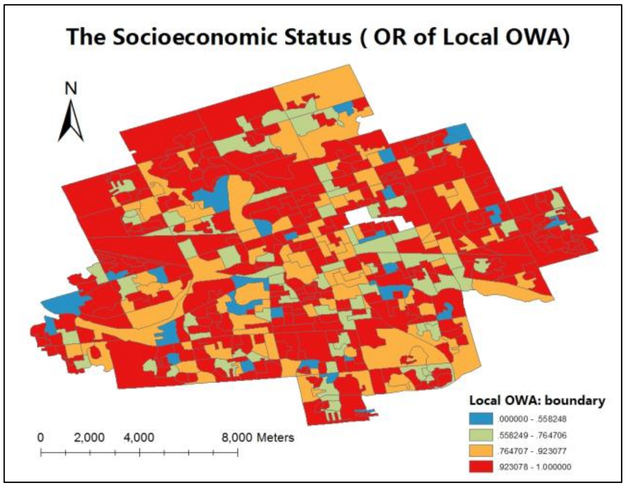
4.4.2 Overall Local OWA Scores

Four sets of results of the local OWA method with different neighborhood schemes are presented in Figures 4-14, 4-15, 4-16 and 4-17. Each figure includes five output maps for different values of the α parameter.

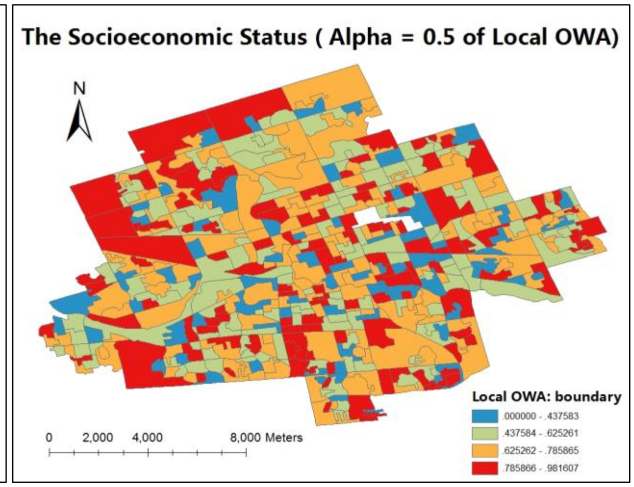
In Figure 4-14, despite varying operators applied, a similar spatial pattern can be observed; that is, the areas (locations) of the same value class are dispersed in the study area. The patterns of high spatial heterogeneity agree with the expectation that the local OWA scores are more localized than the global OWA scores.

The result of OR operator (see Figure 4-14-A) conveys the ‘ideal’ situation (or the most optimistic scenario) of the socioeconomic status of the study area. The highest criterion value is assigned by OR operators for each location. Hence many areas are located in the highest value class, presenting a relatively high socioeconomic status. Figures 4-14-B, 4-14-C and 4-14-D show the results of three compensatory (or *trade-off*) situations of the local OWA methods. With the increasing of the value of α, the evaluation scenario changes from optimistic to pessimistic. The results of AND situation (see Figure 4-14-E) indicates the most pessimistic pattern of the socioeconomic status; it is obtained by assigning the lowest criterion value to each location. In addition, outcomes of local OWA based on the threshold distance neighborhood scheme (see Figures 4-15, 4-16 and 4-17) hold the similar tendency of altering the value of α (associated to OR, *trade-off* and AND).

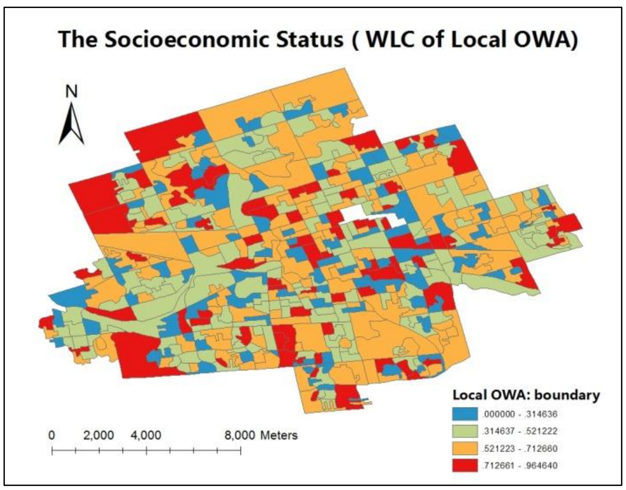
The local OWA method aims at revealing the local information of the neighborhood context. The high value areas in outcome maps indicate locations with relatively high socioeconomic status in the defined neighborhood. It should be noted that the concepts of “relatively high” or “relatively low” are essential for understanding the results of local OWA method. For a given neighborhood, the focal location with the highest value in the neighborhood will be highlighted in the results of local OWA method. By this method, even if neighborhoods with low values have a location with a relatively higher value compared to other locations in the same neighborhood, this location is assigned a higher local weight and local overall OWA score as compared to the corresponding global weight and overall OWA score. Furthermore, two locations sharing the same raw value of all set of criteria might not be assigned the same overall local OWA score. To better understand the results of local OWA method, one should be aware of the difference between the absolute high value areas and relatively high value areas. In fact, the results of global OWA method reveal the area with absolute values, while the results of local OWA method present the area with relative values. It is important to analyze the results of absolute values and relatively values in comparison. Hence results of global OWA and local OWA should be interpreted together.



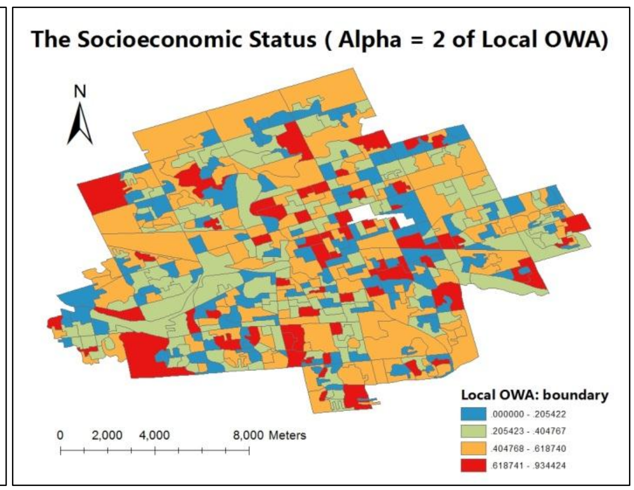
(A) OR



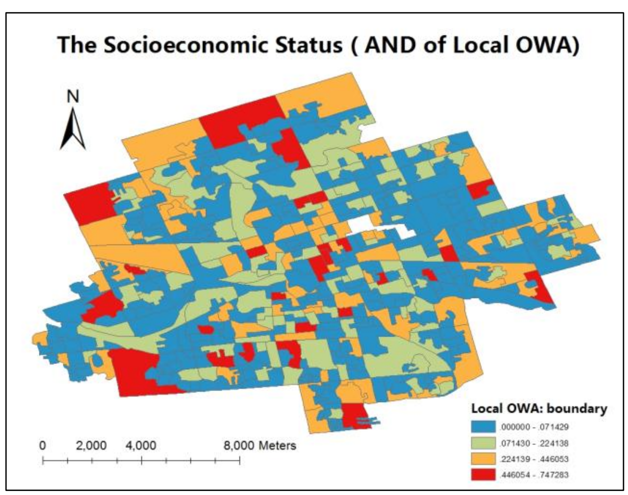
(B) Trade-off α = 0.5



(C) Trade-off α = 1 (WLC)

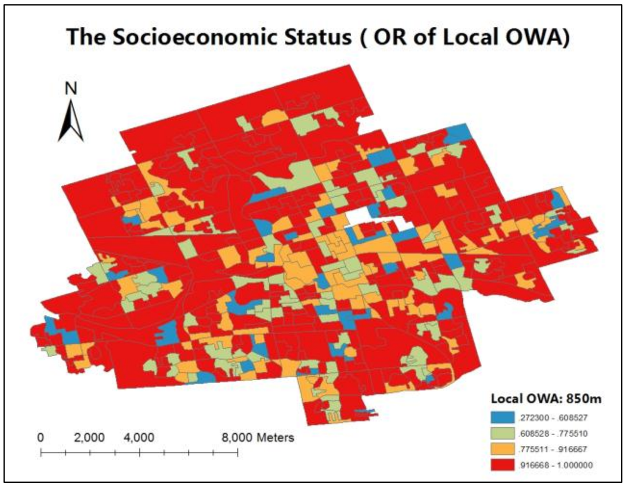


(D) Trade-off α = 2

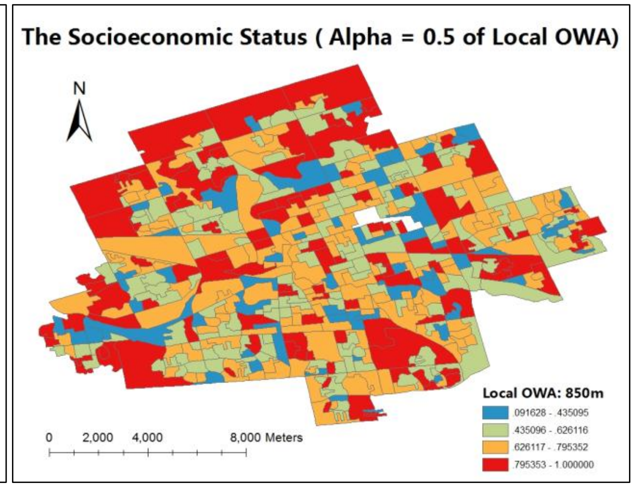


(E) AND

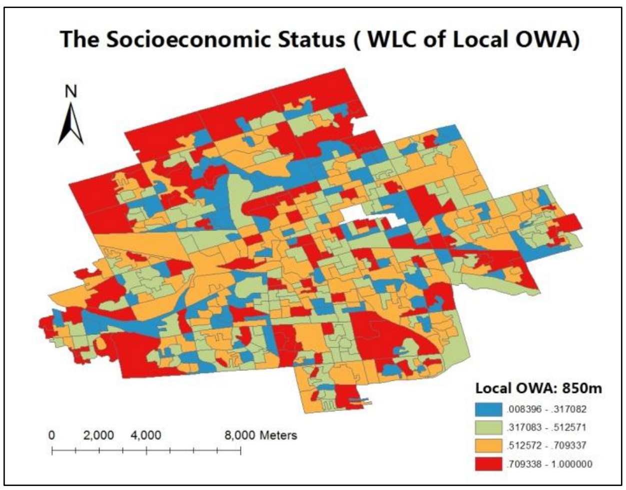
Figure 4-14 Output Maps of Local OWA based on Boundary Neighborhood Scheme



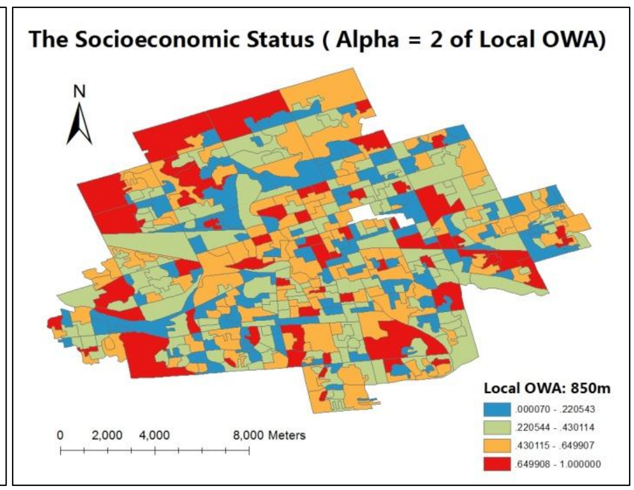
(A) OR



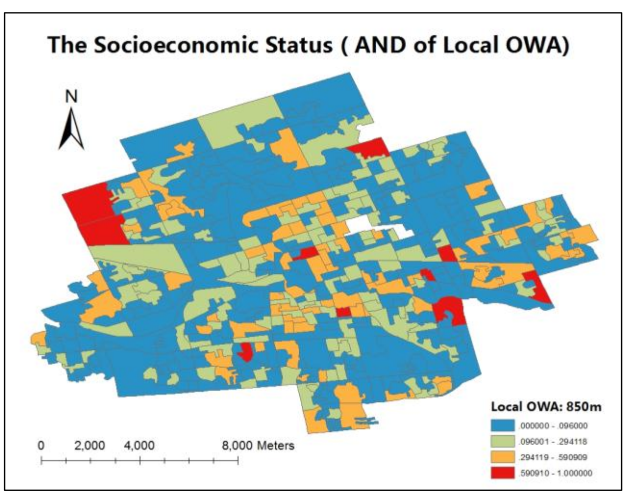
(B) Trade-off α = 0.5



(C) Trade-off α = 1 (WLC)

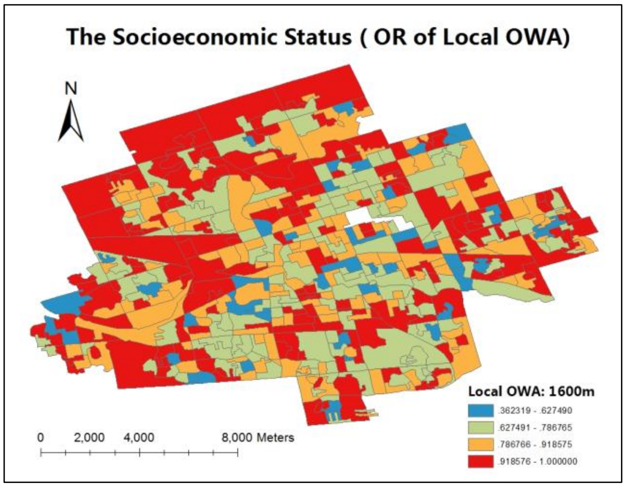


(D) Trade-off α = 2

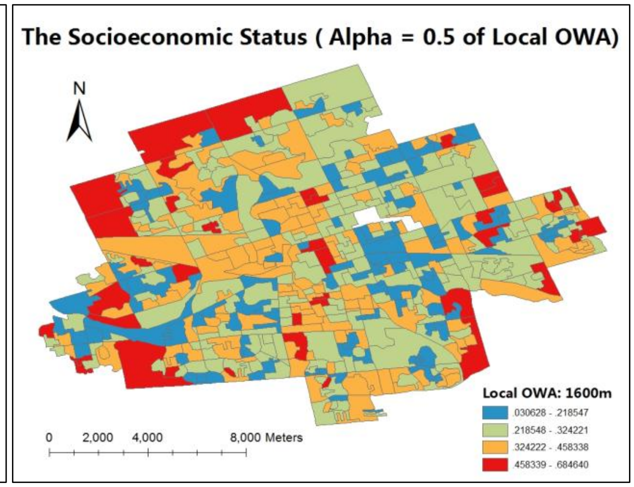


(E) AND

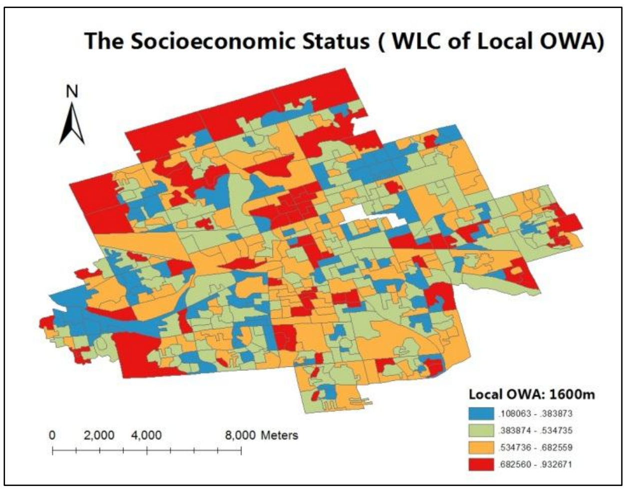
Figure 4-15 Output Maps of Local OWA based on 850m Neighborhood Scheme



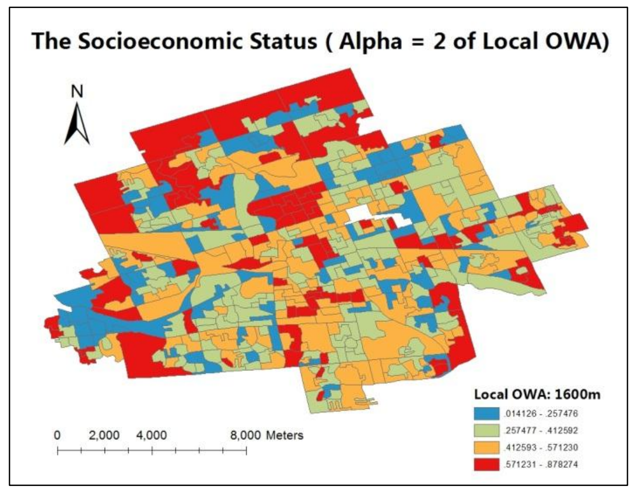
(A) OR



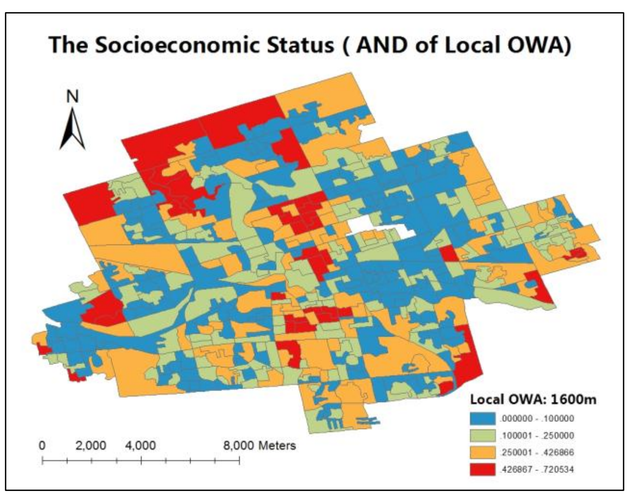
(B) Trade-off α = 0.5



(C) Trade-off α = 1 (WLC)

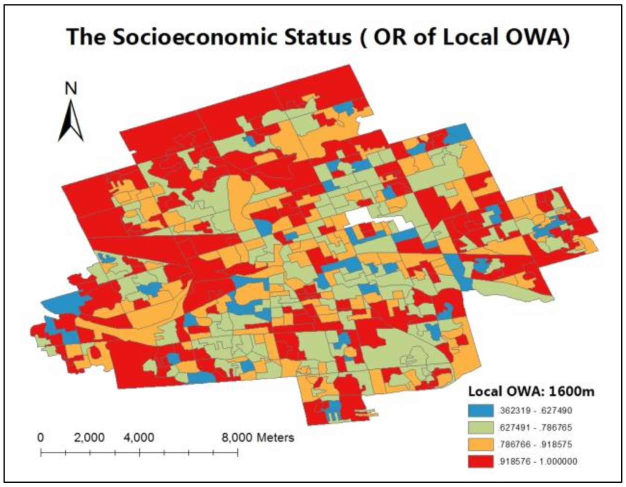


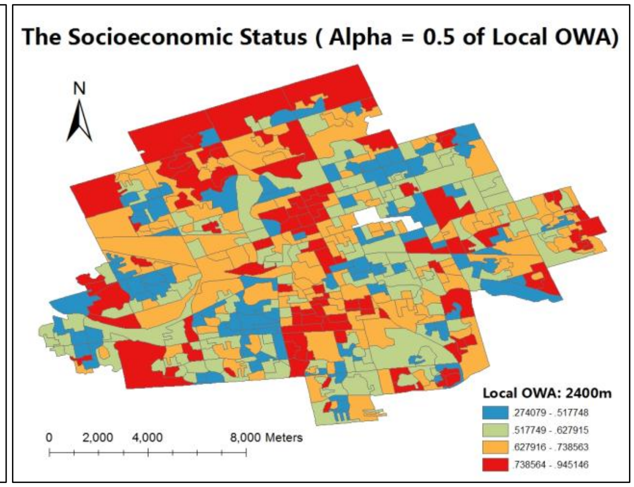
(D) Trade-off α = 2



(E) AND

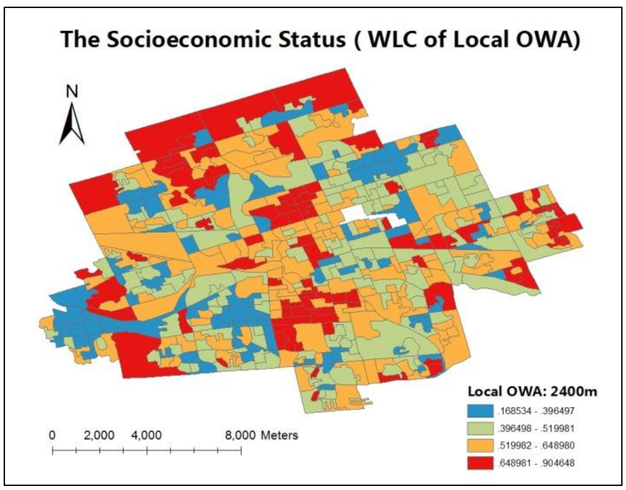
Figure 4-16 Output Maps of Local OWA based on 1600m Neighborhood Scheme

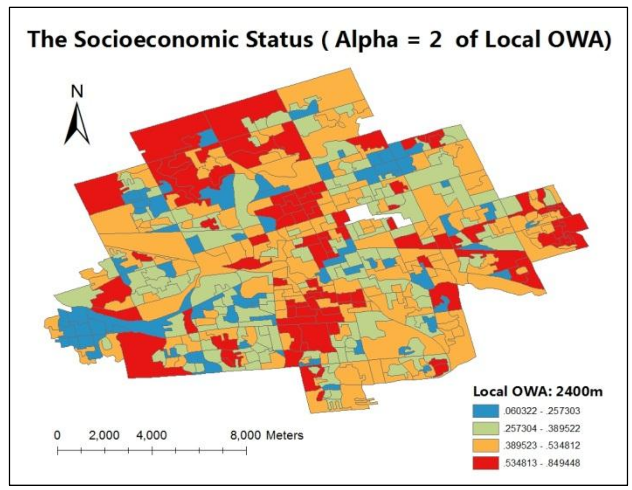




(A) OR

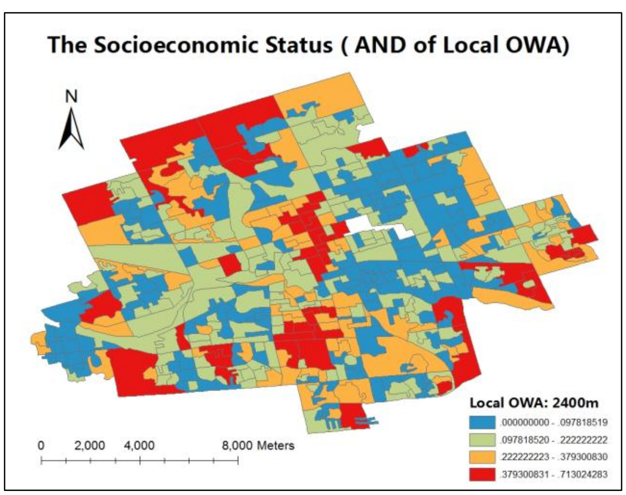
(B) Trade-off α = 0.5





(C) Trade-off α = 1 (WLC)

(D) Trade-off α = 2



(E) AND

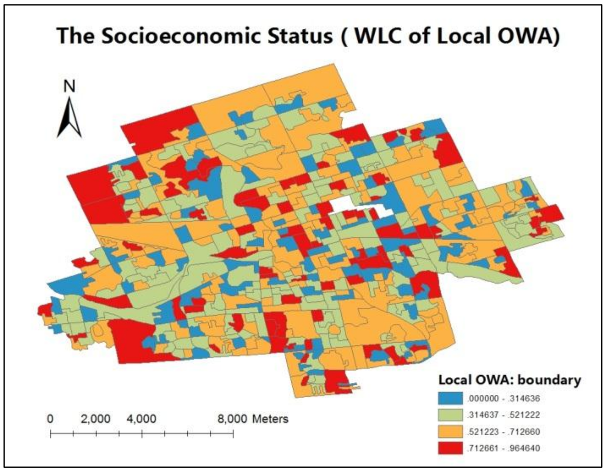
Figure 4-17 Output Maps of Local OWA based 2400m Neighborhood Scheme

4.4.3 Comparing Local and Global Overall OWA Scores

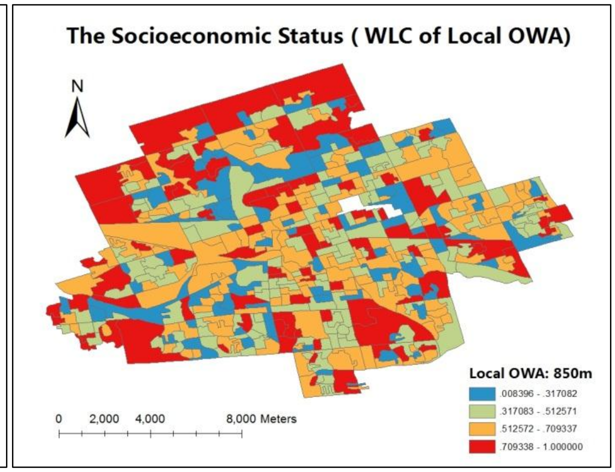
The WLC operator is selected as an example in the following illustration of the comparisons between the global and local OWA method. Figure 4-18 shows five output maps of WLC (see also Figures 4-13 to 4-17).

In this case study, the spatial pattern of global WLC (Figure 4-18-E) indicates that northwestern London has a higher socioeconomic status than the central and eastern areas of the city. However, the WLC results of global OWA only convey the global trend by showing areas with absolute values while local OWA can indicate the relative differences within the northwestern area of the city. The results the local WLC operator (see the Figures 4-18-A and 4-18-B) show that the locations with high values are evenly distributed in the central and eastern areas indicating the locations with the relatively high socioeconomic status in the low socioeconomic status neighborhoods. Compared with the global WLC (Figures 4-18-C and 4-18-D), although high value locations appear in the central and eastern parts of the city (the low value areas in the global trend, the high value locations also tend to cluster together in the northwestern area of the city. This implies that the spatial pattern of the local overall OWA scores generally approach the global pattern along with the increasing of the value of threshold distance.

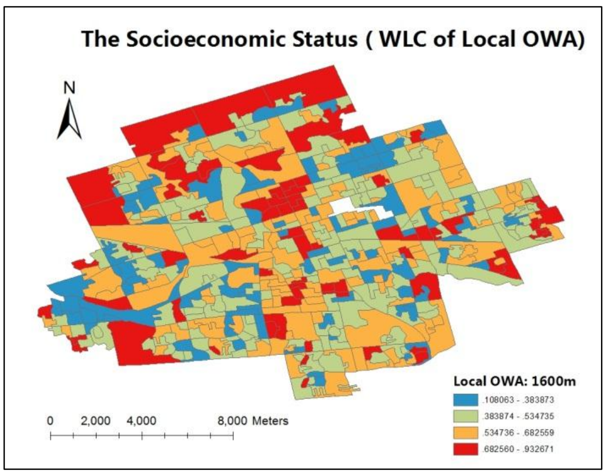
One of the aims of changing the threshold distance is to examine the spatial pattern of neighborhoods. Selecting small threshold distance results in more localized pattern of both highest and lowest values of the overall OWA scores. This means that high and low values can be located next to each other creating a dispersed spatial pattern. A gradual increase of the threshold distance results in the increasing clustering of areas having similar (high or low) score in the results of local OWA method. The clustered units form the relatively homogenous neighborhoods of low and high socioeconomic status (see Figure 4-18). This finding is confirmed by the results of spatial autocorrelation (see next Section).



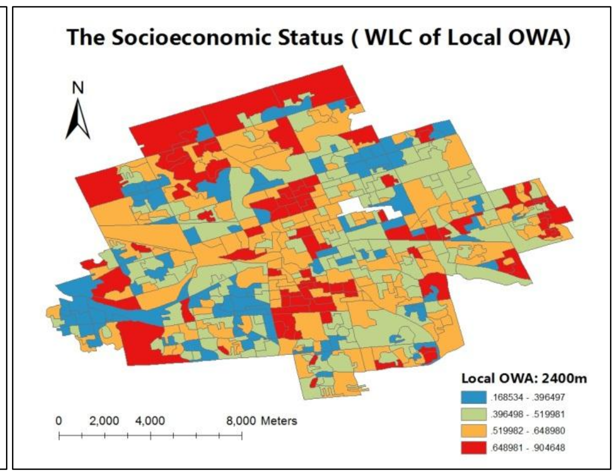
(A) Local WLC on the boundary



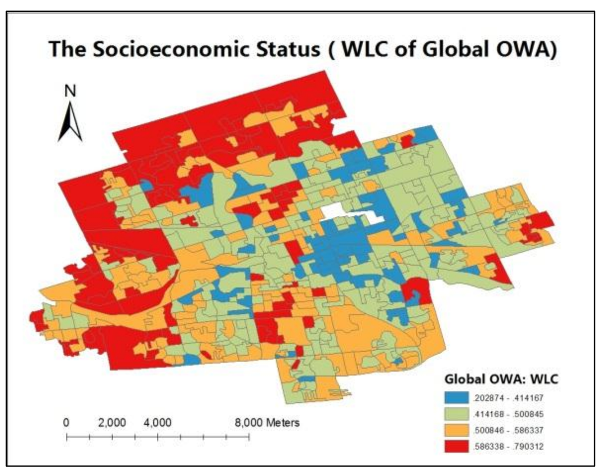
(B) Local WLC based on 850m



(C) Local WLC based on 1600m



(D) Local WLC based on 2400m



(E) Global WLC

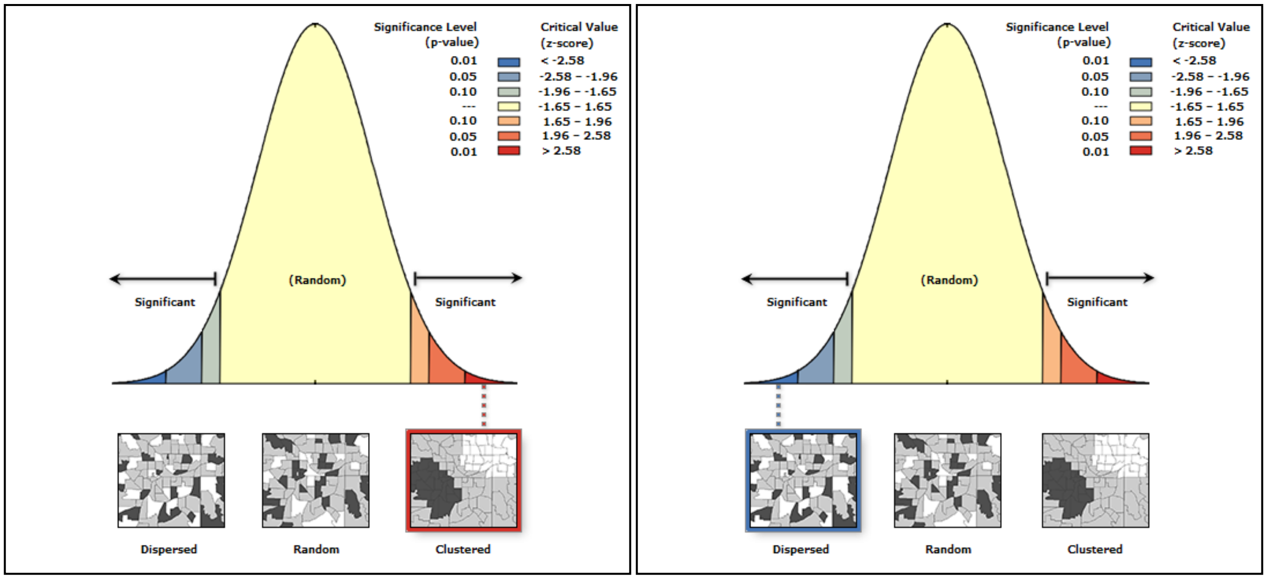
Figure 4-18 WLC Results of Global OWA Method And Local OWA Methods Based on Different Neighborhood Schemes

4.4.4 Comparing Spatial Autocorrelation

The spatial patterns of the overall OWA scores can be qualified by measuring the spatial autocorrelation. Moran's I is used as the index to evaluate the degree of spatial autocorrelation (see Table 4-6 and Figure 4-19). As indicated in Table 4-7, the spatial autocorrelation of global WLC is clustered. Moreover, the values of Moran's I statistic (and associated z-scores) indicate that increasing of threshold distance results in an increasing clustering of similar OWA scores of socioeconomic status. Specifically, the spatial autocorrelation the local OWA methods for the boundary-based case and 850m case are spatially dispersed. The local OWA scores based on the 1600m and 2400m distance parameters are characterized by a clustered pattern. Also, the local OWA patterns are becoming more similar to the global OWA along with increasing the threshold distance (see Figure 4-18). Note that each of the Moran's I statistics (z-score) is significant as indicated in the p-values (see Table 4-6 and Figure 4-19).

Table 4-7 The Spatial Autocorrelation Index for WLC

WLC	Moran's I	z-score	p-value	Spatial pattern
Local_boundary	-0.115	-4.132	0.000036	Significant dispersed
Local_850m	-0.097	-3.460	0.000540	Significant dispersed
Local_1600m	0.134	4.964	0.000001	Significant clustered
Local_2400m	0.283	10.408	0.000001	Significant clustered
Global	0.344	12.652	0.000001	Significant clustered

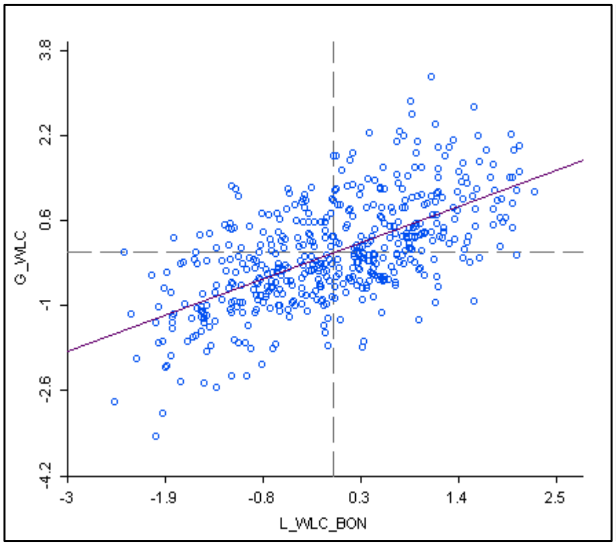


(A) Clustered (B) Dispersed

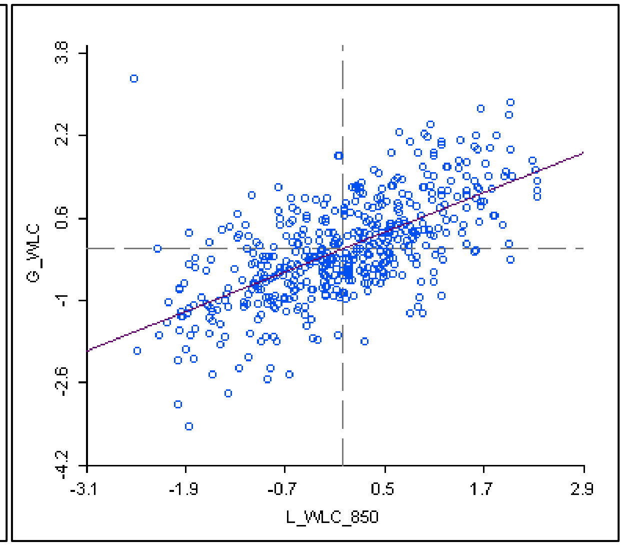
Figure 4-19 Spatial Autocorrelation Statistics

4.4.5 Comparing Scatter Plots

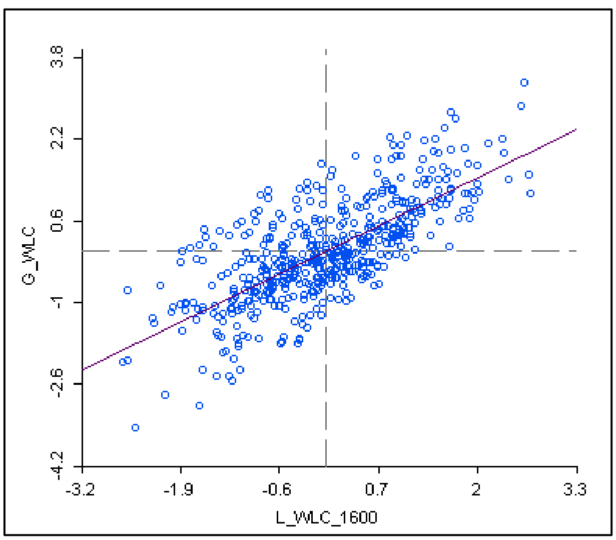
The results of the global and local OWA methods can also be examined by using scatter plots (see Figure 4-20). The y and x axes of the scatter plots represent standardized values for the global and local WLC scores, respectively. The scatter-plot points can be grouped into four classes corresponding to the plot's quadrants. A vast majority of the points is situated the first and third quadrants, where the local and global scores are above their mean values (in the first quadrant) and the scores are smaller their mean values (in the third quadrant). The second quadrant contains points with the global values greater than the mean and the local values smaller than the mean. Points with the global values smaller than the mean and the local values greater than the mean are situated in the fourth quadrant. In general, the points tend to be more clustered around the trend line along with increasing the threshold distance (see Figure 4-20).



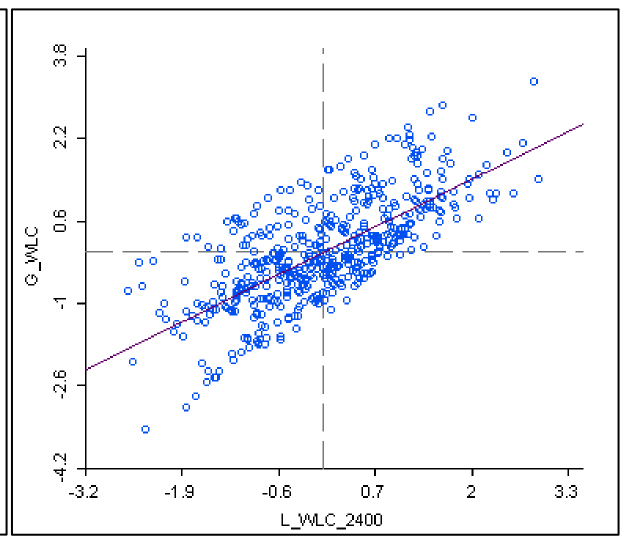
(A) Global WLC vs. Local WLC (boundary)



(B) Global WLC vs. Local WLC (850m)



(C) Global WLC vs. Local WLC (1600m)



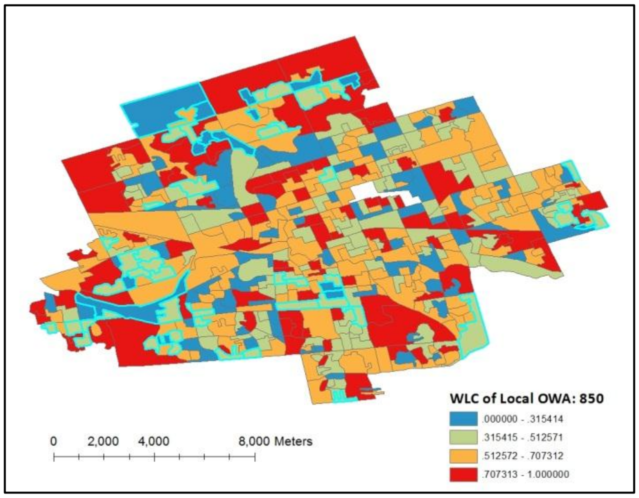
(D) Global WLC vs. Local WLC (2400m)

Figure 4-20 Scatter Plots of Global WLC and Local WLC

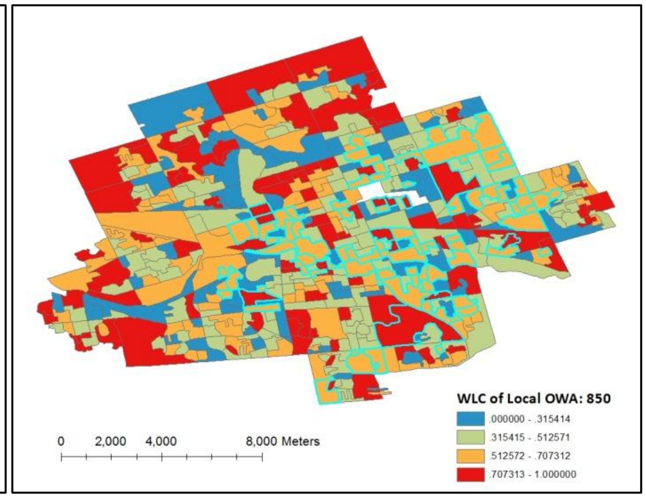
The numbers of points that belong to the second and fourth quadrants can be used as an indication of the differences between the global and local OWA results. The larger the number of points in the two quadrants, the larger the difference is between the two OWA results. In addition, one can select the points in the second and fourth quadrants of the scatter plots to examine the spatial patterns of the associated areas on the criterion map.

The highlighted areas in the Figure 4-21 indicate the corresponding selected points in scatter plots. Focusing on the second quadrant for the global WLC (see Figure 4-21-C), the highlighted areas have high values and tend to be located along edges of the study area. These selected locations are geographically related to locations with the peak value in their neighborhood. To localize the OWA method, the value of these selected areas is reduced to highlight the location with the local peak value. However, the fourth quadrant for global WLC (see Figure 4-21-D) contains a set of locations which are characterized by low values and tend to be situated in the periphery of central London. These selected locations are not characterized by the lowest value but are geographically adjacent to the locations with the lowest value in their neighborhood. In the local OWA method, the value of these selected locations is increased to emphasize the location with the local lowest value.

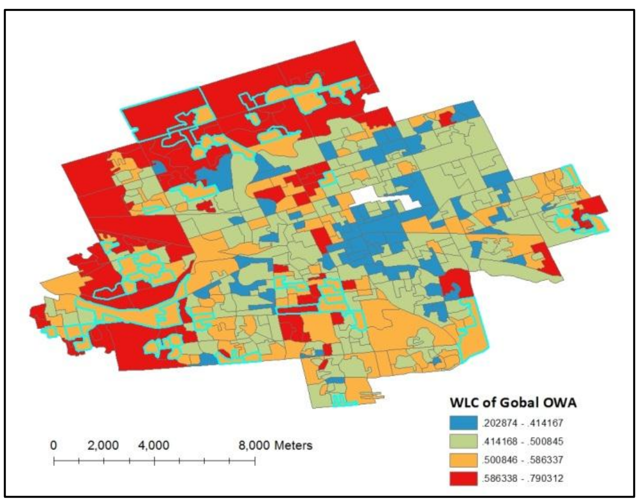
Figure 4-22 indicates the distributions of the selected points of the second and the fourth quadrants from the scatter plots, presented on the outcome maps of local WLC for the boundary-based, 1600m and 2400m neighborhood schemes. For these three neighborhood schemes, the changes of spatial patterns from global to local OWA are similar to the patterns described in the last paragraph. In addition, the number of selected location is decreased (see Figures 4-21). Two observations can be made from Figures 4-20 and 4-21: the points are gradually more clustered around the trend line with the increasing threshold distance, and the number of points in the second and the fourth quadrants decreased. These observations imply that the difference between the local OWA and global OWA method tend to be reduced by enlarging the neighborhood under the distance-based neighborhood scheme of local OWA method.



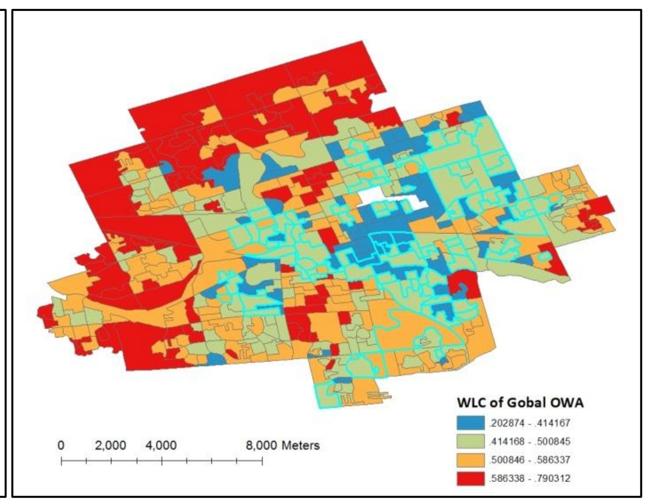
(A) the second quadrant on local WLC (850m)



(B) the fourth quadrant on local WLC (850m)

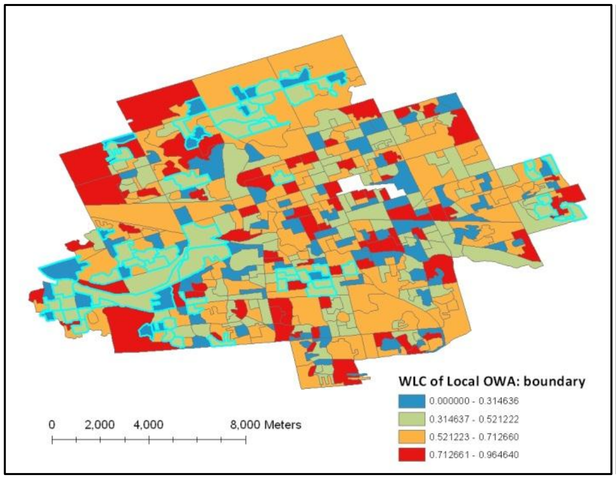


(C) the second quadrant on global WLC

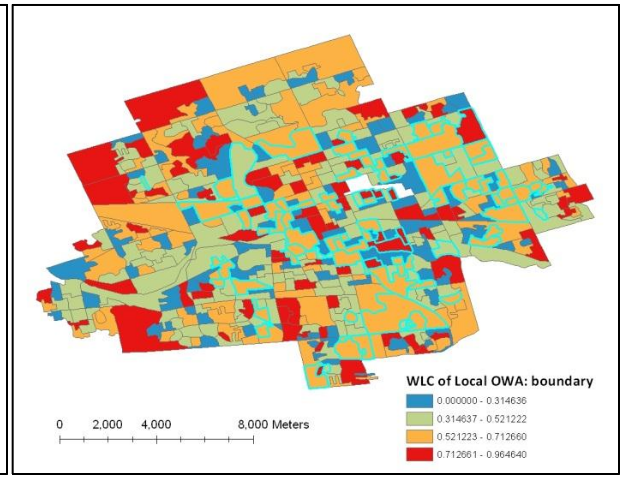


(D) the fourth quadrant on global WLC

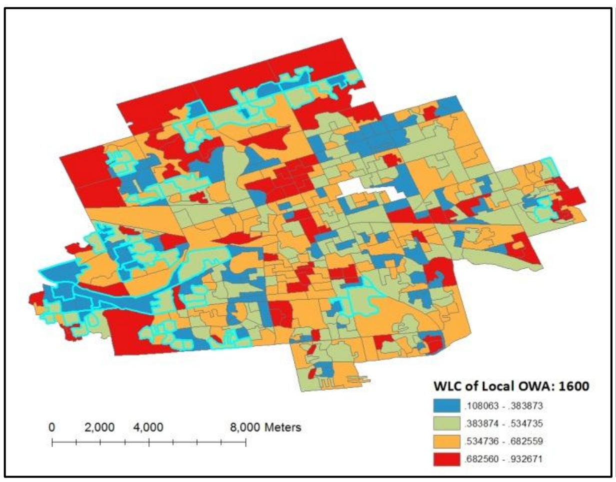
Figure 4-21 Selections from the Scatter Plot (Global WLC vs. Local WLC)



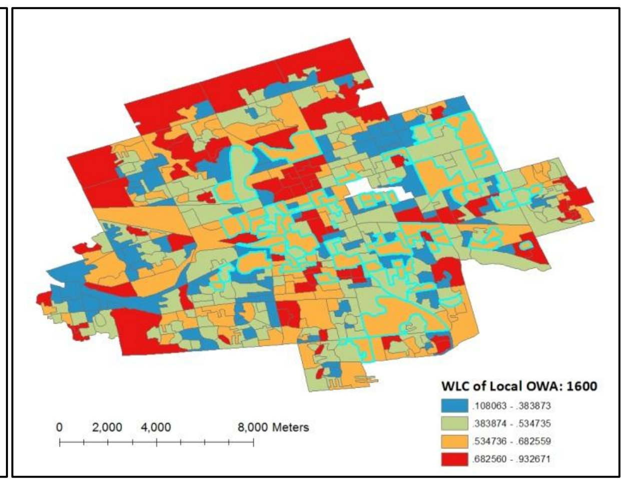
(A) the second quadrant on local WLC (boundary)



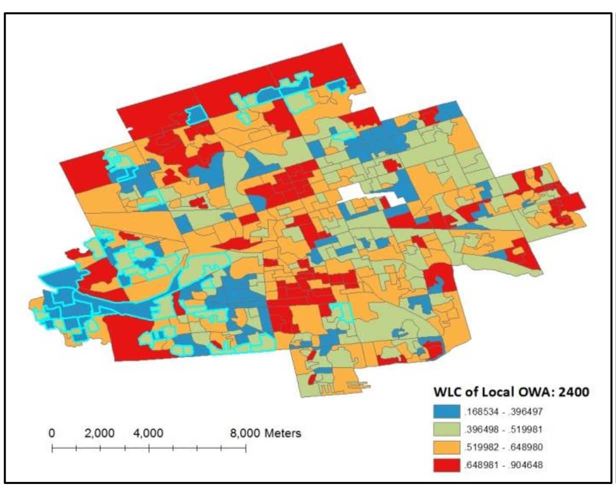
(B) the fourth quadrant on local WLC (boundary)



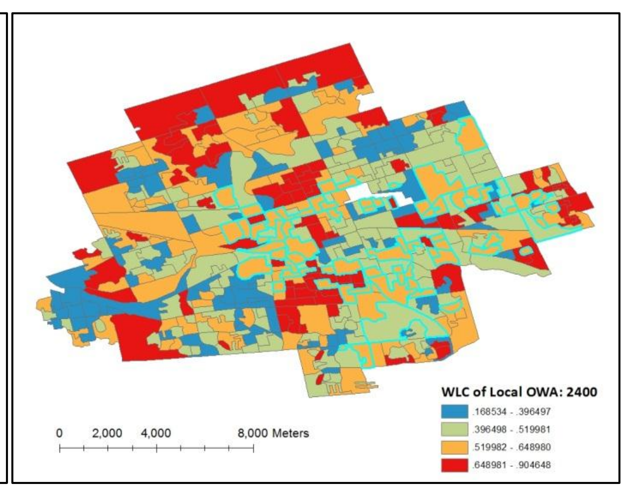
(C) the second quadrant on local WLC (1600m)



(D) the fourth quadrant on local WLC (1600m)



(E) the second quadrant on local WLC (2400m)



(F) the fourth quadrant on local WLC (2400m)

Figure 4-22 Selections from Scatter Plots (Global WLC vs. Local WLC)

4.5 Summary

Three main conclusions can be reached by analyzing the spatial patterns of OWA scores.

First, the results of local OWA method convey more spatial information about neighborhoods. The location with the relatively higher value in the neighborhood is assigned greater criterion value and highlighted in the local OWA patterns. Although the central and eastern regions of London have lower socioeconomic status than the northwestern parts of the city according to the result of global OWA method, locations with relatively higher value in those low-value regions should be noticed. Such local spatial information is provided by the results of the local OWA method.

Second, the neighborhood scheme has a significant impact on the spatial patterns of the local OWA results. With increasing threshold distance, the spatial pattern of outcomes of local OWA changes and turns more similar to the global OWA pattern.

Third, the global and local OWA methods reveal different spatial patterns of socioeconomic status of London. In the global OWA method, the northwest regions of London have a better socioeconomic status than the central and eastern of the city. However, the results of local OWA indicate that locations with relatively high socioeconomic status are dispersed across the whole study area.

Chapter 5

5 Conclusion

This thesis has focused on developing a local form of the global OWA. Related terminologies are first introduced in Chapter 2, followed by the methods chapter in which the procedures of the global and local OWA methods are presented. Then, the various neighborhood schemes are defined and the concept of local criterion weights is introduced. A case study of assessing the socioeconomic status of London, Ontario is presented to illustrate the local OWA method. Finally, the results of local and global OWA methods are compared.

The local OWA method advances research on GIS-based OWA in the following aspects. First, the local OWA method provides a tool for examining spatial patterns locally, while the global OWA method fails to represent the local context. Second, the local OWA gives an opportunity for visualizing and analyzing spatial patterns of the results (overall scores) and the model parameters (e.g., the local criterion weights). The parameters have constant values in the global OWA model (e.g., the criterion weight has a single value for a given criterion). Third, the neighborhood scheme is defined as the parameters of the local OWA method. The changeable neighborhood schemes increase the flexibility of OWA and make it more practical for real world problems. Fourth, the global OWA is a special case of the local OWA method. By defining a suitable distance-based neighborhood scheme, the local OWA method can generate the same results as the global OWA.

One of the limitations of this research is related to the problem of zero local range value for a neighborhood scheme. To avoid this situation, rules need to be followed when defining the neighborhood scheme, thus flexibility in defining the neighborhood scheme is confined. For example, in the case study of London, Ontario the threshold distance cannot be less than 850m. On the other hand, when the criterion values have no significant spatial variation, the value of local range has high possibility to be zero in the given neighborhood. Therefore, such criteria are not applicable in the local OWA method. Another limitation is that due to the lack of data of the neighborhood partition, it is unable to discuss the precise definition of neighborhood in the sociology field.

Future research should focus on exploring how defining a given neighborhood scheme affects the results in the local OWA method; that is, some theoretical foundation should be developed for the selection of neighborhood scheme. This thesis also suggests that in the future, the theory of localizing the conventional OWA method can be applied to other approaches in GIS-based multicriteria analysis.

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Appendix

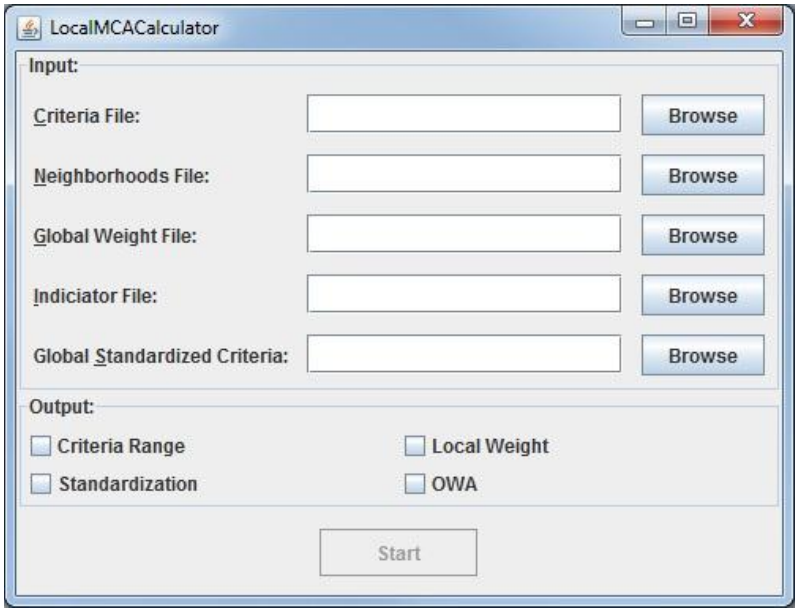

Figure A-1 Interface of Local Calculator

Existing GIS systems do not provide modules for the local MCA procedures. Therefore a local MCA calculator was developed using JAVA. The core of the calculator consists of procedures for generating local range and ordered criterion weights (see Section 3.1.4 and 3.2.3). Figure A-1 shows the interface of the local calculator. It requires five inputs and has four output options. The input files are in the text format. In this case study, the raw criterion values of six criteria should be imported into the 'Polygon File'. The neighborhood schemes, based on three different distances (850m, 1600m and 2400m) and the boundary, should be respectively imported into the 'Neighbor File'. The table of global criterion weights should be imported into the 'Global Weight File'. The types of criteria (1 = Maximum and 0 = Minimum) (see Table 4-1) should be imported into 'Indicator File'. The table of global standardized criteria is imported when the 'OWA' option of output is checked.

There are four outputs of the OWA method. The first three output options ('Criteria Range' 'Local Weight' and 'Standardized Criteria') are designed for obtaining results of the intermediary steps of the OWA method. Selecting "OWA" option can generate the final outcome of the local and global OWA procedures.

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