EVALUATING THE POTENTIAL FOR MIXED-USE URBAN LAND DEVELOPMENT USING MULTI-CRITERIA DECISION ANALYSIS: A CASE STUDY IN THE CITY OF SAN DIEGO

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DEDICATION

This thesis is dedicated the author’s wife, family, and close friends, who supported him in deciding to quit his job and drive across the country for graduate school. Further dedication to the most beautiful and supportive wife and the best family the author could ask for!
“Just keep truckin’ on...” -JG
ABSTRACT OF THE THESIS

Evaluating the Potential for Mixed-Use Urban Land Development using Multi-Criteria Decision Analysis: A Case Study in the City of San Diego
by
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Master of Science in Geography (GIScience)
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Multi-criteria decision analysis in a GIS is a method of solving spatial problems when given a set of conflicting alternatives. It includes the conflation of maps and criterion weights to get a final value for each unit of scrutiny in the research area. Weighted linear combination (WLC) is a procedure often implemented in multi-criteria decision analysis that can be used to present the decision maker with a collection of ranked alternative locations. The conventional WLC method, often referred to as the global model, is based on an assumption of spatial homogeneity in that its parameters do not vary based on geographic location. Contrariwise, its local form assumes spatial heterogeneity in that its parameters do indeed vary based on geographic location employing the concept of a neighborhood. Theoretically, in doing so, the local model is seen to replicate the diverseness of the real-world more truthfully. A case study assessing the ripeness of parcels for mixed-use development in the City of San Diego is presented. This research uses MCDA4ArcMap, an add-in for ArcGIS, by exploiting its global WLC and local WLC capabilities with its neighborhood definitions in a vector based setting. The results highlight the significant differences between the outputs of the global and local WLC methods.
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1. Introduction

In recent decades in the United States, especially in the southwest, historically undeveloped land was developed at a fast pace (Alig, Kline, & Lichtenstein, 2004). This phenomenon, with significant ramifications in urban land management, can be attributed to the global trend of rural-urban migration (Ward, Murray, & Phinn, 2003). In the years following the Second World War, the central areas of many cities experienced a financial disinvestment and a systematic outmigration (Levy, Comey, & Padilla, 2007). This contributed to the rise of abandoned and vacant parcels in the downtown areas of hundreds of cities (Levy et al., 2007). The outmigration of inner city residents to the urban fringes was fueled by a number of governmental policies and historical events, which promoted suburban living (Duany, Plater-Zyberk, & Speck, 2000). The organically developed traditional neighborhoods, seen in sections of older cities like Washington, D.C., are represented by mixed-use and pedestrian friendly communities that have proved to be a sustainable form of growth with minor economic and environmental impacts (Duany et al., 2000). Suburban sprawl ignores the viability of the traditional neighborhood and produces financial and environmental problems (Duany et al., 2000).

Growth outside city boundaries poses negative impacts on sensitive watersheds, wildlife habitats, riparian areas, and water supply (Alig et al., 2004). For example, from 1970 to 1990, Los Angeles grew 45% in population and disproportionately 300% in size (Duany et al., 2000). To accommodate for this trend, an area equal to the size of the state of Delaware is paved every year in the United States (“Grassroots Action Project,” n.d.). The amount of infrastructure needed to support suburban sprawl is extremely high and inefficient especially when compared to that of the traditional neighborhood. Overall, this translates into thousands of acres of forests, countryside, and farms being lost each day, totaling well over 50,000 square miles since 1970 (The Trust for Public Land as cited in Duany et al., 2000). As suburban areas grow, so do the economic and environmental consequences (Duany et al., 2000). The continuation of urban sprawl can be attributed to cheaper land prices and simplicity of construction (Thompson, 2016). Cheaper land prices cause developers or households to venture further from the urban core where in theory, the cost of land is highest (Thompson, 2016). The many criteria and complex principles that go into redevelopment of old urban centers makes it an unattractive alternative to urban sprawl.
That being said, development decisions in already existing urban areas have become increasingly complex. Developers need to make challenging and contradictory decisions incorporating viable development while remaining economically competitive (Joerin, Theriault, & Musy, 2001). As the population grows and urban migration continues, the inefficiency of suburban sprawl has been realized (Ward et al., 2003). Developers now rely on vacant lots in inner cities as an important component of efficient development, which is a concept that is increasingly supported by city policies (Levy, Comey, & Padilla, 2007). For example, in 2005 the New York City Department of City Planning rezoned the Williamsburg neighborhood of Brooklyn to support and encourage development of this kind. A systematic approach to site selection calls for effective decision support methods to assist developers and decision makers responsible for land allocation decisions.

1.1 Significance of MCDA and GIS

Innately, when making any type of decision, humans tend to rely on an intrinsic framework of tradeoffs which often includes multiple decision criteria (Rinner & Voss, 2013). At the most rudimentary level, a multi criteria decision problem involves a set of alternatives that are evaluated on the basis of conflicting and disproportionate criteria according to the partialities of the decision maker (Malczewski, 2010). Using the same approach, the marriage of MCDA methods to GIS can be applied to evaluate complex spatial decision problems.

The process of decision making in urban development can benefit from research on integration GIS with multi-criteria decision analysis (MCDA) methods (Jankowski 1995). Important and complex spatial decisions, such as whether to allocate land to development or not, requires information and tools to assist in understanding the inherent tradeoffs (Greene, Devillers, Luther, & Eddy 2011). At its core, a spatial decision has at least two components: action (what to do?) and location (where to do it?) (Malczewski, 2011, p. 439). MCDA provides a powerful set of tools for structuring and prioritizing decision alternatives (Malczewski 2006). MCDA presents the user with solutions to complex decision problems (Lofti et al., 2009). In doing so, it allows the user to make an informed decision for site selection for future urban development (Lofti et al., 2009). As the global population increases, the potential for development of environmentally sensitive areas will make
concerns of these kinds increasingly important (Ward et al., 2003). The capabilities of MCDA integrated with GIS are attractive for supporting spatial decision making using large amounts of data while attempting to find compromise solutions meeting the needs of developers and urban growth policies (Lofti et al., 2009). There are a variety of methods within MCDA that can be used to present the user with a set of ranked decision alternatives (Carter & Rinner 2014). Among the most common and easiest to understand methods is the weighted linear combination (WLC). Despite its simplicity, WLC offers a viable tool for planners to make informed and environmentally viable decisions, many of which involve redevelopment of parcels in inner cities.

1.2 Limitations of Conventional WLC

Amalgamating MCDA with GIS is a fairly standard practice in spatial decision making. The particular procedure of exploiting WLC (weighted linear combination) in a GIS-based setting to tackle spatial decision problems has been widely used in various application domain areas (Malczewski, 2006). These include but aren’t limited to site-selection, environmental management, transportation, and urban and regional planning (Jankowski, 2015). That said, the limitations of WLC and other MCDM methods should be noted including the assumption of spatial homogeneity and failing to adequately represent spatial variability. MCDM methods can be subdivided into two classes; spatially implicit and spatially explicit, depending on the nature of the evaluation criteria (Carter & Rinner 2014). Spatially implicit criteria are criteria derived from a spatial component and are based on the assumption that its parameters do not vary as a function of geographic space, commonly referred to as the global approach (Malczewski 2011). Conventionally, the global approach is based on the assumption that model parameters do not vary as a function of geographical space. The global approach assumes spatial homogeneity and is often unrealistic in real-world applications (Malczewski 2011). This assumption is seen as limiting as it fails to adequately represent spatial variability inherent in the real-world decision situations.

In recent years, the limitations of the global approach has led to the realization in the value of the local approach (Malczewski 2011). Malczewski (2011) introduced the theoretical model of local weighted linear combination (LWLC). This approach tries to
combat the assumptions and limitations made by the global approach in an attempt to account for the spatial heterogeneity of the real-world (Malczewski 2011).

In sum, global WLC is the conventional procedure based on an assumption of spatial homogeneity. The new method, known as LWLC, attempts to represent actual spatial heterogeneity. This research aims at advancing the LWLC model through its practical application in a problem of urban land use allocation, in which vacant land parcels are evaluated for specific land use functions.

1.3. Current Global Trends and the City of San Diego

Suburban sprawl was the main concern of Americans in a poll conducted by the Pew Center in the late 1990s (Alig et al., 2004). The world’s population has been growing at a rapid pace and is projected to increase by more than 2 billion people in the next 30 years (Alig et al., 2004). The majority of this growth is projected to be concentrated in urban areas (Alig et al., 2004). As the population increases so does the amount of developed land, a phenomenon that has not gone unnoted by the general public (Alig et al., 2004). Furthermore, in 1999 alone, over 1000 measures were introduced in state legislatures to change planning laws to make development in the US more orderly and sustainable (Alig et al., 2004). Particularly, effective evaluation and planning of urban growth is necessary for ensuring adequate infrastructure, efficient resource consumption, employment opportunities, and to maintain or achieve environmental health standards (Ward et al., 2003).

The SANDAG Regional Comprehensive Plan (RCP) provides a planning blueprint for how and where the San Diego region and its local municipalities should grow (Regional Comprehensive Plan, 2004). The major emphasis of the RCP is on mixed-use development in existing urbanized areas near transit and downtown centers (Regional Comprehensive Plan, 2004). The fundamental challenge is how to intelligently use the small amount of remaining undeveloped land specifically, in urban areas (Regional Comprehensive Plan, 2004). Coordinating this development is limited by a number of community, environmental, and financial constraints (Regional Comprehensive Plan, 2004). Given the complexity and amount of constraints in urban land use decisions, it seems as though they can effectively be supported by the execution of MCDA integrated with GIS (Lofti et al., 2009).
Growing smarter means guiding the development of our land use in ways that encourage the creation of unique spaces where people can live, work, and play all while being connected to a robust transit system. Instead of continuing to expand into the rapidly vanishing open spaces east of our urban areas, the new view calls for making room for our growing population within the existing urban core and in turn creating unique centers where residents have a variety of transportation choices (SANDAG, 2010b).

Population projections indicate that San Diego’s regional population will increase by approximately one million from 2000-2030 (Regional Comprehensive Plan, 2004). In addition, lifestyles are evolving, suburban homes are being sold and their owners more frequently than before opt for residences in urban neighborhoods (Regional Comprehensive Plan, 2004). Developing the region sustainably means incorporating smart growth principles (Regional Comprehensive Plan, 2004). These principles aim to create high-density walkable mixed-use communities that closely link jobs with housing and transit (Regional Comprehensive Plan, 2004). In turn, it minimizes land consumption in agricultural and rural areas and stimulates reinvestment in existing communities (Regional Comprehensive Plan, 2004). Local jurisdictions land use and development plans need to accommodate these principles. Again, the traditional neighborhood is proven to be sustainable. If the region continues with business as usual and local jurisdictions do not grow within the suggested guidelines, home prices will continue to increase and ease of accessibility will decrease bringing about a housing and traffic crisis with destructive ramifications.

1.4. Problem Statement and Research Questions

The purpose of this thesis is to tackle complex urban development decisions through the practical implementation of theoretical MCDA methodologies. The first area of research is to examine and evaluate the potential for development or redevelopment of vacant parcels in an urban area, while taking into account a combination of livability principles. The research objective in this area is determining the efficacy of MCDA methodology for separating parcels that are better suited for development under multiple constraints from less suitable parcels. The second area of research includes the research objective formulated around employing two forms (global and local) of the WLC model. The objective here includes comparing the results of global WLC with LWLC obtained with five respective
neighborhood definitions (Rook Contiguity, Queen Contiguity, Threshold Distance, K Nearest Neighbors, and Automatic). The automatic neighborhood scheme is flexible in the fact that it extends k nearest neighbor and adds a neighbor whenever a local range cannot be calculated.

The overall problem involves multiple evaluation criteria such as transit jobs accessibility, housing unaffordability, jobs density, health care opportunities, culture and arts, and pedestrian environment that need to be addressed and taken into consideration when searching for suitable, open for development or redevelopment parcels, specifically in urban areas. Again, the first research area involves finding vacant or redevelopment parcels that are suitable for development and apply a rank-ordering scheme that accommodates for a variety of environmental and socio-economic criteria. However, before addressing the research objective formulated for this area, the particular type of development needs to be defined. This is important because the type of development is a determining factor in selecting the evaluation criteria. To address this, the project will use mixed-use as the development type. Mixed-use development is often promoted as a way of limiting suburban sprawl through supporting compact and walkable communities that are conveniently located to transit (Regional Comprehensive Plan, 2004).

In order to address both research objectives, the project will use MCDA4ArcMap (Voss & Rinner 2016), a new add-in for ArcMap that extends its current MCDA capabilities and specifically employs the global and local techniques of WLC method in a vector based setting. It has been suggested in the literature that an interactive graphical tool be employed to visually assess the impacts of specific evaluation criteria because of the many parameters that influence MCDA outcomes (Rinner & Voss, 2013). The cartographic visualization of evaluation criteria is helpful in arriving at a solution of a multiple criteria evaluation problem through a visual interpretation of the results. Presenting and distributing the MCDA outcomes in a thematic map aids in the exploration of the impact of the input parameter settings allowing for map-centered analytics. The MCDA4ArcMap tool addresses this issue by combining innovative MCDA methods with interactive thematic maps for use with vector data (Rinner & Voss, 2013). The application of MCDA4ArcMap addresses the first research question:
How applicable is MCDA4ArcMap to the thesis’ case study?

Answering this question is a crucial part of the research because it will help to determine MCDA4ArcMap’s overall applicability in addressing a problem of this kind. It will also address the first research objective.

To the best of the author’s knowledge, MCDA4ArcMap is the only tool that is capable of employing both global and local WLC using polygon (vector) geometry coupled with the ability to choose from a variety of neighborhood definitions. MCDA4ArcMap will be used for comparing the efficiency of global and local MCDA approaches for urban site selection given multiple constraints. The second objective in the research methodology involves the utilization and visualization of the local and global techniques of WLC. To complete this objective, both of the techniques will be implemented in ArcMap using MCDA4ArcMap. Additionally, as part of the research in the first objective, the author will tested and applied the global version and more importantly the local version of WLC to a real world problem thus determining, which parcels are suitable for development. The implementation of global and local WLC using MCDA4ArcMap facilitated answering the second and third research questions:

[2] Which parcels in the City of San Diego are suitable for mixed-use development under the environmental, economic, urban, and political constraints?

[3] How do the local WLC results compare to the global WLC results?

According to Malczewski (2011), research is needed to test the local WLC approach in real-world situation. That being said, the answers to the above research questions will help to determine the real-world applicability of specific MCDA technique (local WLC) in solving a real-world problem.

Malczewski (2011) stated that finding the most appropriate size, shape, and type of the neighborhood (zone or region) is a problem in using local WLC. In vector based processing, neighborhoods consist of oddly shaped groups of polygons (Carter & Rinner 2014). According to the case study performed by Carter and Rinner (2014), choosing and defining the appropriate type of neighborhood depends on the particular problem at hand. The most
common statistic that is calculated within a neighborhood is mean which finds the mean value in each defined neighborhood. However, using contiguity, distance, k-means, and immediate neighbor statistics is also possible (Carter & Rinner 2014). The quest for an appropriate neighborhood definition leads to the fourth research question:

4. What is the most appropriate neighborhood definition to solve the problem at hand?

This question will be answered by using and comparing the vacant parcel evaluation results obtained with each neighborhood definition that is available in the MCDA4ArcMap tool.

Overall, the major undertaking of this research is the application of local WLC and the assessment of its effectiveness in identifying suitable parcels for mixed-use development in an urban setting.

2. Theoretic Background

2.1. MCDA in GIS

Approaching land-use suitability and site selection through GIS originated from hand drawn overlay methods used by landscape architects in the late 1800s and early 1900s (Malczewski 2004). As GIS came to fruition in the 1970s and 1980s, using digital map overlays for site searching became commonplace (Carver 1991). Although this procedure identified locations that fulfilled specified criteria, it was seen as limiting (Carver 1991). There was no procedure for evaluation and decision support while presenting the user with an ordered list of suitable sites (Carver 1991). The theoretical framework that influenced MCDA, came from concepts developed in behavioral economics in the mid-20th century (Jankowski 2015). These concepts articulated the psychological drive and tradeoffs behind human decision making adopting them into models and later influenced the fundamentals of MCDA (Jankowski 2015). Taking MCDA techniques and integrating them with GIS has significantly advanced decision making methods and the analysis of land suitability for site selection (Malczewski 2004). Once combined with GIS, MCDA lifted previous limitations to research in the analysis of site selection, land suitability, and spatial decision alternatives (Malczewski 2006).

Spatial decision problems naturally involve an abundance of possible decision alternatives and various conflicting criteria (Malczewski 2006). That being said, efficiently
utilizing and employing these approaches is crucial. Developing a framework for spatial planning in a study area, while finding compatibility between natural and human environments is crucial to help decision makers achieve this goal (Abdullah 2014). The MCDA involves the employment of spatial data, the decision maker’s priorities, and aggregation of the data with priorities according to specific rules (Malczewski 2004). The multicriteria decision rules can be categorized into the Multi-Attribute Decision Analysis (MADA) method, which is a data driven approach, and the Multi-Objective Decision Analysis (MODA) method which is a mathematical modeling approach (Malczewski 2004). Both approaches can be useful for planning and a variety of other practical applications which require decisions about allocation of resources (Joerin et al., 2001).

2.2. MCDA Methods in Spatial Decision Problems

Spatial decision problems such as site selection, allocation of resources, land development tactics and maintaining infrastructure are better managed with a formal analysis. Numerous case studies in the literature have employed the MADA and MODA approaches to articulate and prioritize decision alternatives (Gomes & Lins 2002). MODA is particularly useful when deciding whether to allot urban land to green space or housing (Eastman, Weigen, Kyem, & Toledano 1995). Gomes and Lins (2002) used the MODA methods to select the best municipal district based on characteristics that were considered ideal by the decision maker. However, in some circumstances, the MODA model falls short if the decision maker wishes to include his/her preferences (Gomes & Lins 2002). To address this shortcoming Gomes & Lins (2002) proposed a modified MODA model (equation 1) including the decision maker’s preferences. In the model (Xi, Yi) represent the objective values for the alternative i; λi are the decision variables representing the decision maker’s preferences for the alternative i, i = 1 , n (Gomes & Lins 2002).
In contrast to the MODA, the MADA approach has been used in about 70% of MCDA applications integrating GIS with multicriteria decision analysis (Malczewski 2010). MADA is usually concerned with choices from a small set of discrete actions (Jankowski 1995). MADA is best employed when working with a single objective, such as recommending the site for a new building, because the user can focus on relevant factors with measurable attributes (Greene et al., 2011). Given the large number of techniques within MCDA, problems arise when trying to select a suitable technique (Greene et al., 2011). However, spatial decision problems, such as urban planning and environmental management, are commonly tackled using methods within the MADA approach (Jankowski 2015).

Analytical Hierarchy Process (AHP) is disputably the most widely used MADA method with a variety of applications in land and spatial management (Jankowski 2015). This method uses a hierarchical structure of criteria and both additive transformation function and pairwise comparison of criteria to form criterion weights (Brown, Stinson, & Grant, 1986). The case study discussed in Lofti et al., (2009) focused on managing unplanned urban expansion because it negatively affected several socio-economic and environmental factors in the region. Lofti et al., (2009) found that the AHP approach effectively assisted planners in solving urban management problems with a large number of alternatives. The AHP approach has a good track-record in efficiently solving problems involving a large number of alternatives (Malczewski 2006). The results presented in Lofti et al., (2009), explicitly illustrate how applying MADA method can successfully solve complex planning in the domain of environmental concerns.

Problems in managing land in urban areas may be best solved using methods from both approaches. A combination of methods within MADA and MODA may prove beneficial in
certain circumstances (Malczewski 2006). An example of such an approach can be found in Jankowski at al., (2014) who developed an integrated method of finding the optimal locations of sensors with MODA and next evaluating different alternative location configurations with MADA. Yet, in practice, this approach is a highly intricate process containing its own assumptions, uncertainties, and sensitivities. For some spatial decision problems, several of the most common MCDA techniques can be limiting. The main challenge is how to tailor such techniques to particular planning, environmental, and other needs (Ward et al., 2003). Furthermore, another challenge exists in determining how MCDA can be used as a method for addressing viable urban development (Ward et al., 2003). Common spatial decision problems, such as site selection and land use allocation, are complex and require the integration of diverse data (Carver 1991).

In most circumstances, to be successful, the sustainability of development projects depends on a consensus of priorities by several different stakeholders. A comprise of this kind is widely regarded as idealistic. An issue in MCDA is that its methods conventionally take into account the preferences of a single decision maker whereas often decisions are made by interest groups. Realizing the significance of this shortcoming, Boroushaki and Malczewski (2010) developed and implemented a collaborative approach to decision making. Boroushaki and Malczewski (2010) present a web-based GIS-MCDA as a collaborative solution for spatial planning and decision making. This approach helped alleviate the issue by taking into account the preferences of the general public through a WebGIS-based collaborative decision support tool. Though the collaborative approach effectively addressed preference concerns, additional issues were articulated such as the participants not fully understanding the underlying methods deteriorating the systems effectiveness. In general, the overarching complications routinely revolve around the diversity and number of MCDA procedures that can be applied, the assumptions made by these procedures, and the biases in decision making.

2.3. Theory Behind WLC

The significance of the local form of WLC is grounded in Malczewski’s (2011) article, which develops, implements, and advocates for the practical application of the local form of the WLC model (Equation 2). In general, the WLC model is an additive weighting method
that is used to calculate an index value by scoring or ranking each decision alternative (Carter & Rinner 2014). In eq. 2, \( V(A_i) \) is the overall value of the \( i \)th alternative at location, and \( v(a_{ik}) \) is the value of the \( i \)th alternative with respect to the \( k \)th attribute measured by means of the value function.

**Equation 2. Global WLC model.**

\[
V(A_i) = \sum_{k=1}^{n} w_k v(a_{ik})
\]

As mentioned before, the conventional global method, assumes a spatial homogeneity of the decision maker’s preferences, which assigns the same criterion weight to every decision alternative (Malczewski 2011). The local form of WLC takes into account the spatial heterogeneity of the real world by employing the range sensitivity principle (Malczewski 2011). This principle gives greater weight to criteria with large ranges over criteria whose ranges are smaller (Carter & Rinner 2014). The principle attempts to mimic the nature of trade-offs inherent to real-world decision making (Fischer 1995). The local form can be written as follows (Equation 3):

**Equation 3. Local WLC model.**

\[
V(A_i^q) = \sum_{k=1}^{n} w_k^q v(a_{ik}^q)
\]

where represents the local score of location \( i \) within the \( q \)th neighborhood, \( w_k^q \) represents the locally adjusted weight assigned to the \( k \)th criterion within the \( q \)th neighborhood, and \( v(a_{ik}^q) \) represents the value of the \( k \)th criterion at location \( i \) as determined by standardizing the value of the \( k \)th criterion with respect to all values of the criterion \( k \) within the local neighborhood, \( q \) (Carter & Rinner 2014).

The importance is further demonstrated in the MCDA section of the not yet published Wiley Encyclopedia of Geography where its significance is highlighted as a recent advancement at the intersection of MCDM and geography. Specifically, it states that current advances within the amalgamation of MCDA and geography have been centered on developing spatially-explicit MCDA methods as shown by the development of the local version of the WLC model (Jankowski 2015). After the publication of Malczewski (2011), there have been very few studies that aim to implement and test the real-world applicability
of the local WLC model. Even though the publications are few, their impact and innovation in the field has been noticeable.

### 2.4. GIS-based Local WLC in Spatial Decision Problems

Carter & Rinner (2014) examined the use of the local WLC procedure with vector data in a case study evaluating heat-related illness in the City of Toronto. To accomplish their research objectives, it was necessary to develop an application that performs a vector-based local WLC analysis. Furthermore, creating a custom application allowed the user to select a neighborhood definition for the local weights (Carter & Rinner 2014). The overall framework of the methodology followed the logic of the custom application. First, data for the case study was input and the neighborhood definition was selected. Next, the standardized global score was calculated for each polygon then multiplied by the corresponding weight and then summed and stored in a new file in the analysis layer (Carter & Rinner 2014). Subsequently, a neighborhood was defined and the local range of each attribute within the neighborhood was determined and standardized (Carter & Rinner 2014). These products were multiplied and summed resulting in a local WLC score for each polygon (Carter & Rinner 2014). Specifically, three neighborhood definitions were used and compared. These include first-order contiguity, distance-based, and k-nearest neighbors. Contiguity delineates the neighborhood of the \( i \)th polygon and all polygons whose boundaries touch said \( i \)th polygon (Carter & Rinner 2014). The distance designation creates neighborhoods composed of polygons that are within a specified distance while the k-nearest neighbor creates a neighborhood composed of only the nearest \( k \) neighbors as defined by the user (Carter & Rinner 2014). According to Carter & Rinner (2014), neighborhood definition had a significant effect on the local WLC results.

The result of the local WLC method was compared to the result of the global WLC method by a visual analysis of the spatial patterns. The spatial patterns were also quantified through Moran’s Index and Getis-Ord’s G statistic to distinguish high and low clustering and spatial relationships (Carter & Rinner 2014). The results of each neighborhood definition were also analyzed. To quantify the effect of local WLC and its neighborhood definitions compared to global WLC a sensitivity analysis was performed. Overall, their research found that allowing for a local variation in the criteria weights (local WLC), the local
characteristics of the environment surrounding each location were more accurately modeled (Carter & Rinner 2014).

A case study by Liu (2013), proposed a local form of the Ordered Weighted Averaging (OWA) method to study the socioeconomic status of neighborhoods in London, Ontario. The OWA method implements a combination of techniques, one of which is the WLC method. Liu (2013) also implements and compares the global and local methods and neighborhood definitions using vector data. In this example, a custom application was not developed and most of the analysis was performed in ArcGIS. The framework of Liu’s methodology revolves around identifying and standardizing global and local weights, defining a neighborhood, and then comparing the results. Particularly, the neighborhood definitions used and compared were distance-based and boundary-based. The distance-based method finds neighbors according to the threshold set by the user and three thresholds were set in this study. The boundary-based method identifies neighborhoods based on shared boundaries (Liu 2013).

The results of the WLC method and neighborhood definitions were visualized as a demonstration to compare the global and local OWA methods (Liu 2013). Additionally, Moran’s I was used to evaluate spatial autocorrelation between the local and global methods. Further, the results of the two methods were examined using scatter plots with the x and y axes representing the values of the global and local scores to help identify relationships (Liu 2013). Overall, Liu (2013) also found that when compared with the global method, the local method allowed for a more accurate examination of spatial patterns. Moreover, it was confirmed that the neighborhood definition had a significant impact on the spatial patterns of the local methods results, especially in the distance-based method.

In these case studies, and in much of the literature, several common limitations were encountered. The sensitivity, subjectivity, and the zero range problem seem to be the common themes when working with the local variant of specific models. The zero range problem occurs when the definition of neighborhoods is too limiting to exhibit variability in any of the attributes and a local range of zero is produced (Carter & Rinner 2014).

Nonetheless, the Automatic definition in MCDA4ArcMap attempts to avoid this situation by adding a polygon whenever the calculation of the local weights is zero (Voss & Rinner 2016).
The spatial pattern of the real world is heterogenic, a concept that especially rings true in an urban context. The capability of MCDA to accommodate spatial heterogeneity is represented in the form of local WLC giving it a high potential for greater understanding of the decision problem at hand. These factors clearly assist in the understanding of why this particular type of research is important and how it will advance knowledge.

3. Study Area and Methods

3.1. City of San Diego and Surrounding Urban Areas

The research is focused within the City of San Diego and several adjacent urban areas including Imperial Beach, Chula Vista, National City, Lemon Grove, La Mesa, and El Cajon (Figure 1). Areas such as Santee, Poway, and Bonita were excluded because there population density was considered too low and spread out to be included in the study. The City of San Diego has a population of well over 1.3 million while the adjacent areas mentioned above have a combined population of over half of a million (Regional Comprehensive Plan, 2004). The adjacent jurisdictions were chosen because 1) they are highly urbanized and part of the city infrastructure and 2) because under certain circumstances, it is impossible to calculate the local weight because of an unfortunate neighborhood arrangement therefore expanding the research area is an attempt to limit potential issues (Carter & Rinner 2015). The objective is to identify vacant and redevelopment parcels in the study area that are most apt for mixed-use development while considering the local characteristics of the built environment surrounding each parcel and/or neighborhood. The City of San Diego is particularly well suited for this type of research. The city is a good representation of a growing urban area containing parcels that are ripe for development and, at the same time, its policies make urban redevelopment possible.
3.2. Dataset Description

Two datasets were used to answer the research questions: 1) a database of livability metrics collected from a variety of sources categorized by Census Block Group (CBG); and 2) GIS vector-based parcel data acquired from the San Diego Association of Governments (SANDAG) consisting of vacant and redevelopment parcels for San Diego County.

3.2.1. Livability Criteria

Criteria for determining mixed-use development and their corresponding data values were obtained from a livable transit corridor metric calculator accompanied by a livability handbook (Ferrell et al., 2016). The handbook is designed to be a guideline to aid in community livability while the calculator aims to quantify said guidelines. Both of these
sources were created and are maintained by Dr. Christopher Ferrell and Dr. Bruce Appleyard of San Diego State University.

The handbook uses a variety of methods and data sources to measure transit corridor livability (Ferrell et al., 2016). These are categorized into six transit corridor livability principles including as seen in Table 1. Further, within each of the six principles there are two sub-categories, twelve overall, that represent a metric of people and place characteristics (Table 1). With the guidance of an urban planning expert and co-creator of the handbook, Dr. Bruce Appleyard, six of the metrics were chosen as criteria for the thesis case study as they most readily pertained to mixed-use development principles.

The first metric chosen was transit jobs accessibility. This metric is a measurement of jobs within a 45-minute transit commute. It was calculated using the EPA’s Smart Location Database which houses data on travel time and demand (Ferrell et al. 2016). The second metric utilized was housing unaffordability which is a measure of the ratio of household income to rent. It was computed by an aggregation of income data from the 2010 U.S. Census and data from HUD’s Housing Affordability Index Data Set (HAI). This metric provides a general indication of relative rental market affordability (Ferrell et al., 2016). Third, is a metric called jobs density which provides a measure of the density of jobs per acre obtained from the U.S. Census. The next metric used was health care opportunities that measures health care jobs per acre, which was also obtained from the U.S. Census. The fifth metric used was access to culture and arts, which measures arts employees per acre. Data for this metric was obtained from the U.S. Census and was calculated by summing the number of arts, entertainment, and recreation jobs. The last metric chosen as evaluation criterion was pedestrian environment, which is a measurement of intersection density. According to Ferrell et al., (2016), it was computed by calculating the percentage of four-or-more-way intersections from TomTom street centerline data in ArcGIS. Overall, these metrics provide an empirically-based set of analytic tools that follow desired geographic qualities for assessing mixed-use development.
According to Ferrell et. al., (2016), the goal of the livability calculator is to capture a single corridor and its livability characteristics based on Transit Corridor Livability Principles. The livability calculator workflow involves previous identification of the spatial extent of the study area with the purpose of detecting the CBGs that intersect with said extent to extract the associated GEOID number. The final step is inserting the GEOID number corresponding to each CBG in the excel-based calculator and analyzing the resultant score or metric along with charts and graphs for each category of livability.

### 3.2.2. SANDAG Parcel Dataset

SANDAG maintains a publically available, free web-based GIS data warehouse of vector and raster data relevant to San Diego County. It provides GIS data for everything including, addresses, parks, lakes, census, zoning, and properties. These layers are usually downloaded in the form of a shapefile and are created from various data overlays, satellite/airborne imagery, local jurisdiction policy, and other ancillary information (SANDAG, 2010a).
3.3 Dataset Processing

The SANDAG data warehouse includes a variety of parcel datasets with a polygon geometry type. However, two parcel datasets from 2010, vacant and redevelopment, were used as the core datasets in the research. The vacant parcel dataset indicates where vacant and agricultural lots are available for potential development in San Diego County. In total, there were 17,309 vacant parcels in the dataset. The redevelopment parcel dataset identifies existing parcels that are suitable for development, redevelopment, and infill for the purpose of distributing the projected region’s future growth in existing urban areas (SANDAG, 2010a). This dataset contains 20,008 parcels. According to SANDAG (2010a) metadata, the land use information was reviewed by each of the local jurisdictions along with the county to ensure its accuracy.

Figure 2. The vacant/redevelopment parcels used in the case study.
Preliminary processing of the parcel data was necessary to achieve the research objectives. A City of San Diego and a local municipality boundaries shapefile (representing the adjacent jurisdictions) were acquired from SANDAG and displayed in ArcGIS as feature class layers. The desired municipalities were selected, exported to a new feature class, and merged with the city boundary feature class to create one continuous shapefile defining the entire study area. The vacant and redevelopment parcel datasets were combined into one dataset using the merge tool. The resultant parcel layer was overlain with the study area layer and the clip tool was used to create a new dataset containing only the parcels within the study area. The study area used for the research (Figure 2) contained 20,638 parcels with 4,422 being classed as vacant and 16,216 classed as redevelopment (Table 2).

<table>
<thead>
<tr>
<th>Region</th>
<th>Vacant Parcels</th>
<th>Redevelopment Parcels</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>City of San Diego</td>
<td>3,185</td>
<td>13,722</td>
<td>16,907</td>
</tr>
<tr>
<td>Expansion Area</td>
<td>1,237</td>
<td>2,494</td>
<td>3,731</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>4,422</strong></td>
<td><strong>16,216</strong></td>
<td><strong>20,638</strong></td>
</tr>
</tbody>
</table>

As stated previously, the livability scores are categorized and collected using the livability calculator via CBGs and their associated GEOID number. Identification of the GEOID involved downloading CBG vector data from the U.S. Census website. The data was opened as a layer in ArcGIS and the presence of an acceptable GEOID was detected in the attribute table. The parcel dataset was overlain with the CBG dataset and a spatial query was performed that selected features from the CBG layer that intersected the parcel layer. The selected features were exported to create a new shapefile consisting of 998 CBGs in the spatial extent of the study area. In order to join the livability metric data with the parcel data a common field needed to be defined. To join the GEOID attribute from the CBG layer to the parcel layer a spatial join was performed joining the GEOID to the parcel if the centroid of the parcel was within the CBG creating a new polygon feature class. In ArcGIS, the add field tool was employed to add six new fields to said feature class representing the six livability metric categories.
To obtain livability metrics for each parcel in the study area a workflow was established using Microsoft Excel. In Excel, a new worksheet was created with seven fields, one for the GEOIDs and six for the livability metric scores categories. The .dbf file associated with the spatial join output was opened in Excel and the GEOIDs were copied into the new worksheet. From this worksheet, the GEOIDs were input into the calculator one-by-one and the six desired livability metric scores were copied into the new Excel worksheet with their corresponding GEOID. This workflow was repeated until all GEOIDs had corresponding livability metric scores.

3.4 Criterion Weighting

Inherently, the nature of decision making involves the preference of particular criteria relative to another. The perceived importance of individual criterion relative to the other criteria is quantified by the criterion weights (Carver, 1991). Criterion preferences are commonly represented by weights given the notion that the sum of weights equals 100% of preferences (Jankowski, 2015b). Among the variety of existing criterion weighting techniques the pairwise comparison technique is regarded as a theoretically-sound approach to computing weights by comparing and ranking criteria pairs.

3.4.1. Pairwise Comparison

The pairwise comparison method compares the importance of one criterion against the importance of the other criterion (Jankowski, 2015b). The verdicts of said comparison are commonly expressed on a scale of 1 – 9 (Table 3), where 1 signifies equal importance and 9 symbolizes a tremendous importance of one element over the other element (Jankowski, 2015b). The results of each comparison are arranged in a pairwise, square comparison matrix. The elements of the matrix are calculated and a weighted sum is created for each row. The outcome is a rank-ordered list of criteria with assigned weights totaling 100.

<table>
<thead>
<tr>
<th>Level of Importance</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
</tr>
<tr>
<td>2</td>
<td>Slightly more important</td>
</tr>
<tr>
<td>3</td>
<td>Weakly more important</td>
</tr>
<tr>
<td>4</td>
<td>Weakly to moderately more important</td>
</tr>
<tr>
<td>5</td>
<td>Moderately more important</td>
</tr>
<tr>
<td>6</td>
<td>Moderately to strongly more important</td>
</tr>
<tr>
<td>7</td>
<td>Strongly more important</td>
</tr>
<tr>
<td>8</td>
<td>Greatly more important</td>
</tr>
<tr>
<td>9</td>
<td>Absolutely more important</td>
</tr>
</tbody>
</table>

Ranking and comparing criteria is a subjective task that is usually influenced by the decision maker’s personal preferences along with the overarching research goal. That being said, the ranking and weighting of the criteria in this case study was influenced by three main factors including the researchers inclinations derived from an extensive literature review, the type of development being considered (mixed-use), and consultations with an urban-planning professional. The pairwise comparison method was established and carried out based on the factors stated above using the BPMSG AHP Online System (Brueggerman & Eklundh, 2016). Table 4 explicitly presents the pairwise comparison technique and how each criterion was ranked relative to another. Once complete, the software outputted a table indicating a final rank order of the criteria with an attached weight (Table 5). The resultant weight for each criterion represents its respective importance.
Table 4. Criteria Ranking using pairwise comparison. The bold font indicates the criteria and/or level of importance selected.

<table>
<thead>
<tr>
<th>Which criterion is more important?</th>
<th>Ranking Criteria using Pairwise Comparison</th>
<th>How much more important? (refer to table 3 for definitions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Access to Culture and Arts or Healthcare Opportunities</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>2 Access to Culture and Arts or Housing Unaffordability</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>3 Access to Culture and Arts or Jobs Density</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>4 Access to Culture and Arts or Pedestrian Environment</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>5 Access to Culture and Arts or Transit Jobs Accessibility</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>6 Healthcare Opportunities or Housing Unaffordability</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>7 Healthcare Opportunities or Jobs Density</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>8 Healthcare Opportunities or Pedestrian Environment</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>9 Healthcare Opportunities or Transit Jobs Accessibility</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>10 Housing Unaffordability or Jobs Density</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>11 Housing Unaffordability or Pedestrian Environment</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>12 Housing Unaffordability or Transit Jobs Accessibility</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>13 Jobs Density or Pedestrian Environment</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>14 Jobs Density or Transit Jobs Accessibility</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
<tr>
<td>15 Pedestrian Environment or Transit Jobs Accessibility</td>
<td>1 2 3 4 5 6 7 8 9</td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Final Criteria Weights representing an amalgamation of perspectives.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Criteria</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Transit Jobs Accessibility</td>
<td>44.7%</td>
</tr>
<tr>
<td>2</td>
<td>Pedestrian Environment</td>
<td>25.0%</td>
</tr>
<tr>
<td>3</td>
<td>Jobs Density</td>
<td>14.4%</td>
</tr>
<tr>
<td>4</td>
<td>Housing Unaffordability</td>
<td>8.2%</td>
</tr>
<tr>
<td>5</td>
<td>Health Care Opportunities</td>
<td>4.8%</td>
</tr>
<tr>
<td>6</td>
<td>Culture and Arts</td>
<td>2.8%</td>
</tr>
</tbody>
</table>
3.5. MCDA4ArcMap

Imperative to achieving the research objectives, it was necessary to identify and utilize GIS software that was capable of performing a vector based global/local WLC modeling on polygon geometry.

As discussed previously, MCDA4ArcMap is an open-source tool for MCDA written in C# programming language within the .NET environment. It serves as a geovisualization tool for exploiting vector data and is implemented as an add-in in ArcMap (Rinner & Voss, 2013). The analytical functionality of the tool includes the WLC and LWLC method.

The workflow of the add-in is briefly summarized in the following steps: (1) Download and install add-in; (2) Add data to the data manager and select fields to be used as criteria (Figure 3); (3) choose the normalization strategy (Figure 4); (4) choose MCDA method - WLC or LWLC and neighborhood definition (Figure 5); (5) input weights and choose benefit type (Figure 6); (6) choose symbology and visualize result (Figure 7).

Figure 3. Data Manager for viewing and selecting criteria.
Figure 4. Selection of desired normalization strategy

![Normalization Strategy Selection](image1)

Figure 5. MCDA Method Selection and Neighborhood Definition windows.

![MCDA Method Selection](image2)

Figure 6. Criteria with assigned weights. The locked and benefit checkbox is enabled for all criteria.

![Criteria with Weights](image3)
3.6 Global WLC Workflow

Calculating, mapping, and analyzing the global and local WLC scores is an imperative step towards answering all research questions. The general MCDA4ArcMap workflow was followed to calculate global WLC scores using the WLC tool. The investigation began by adding the parcel dataset to the TOC in ArcMap, displaying the data manager, and selecting the six fields representing the desired criteria. The maximum score normalization strategy was selected and the WLC tool was chosen from the MCDA Methods drop-down menu. The maximum score normalization strategy produces criterion values between 0 and 1 with 1 being the best score (Voss, 2016). For benefit criteria, the result is anchored at one and for cost criteria at zero. Generally, upon the selection of desired MCDA method, the criteria are normalized and the global or local score of each attribute is calculated before the user is given a chance to enter the desired weights. That being said, after choosing the WLC tool, the resulting global WLC scores were not reflective of the desired weights. On the criteria tab, the desired weights obtained in the last step of pairwise comparison (Table 5) were entered in the numeric field for every single criterion and the scores were re-calculated accordingly.
Furthermore, the lock mechanism was checked for all criteria (Figure 6) as the weights were already established and not subject to an interactive decision making process (Voss & Rinner, 2016). Depending on the interpretation of criteria and their meaning in the given evaluation context, criteria may be treated as either cost (lower values are preferable) or benefit (higher values are preferable). Given that notion, a higher value was preferred for all of the case study’s criteria thus the benefit check box was checked for all (Figure 6). The global WLC scores were then re-calculated once again reflecting the benefit type. Global WLC score calculation consisted of the criteria being multiplied by the assigned weight and summed up for each decision alternative. The resulting global WLC scores were then stored in the result table tab, which was exported and saved as a text file.

A fitting symbology scheme was selected (Figure 7) and added to ArcMap’s TOC using the add as managed layer button in MCDA4ArcMap. The resultant layer is a temporary replica of the inputted shapefile but with the global WLC scores stored as a new field in the attribute table called WLCResult. Being temporary, the layer and symbology will be lost if ArcMap is closed. The layer was exported as a shapefile and layer file to preserve topology, symbology, and the newly added field.

3.7 LWLC Workflow

A similar workflow was required to calculate the LWLC scores for each neighborhood definition. The LWLC tool was chosen as the data and criteria were already loaded from the previous step and did not need to be prepared again. For a second time, the LWLC scores were calculated upon method selection giving values that do not reflect the desired weights. The maximum score normalization strategy was selected, the pre-defined weights were entered, type of neighborhood selected, and benefit type was assigned thus re-calculating the scores to reflect the accurate weights.

The implementation of LWLC is intricately linked to the concept of and the definition of a neighborhood (Carter & Rinner, 2014). This was executed through utilization of the neighborhood definition tool window (Figure 5). Specifically, the tool supports five neighborhood definitions (Figure 8). The first four of the five supported neighborhood definitions are commonly used within a GIS. The neighborhood options include: rook contiguity, queen contiguity, threshold distance, k-nearest neighbor, and automatic (Figure 8).
Figure 8. Visual Representation of Neighborhood Definitions. The green polygon is the seed, the blue polygons belong to the cluster, and the black polygons are excluded from the neighborhood. Voss & Rinner (2016).
Both the rook and queen contiguity-based methods come from the possible movements of their respective name giving chess pieces (Voss & Rinner, 2016). The rook neighborhood is restricted to polygons that share a common polyline border (Figure 8), not a vertex, shown as the black polygon. In the queen-based method a neighborhood is defined by polygons that share a border or vertex. Both of these neighborhood schemes are limited to direct neighbor contiguity and a higher order contiguity is not available in the tool. The distance definition is based on a user-defined threshold distance between the centroids of each polygon. Every polygon with its centroid within the given distance belongs to the neighborhood. The distance is measured using the Euclidean distance, not the shortest path distance (Voss & Rinner, 2016). As a default setting, not more than twenty neighborhood polygons are considered in the analysis, however, this can be increased if need be. The k-nearest neighbor definition is similar to the distance definition but instead of considering all polygons in a specified distance, the closest $k$ polygons are taken into account with the ability to increase $k$ to maximum of 19. As mentioned previously, sometimes it is impossible to calculate local weights because of an unfortunate neighborhood arrangement, which does not afford a sufficient variability in criteria values. The automatic definition attempts to overcome said situation by iteratively adding a polygon, using the k-nearest neighbor scheme by increasing $k$ until there is a variation in the local range so a weight can be calculated, up to $k=1000$. Note that the number of neighbors on the setting tab in the neighborhood definition window needs to be manually changed to 1000 to reflect this possibility.
3.7.1. Software Limitations

Completing the said workflow using the LWLC tool on the full dataset (20,638 polygons) was impossible. ArcMap 10.4 could not support processing such a large calculation and the software consistently crashed on PC running Windows 10 with dual processors, one terabyte of memory, and 64 gigabytes of RAM. It was concluded that the dataset (parcels) needed to be dissected or grouped by a feature such as neighborhoods. This workaround was thought not only to lessen the intensity of the calculation but produce more desirable results given the nature of LWLC neighborhood schemes. The dataset was grouped by U.S. Census sub regional areas (SRAs) which are aggregations of census tracts. After downloading the shapefile from the U.S. Census website a spatial query was implemented to select SRAs that fell within the study area and the query result was saved as a separate shapefile. A spatial query was also implemented to perform the actual parcel grouping using the spatial query search parameters which selected features from the parcel dataset that have their centroid in a given SRA. Then each cluster of parcels was separately exported as a shapefile. This process created twenty-four neighborhoods consisting of: Central San Diego, Peninsula, National City, Southeastern San Diego, Mid-City, Kearny Mesa, Coastal, University, Del Mar-Mira Mesa, North San Diego, Poway, Elliot-Navajo, Sweetwater, Chula Vista, South Bay, Jamul, Spring Valley, Lemon Grove, La Mesa, El Cajon, Santee, Ramona, San Dieguito, and Escondido.

The research applied all five supported methods of the neighborhood scheme. Since the study area was partitioned into twenty-four sub regions and five neighborhood schemes were applied in this case study resulting in 120 iterations of the workflow.
Three of the five schemes allowed for user-defined parameters that created several issues, which will be discussed in the results section. Given the large amount of polygons under investigation and the discrete nature of the data, the division by zero error was often encountered. According to Liu (2013), the specified threshold distance should be large enough to guarantee that each location has at least one neighbor. After many trial runs, the maximum allowable threshold distance was selected, which ensured that each parcel had at least one neighbor. According to Carter & Rinner (2014), in certain circumstances neighborhoods that are too small to exhibit variability must be avoided in order to produce valid results. Subsequently, the k-nearest neighbor parameter was increased to \( k = 19 \) to avoid the division by zero error and the automatic setting was increased to \( k = 1000 \) for the same reason. These results will be discussed further in the following sections.

Once the neighborhood parameters were set the results were mapped. Again, the outputs from MCDA4ArcMap are temporary and contain vital information. The LWLC output creates a temporary layer and adds a new field to the attribute table called LWLCSRResult containing the overall LWLC scores for each record or parcel. The tables produced in the result table tab include intermediate steps like local range, normalized criterion, and the local weight. The tables were saved as text files for each output and the temporary layer and selected symbolizations were exported to a shapefile and a layer file for preservation and further analysis. Finally, the datasets corresponding to the study area partitions were appended according to their related neighborhood definition generating a total of five LWLC maps.

### 3.8. Analysis Procedure

First, a visual assessment comparing the WLC map to the each of the LWLC maps was performed in order to understand the effects of the local procedure and how it differentiated from the global procedure. Additionally, each of the five LWLC maps was compared to each other to examine the influence of the selected neighborhood type on the model’s output. Specifically, determining the effectiveness of the models output through the selected neighborhood type by its ability to provide a LWLC score to every polygon (20,638 polygons) in the study area.
The spatial patterns of the overall WLC/LWLC scores can be quantified by measures of spatial autocorrelation. Particularly, local Hot Spot Analysis operationalized by Getis-Ord Gi* statistic was used to distinguish high-highs (high values surrounded by high values) from low-lows (low values surrounded by low values) spatial clustering and local Cluster and Outlier Analysis (Anselin Local Morans I) to identify spatial outliers. Both of these spatial dependency metrics were implemented in ArcGIS 10.4 using the WLC/LWLCResult field as the input, fixed distance band as the conceptualization of spatial relationships, and the distance band threshold set to 7250. Both spatial dependency measures were calculated for all models yielding twelve output maps. The results of these methods are shown and described in the results section.

4. Results

The spatial patterns in the output maps were visually and statistically inspected. Initially, the output maps of each WLC/LWLC pair were visually examined and compared to one another. The spatial patterns were then quantified through the measures of spatial autocorrelation. The result is a mash up of comparisons between WLC/LWLC output maps and spatial autocorrelation output maps. A visual assessment of the spatial patterns of the WLC/LWLC outputs is crucial for accurately interpreting the effects each method has on the spatial arrangement of mixed-use parcels.
4.1 Spatial Patterns of WLC Results

Figure 9 presents the results of the global WLC. The highest scored parcels (scores closer to 1 and shown in red), representing parcels that are more promising for mixed-use type development, are found in a variety of areas. The more promising areas are found in central downtown San Diego extending both into the north and northeast parts of the urban core. Furthermore, clusters of high scoring parcels exist in enclaves in all directions from the urban core in suburban and urban regions alike. The appearance of high-scoring parcels in and around the urban core was expected given the amenity rich nature of urban centers. Additionally, the appearance of high-scoring enclaves outside the urban core is not surprising. This mimics the well documented sporadic type of development inherent to San Diego and southern California as a whole.

Figure 9. WLC Result study area. A higher score, shown in red, corresponds to a more promising parcel for mixed-use development. Conversely, a lower score, shown in purple or blue, corresponds to a less promising parcel for mixed-use development.
4.2. Spatial Patterns of LWLC

In contrast to the global result, the LWLC results varied widely depending on selected neighborhood scheme. The LWLC outputs demonstrate a less consistent pattern as seen in Figure 10. The inconsistent pattern is expected given that the idea of the neighborhood is designed to highlight local extremes based on the ranges of criterion values within each neighborhood.

Figure 10 A-E. Output Maps of LWLC based on chosen Neighborhood Scheme
The map displayed in Figure 10-A represents the LWLC output using the rook neighborhood definition. Since the data is discrete and rook’s neighborhood is defined by polygons that share a common border, only 199 parcels received a viable score. Similarly, Figure 10-B representing the queen neighborhood definition, presented almost identical results. Here, only 201 parcels received LWLC scores with the reason for the increase coming from two extra neighbors that shared a polyline and a point. Again, this is due to an insufficiently diverse neighborhood leading to a division by zero error. The parcels that did receive scores varied between high and low with no notable pattern and were obviously contiguous neighbors. Therefore, the zero-range problem was exceedingly evident making the rook and queen neighborhood definitions limiting in dealing with non-contiguous vector data and in the research.

Figure 10-C presents the output from the distance definition. This scheme was more robust in dealing with the zero range issue as distance-based neighborhoods resulted in LWLC scores applied to all but 219 parcels. The distance threshold was set at the maximum allowable distance (US feet) for each of the 24 regions as the actual distance used varied per region. The results demonstrate a spatial pattern of clustering with high scores in the urban centers and low scores around the fringe. They also demonstrate pockets of similar scores, which makes sense given the concept of threshold. However, some spatial randomness does exist. Clusters of high and low scores adjacent to one another are seen in the urban core and the surrounding areas. For example, the rural southeastern section of the study area near the US-Mexico border exhibits neighboring clusters of high and low scores whereas high scores were not seen in any other results in this area. Additionally, a distance threshold boundary is explicitly seen directly northeast of the urban core exhibiting an adjacent high-low cluster. Relative to the other outputs, the results indicate large clusters of parcels having moderately low scores. This can be attributed to the large distance threshold used as the amount of high scores decreases away from the central point of the neighborhood usually receiving the highest score. Essentially, with the increasing distance threshold the LWLC results seem to converge with WLC (global) results.
The zero range problem was encountered using k nearest neighbor definition (k=19). Out of 20,638 parcels only 14,176 were able to receive a local score deeming it less robust than the distance definition. The map displayed in Figure 10-D reveals the spatial pattern of LWLC using the k nearest neighbor definition. The resulting spatial pattern seemed to be consistent with the other maps with clustering of high scores in the urban core and surrounding urban centers while low score clustering occurred around the periphery. Upon the closer inspection, a random pattern of isolated clusters of high and low scoring parcels was observed within the broad spectrum of the entire study area. The most notable pattern was the seclusion of high scoring parcels in the northern section of the study area observed on every output map. One explanation for this is that the k nearest neighborhood definition creates rigid and relatively smaller neighborhoods not providing as much flexibility as it should. When k takes on a large value it creates rigid but larger neighborhoods and that seem to simulate the distance definition. While the creation of isolated locations is expected when using LWLC, the enormous amount of small isolated high and low scoring neighborhoods can be attributed to the fixed neighborhood definition and the discrete or separate and distinct nature of the parcel data.

Perhaps the most promising tool in achieving the research objectives was the automatic definition (Figure 10-E). The overall flexibility of the automatic definition of neighborhood appeared to overcome the limitations imposed by the fixed k number and other definitions. The elasticity of the definition prohibited the occurrence of the division by zero error as a neighborhood was always able to be calculated by adding polygons as needed thus producing valid results. The observed spatial patterns were similar to that of the others from the high scoring urban centers to the heterogenetic neighborhoods a known characteristic of the LWLC method. The map created by the automatic definition was fairly similar to the k nearest neighbor map however, more parcels were considered in the neighborhood calculations. This is accredited to the parallel fundamentals in which a neighborhood is delineated. In one delineation the closest nineteen polygons (k=19) are taken into account whereas the other starts with closest three polygons (k=3) and expands up to 1000 (k=1000) or until it is large enough to exhibit variability for a score to be calculated.
4.2.1. Comparing Spatial Autocorrelation

The degree of spatial autocorrelation across the study area is displayed statistically in Table 6 and mapped in Figures 11 A-L. The Hot Spot Analyses (Figures A, C, E, G, I, and K) generally shows statistically significant positive spatial autocorrelation throughout the study area. Furthermore, the Hot Spot Analyses indicate that strong spatial dependency exists among high and low values demonstrated in Table 6 with the presence of a high z-score (7.21) and low p-value (0.04). Particularly, as expected, strong spatial dependency exists among high values in and around the urban core and among low values in the suburban areas. Unsurprisingly, the Hot Spot analysis results for Rook and Queen neighborhoods (Figures 11 C and E) did not provide any accurate or useful information given the extremity of the zero range problem where scores were only able to be calculated for about 200 parcels out of 20,638 parcels. Likewise, further exploration exposed a z-score near zero (-0.46) indicating no apparent spatial clustering and confirming the visual analysis. One would assume that given the spatially limiting nature of the LWLC method there would be more variation in the presence of hot and cold spots. Again, the discontinuous nature of the data and the subjectivity of the spatial autocorrelation parameters (distance threshold) contribute the seemingly large and uninteresting clusters of high value parcels surrounded by other high value parcels (hot spots) and conversely, low value parcels surrounded by other low value parcels (cold spots) Seemingly, an interesting pattern would display small rigid clusters of high value parcels adjacent to clusters of low and random valued parcels. Overall, the Hot Spot Analysis only provided minimal insight into the complexity of spatial patterns created by the WLC and LWLC tools.
Table 6. Spatial Autocorrelation measure averages using Hot Spot Analysis and Outlier and Cluster Analysis for global and local WLC scores

<table>
<thead>
<tr>
<th>Spatial Autocorrelation</th>
<th>Hot Spot Analysis</th>
<th>Outlier and Cluster Analysis</th>
<th>Spatial pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global WLC</td>
<td>z-score = 7.21</td>
<td>z-score = 15.95</td>
<td>Clustering of high values</td>
</tr>
<tr>
<td>LWLC: Rook</td>
<td>z-score = -0.46</td>
<td>z-score = 0.21</td>
<td>No significant clustering</td>
</tr>
<tr>
<td>LWLC: Queen</td>
<td>z-score = -0.46</td>
<td>z-score = 0.64</td>
<td>No significant clustering</td>
</tr>
<tr>
<td>LWLC: Threshold Distance</td>
<td>z-score = 2.67</td>
<td>z-score = 7.06</td>
<td>Clustering of high values</td>
</tr>
<tr>
<td>LWLC: K Nearest Neighbor (k=19)</td>
<td>p-value = 0.06</td>
<td>p-value = 0.14</td>
<td>No significant clustering</td>
</tr>
<tr>
<td>LWLC: Automatic</td>
<td>z-score = 5.03</td>
<td>z-score = 5.63</td>
<td>Clustering of high values</td>
</tr>
</tbody>
</table>

The Cluster and Outlier Analyses (Figures B, D, F, H, J, and L) was specifically used to detect spatial outliers or anomalous patterns. The output maps show the resultant local Moran’s I statistic with negative values representing an outlier or an object that has neighboring objects with dissimilar values. Given the homogeneity of global WLC, the WLC Outlier Analysis presented few but interesting and unexpected spatial outliers in a variety of locations most notably in the outer urban centers and certain suburban areas. In contrast, as expected, the heterogeneity of LWLC spurred a large increase in the presence of spatial outliers which can be interpreted in Table 6 by the relatively lower z-scores (7.06 and lower). Outliers appeared in similar locations as in the global WLC, however, a widespread and more interesting assortment was presented. Besides the Rook and Queen neighborhood definitions, the most outliers were seen in the k nearest neighbor and automatic delineations represented by the comparatively lower z-score and lower p-values. Yet again, outliers were observed mostly in the outer dense urban areas directly north, north east, and south of the urban core. The high frequency of outliers seen in dense urban areas as opposed to suburban and rural areas is attributed to the high volume of parcels in conjunction with the real-world diversity of people, place, and services in these facility rich neighborhoods. The interesting and less consistent collection of outliers is expected given that the fundamentals of the LWLC formula was built to focus on local extremes centered on the criterion ranges within each neighborhood.
In Figures 11 A-B an interesting area directly north of the city in a dense suburban area exists where hot spots are surrounded by cold spots (14A) while in 14B the same area is depicted as high-high. This can be attributed to the slight change in WLC scores where specifically, in Figure 11 A, the hot spot had a WLC score of 0.23 while the surrounding cold spot had a WLC score of 0.22. That being said, even though the scores are relatively similar they are drastically different than their neighbors thus enabling them to be classified as hot and cold spots. However, in Figure 11 B, this same area is classified as a high-high cluster because a WLC score of 0.22 and 0.23 are relatively high scores in the perspective of the whole area and do not qualify as outliers.

Overall, the Cluster and Outlier Analysis provided a more in depth perspective into the spatial patterns. These findings will be discussed in more depth citing specific examples in the next section.

Figure 11 A-L. WLC/LWLC - Spatial Autocorrelation Hot Spot and Outlier Analysis.
(G) LWLC Distance – Hot Spot Analysis  (H) LWLC Distance – Outlier Analysis

(I) LWLC K=19 – Hot Spot Analysis  (J) LWLC K=19 – Outlier Analysis
4.2.2. An Illustrative Example Comparing Global WLC, LWLC, and Spatial Autocorrelation

Given the large study area, the big dataset, and the numerous outputs a simple workflow needed to be established for comparing and analyzing these features. The workflow is summarized in the following steps: (1) Organize all outputs in the ArcGIS TOC starting with global WLC followed by LWLC (one neighborhood scheme) and continuing with the corresponding Hot Spot and Outlier Analyses; (2) Zoom in to a desired AOI (Area of Interest); (3) Enable/disable all layers in the order mentioned above; (4) Repeat steps 1-3 with another neighborhood scheme until all neighborhood schemes have been analyzed. Comparing the results in this manner is crucial in highlighting the significant differences between both multi-criteria methods. Additionally, it helps in gaining a clearer understanding of the emerging spatial patterns and identifying parcels that are more promising for mixed-use development.
This workflow is demonstrated in Figure 12 on the example of the University of California San Diego campus as the AOI. This area is within the City of San Diego study area. The results of global WLC and final appraisal scores are shown in Figure 12-A while the results of LWLC using the automatic neighborhood definition are shown in Figure 12-B. Specifically, the final appraisal scores for global WLC range from 0.06 to 0.54 while ranging from 0 to 1 for LWLC using the automatic definition. The difference in these ranges is an explicit indicator of the model type. Global WLC is based on the implicit assumption that its parameters do not vary as a function of geographic space translating to a smaller range of criterion values as stated above (Malczewski, 2011). LWLC has a much larger range because it is based on the idea of a neighborhood which produces a greater range of criterion values that varies in relation to its surroundings (Malczewski, 2011). Through examination of the two figures (Figure 12-A/12-B) the differences between the homogeneity and heterogeneity interworking’s of each model parameters are accentuated. Global WLC can be seen as a regional or uniform perspective as its results depict a generalized pattern of parcels in the AOI that are either promising or not for mixed-use development. However, if looking only from this perspective alone, it is uninteresting as it does not easily allow to find parcels suitable for mixed-use development because there is lack of contrast in the resulting pattern that allows to distinguish a particular parcel or parcels from the rest of cluster. LWLC (Automatic) (Figure 12-B) provides further clarity and detail through expressing the relationship between parcels and amenities and how they relate to each other through the use of a neighborhood. It facilitates a more complete inquiry into, which parcels are more favorable than others. Figures 12-C and 12-D aid in answering the question of which parcels if any, are related in terms of the final appraisal score. The Outlier analysis (Figures 12-E and 12-F) elucidates this investigation even further by detecting, which individual parcel or parcels standout from the cluster. Overall, this process breaks down a complex spatial decision and presents the user with a simple set of options.
Figure 12 A-F. Comparative Visual Assessment of WLC, LWLC (Automatic), Hot Spot Analysis, and Cluster and Outlier Analysis on an Area of Interest.

(A) WLC Scores of AOI

(B) LWLC (Automatic) Scores of AOI

(C) WLC Hot Spot Analysis of AOI

(D) LWLC (Automatic) Hot Spot Analysis of AOI

(E) WLC Cluster and Outlier Analysis of AOI

(F) LWLC (Automatic) Cluster and Outlier Analysis of AOI
5. Discussion and Conclusion

Previous studies have noted that the LWLC method is an attractive theoretical concept and that future research should focus on the practical application of the method in a GIS-based setting (Malczewski, 2011). Likewise, prospective research should also emphasize the effects of the neighborhood definition on the results of LWLC with the specific goal of developing best practices for choosing the definition of a neighborhood (Carter & Rinner, 2013). This study supports and expands upon these themes theoretically and practically using a vector based model for spatial data.

This thesis focused on WLC and LWLC and the effect its respective neighborhood definitions had on the results in achieving the desired goal. A case study assessing and identifying parcels that are most promising for mixed-use development is presented to illustrate and compare the results of WLC with LWLC procedure including various neighborhood schemes. Additionally, the case study demonstrated the applicability of the new add-in for ArcMap, MCDA4ArcMap, by testing it against a large dataset and evaluating its outcomes. In doing so, it demonstrated the robustness of using LWLC with vector data in a GIS software environment.

LWLC was shown to provide a different perspective than WLC on the assessment of parcel locations based on a spatially explicit representation of parcel neighborhood. The local geographic characteristics and spatial patterns are more accurately modeled when a local variation in criteria weights is established than in the global WLC method, which does not represent the local context. Logically, utilizing the local characteristics of the environment surrounding each parcel allows for a more real-world representation which in turn provides better solutions for the problem at hand. The flexibility of LWLC through its neighborhood schemes increases its practicality in solving real world problems. Specifically, the LWLC practicality was best exhibited with the automatic definition. However, both the benefits and limitations of the LWLC method were exposed throughout the course of the research.

Several limitations can be attributed to the discrete data type used in this research. Another limitation is exhibited through the zero range problem particularly observed in the rook and queen neighborhood schemes. Discrete data (land parcels) does not commonly share a common polyline or point making the rook and queen definitions limited in forming robust neighborhoods. A possible way of avoiding this situation is a large scale aggregation.
of data, however, this will most likely alter its spatial accuracy and move LWLC results closer to those of WLC. Another way of avoiding this issue is allowing for more user defined flexibility within each local neighborhood scheme and outside of the box type thinking when developing said schemes. The automatic neighborhood definition used in MCDM4ArcGIS add-on software overcomes this limitation through its ability to compensate for the zero range error by adding a polygon when necessary. Overall, when working with discrete data in a vector setting such as parcels, an exceptionally flexible neighborhood scheme, as seen in the automatic definition, should be used as the robust option for defining a neighborhood in the analysis.

The LWLC should not be used as an exclusive MCDM method in spatial decision analysis. As mentioned in the previous section, LWLC should be seen and used as a supplement to global WLC or in conjunction with global WLC. WLC should be used and analyzed as a regional perspective and a way to point out general areas of significance and interest. LWLC should be used as a way to further analyze these interesting areas by providing more detail as to how criteria vary at a local level. Furthermore, the use of sensitivity analysis, such as spatial dependency metrics, is helpful in identifying location alternatives at a localized level while determining the robustness of the local procedure and its respective neighborhood definitions.

Future research should focus on developing an alternative flexible neighborhood scheme similar to the automatic definition. Further research should be developed on a theoretical foundation supporting such scheme. In conclusion, the mixed global-local approach to MCDA/WLC can be applied to particular case studies with the knowledge that it provides more insight into the decision problem than either of the two approaches alone. The subjectivity of parameters within each neighborhood scheme is a challenge that is always present.
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