Chapter 11
Geographic Visualization and MCDA

11.1 Introduction

Geographic Visualization, or geovisualization, refers to specific approaches to the cartographic display of geospatial data. Going beyond traditional thematic mapping, geovisualization environments are characterized by their interactive nature. This interactivity allows for multiple perspectives on the same data, thereby supporting an analyst to explore the underlying phenomena and developing scientific hypotheses about them. Geovisualization technology has been combined with MCDA techniques to support decision analysts with advanced human-computer interaction tools.

This chapter first outlines the development of geovisualization within GIScience and summarizes its basic tenets. Examples from the literature that use the CommonGIS tool are presented in more detail. The use of geovisualization to explore MCDA inputs, as well as MCDA results and MCDA parameter space, is then discussed using the ArcGIS add-on 'MCDA4ArcMap' and a deprivation index for the City of Toronto as an example. The chapter concludes with a discussion of the role of geovisualization and MCDA in public planning and decision making.

11.2 Overview of Geovisualization

11.2.1 *The Development of Geovisualization Within Cartography*

The concept of geovisualization emerged in the Cartography and GIScience literature in the early 1990s. DiBiase (1990) suggests that visualization plays an important role along the continuum of scientific methods, and associates the visual methods in exploration and confirmation with a scientist's 'visual thinking' in a

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‘private realm’, while visual methods for synthesis and presentation act as ‘visual communication’ tools in a ‘public realm’. MacEachren (1994) extends DiBiase’s concept by proposing the map use cube, or cartography-cubed representation. MacEachren (1994) argues that maps are useful along a range of tasks, from ‘revealing unknowns’ in a private environment using highly interactive mapping tools, to ‘presenting knowns’ in a public setting using less interactive (i.e., static) maps. MacEachren (1994) thereby emphasizes the data exploration function of maps as complementary to the traditional communication function of maps. Finally, MacEachren and Kraak (2001) coined the term ‘geovisualization’ and outlined a research agenda for the field.

Based on related research in the area of information visualization, the process of geovisualization can be characterized as one of “overview first, zoom and filter, then details-on-demand”, as posited by Shneiderman (1996, p. 337). In their taxonomy of tools for interactive data display, Buja et al. (1996) distinguish focussing, linking, and arranging functions. Spatial data exploration tasks have also been separated into the following groups (Zhou and Feiner 1998; Andrienko et al. 2002; Keim 2002; Plaisant 2005; Kelsey and Rinner 2009):

- identifying the attribute value of an object;
- querying objects by specified attribute values;
- clustering objects by similar attribute values;
- ranking objects by an attribute;
- comparing objects by their attribute values, as well as comparing spatial patterns of two or more attributes at one point in time, or of a single attribute over time (change); and
- quantifying the association (correlation) between two attributes.

The CommonGIS thematic mapping tool (Andrienko and Andrienko 1999) implements many of the principles of geovisualization. For example, its choropleth map allows the user to interactively modify class breaks, the number of classes, and the classification method. It also supports interactive highlighting of one or more selected classes, removing outliers at both ends of the value range, and comparing values to a reference value or reference object with a single click on the map. These interactive functions change the map symbology ad hoc without delay, as required to support visual thinking with maps. With a view on this functionality, Rinner and Taranu (2006, p. 647) suggest that “an interactive mapping tool is worth a thousand numbers”.

11.2.2 Geovisualization of Large Geospatial Datasets

Visualization is often recommended to explore large, multi-dimensional datasets. Examples in Keim (2001) include stock trading data and satellite imagery with approximately 200,000 and 16,000 data records, respectively. A short decade later, the term ‘big data’ was coined to describe datasets in the order of gigabytes (GB), terabytes, or larger, with their implication on data storage, management, retrieval, analysis, and visualization. For example, Jacobs (2009) shows how a dataset in the order of 100 GB is easily imported into a standard database management system, but turns out to be too large to be queried. Jacobs (2009) also notes that ‘big data’ often only become big through “repeated observations over time and/or space” (p. 40).

Remote sensing, as well as ground surveying, have traditionally yielded voluminous geospatial datasets depending on the spatial and temporal resolutions, at which the data are collected. An example of a large raster dataset originating from remote sensing is the City of Toronto’s 2007 land cover dataset, which represents eight land cover classes at a 60 cm pixel resolution, and is stored in a 3.5 GB image file. An example of a large vector dataset is the OpenStreetMap raw dataset covering the extent of the Province of Ontario, which (at the time of writing) is stored in a 5.44 GB XML file.

Geospatial data are inherently multi-dimensional with usually two (increasingly three) spatial dimensions combined with one or more attribute dimensions. An early model was the ‘geographical matrix’ proposed by Berry (1964), in which places (that are nested within different levels of regions) are associated with multiple characteristics measured by variables (that are also nested in a thematic hierarchy). Geospatial data become even more complex if their temporal dimension is considered (e.g., Andrienko and Andrienko 2005). Recent research in geovisualization examines spatio-temporal data through trajectories of movement of objects. For example, Andrienko et al. (2010) propose space-in-time and time-in-space visualizations for traffic data from GPS tracking of over 17,000 cars during one week.

11.2.3 Geovisualization of Parameters of Analytical Processes

Geospatial datasets that are important for government and business planning and decision making are not always large or complex. For example, the City of Toronto is tracking neighbourhood demographics on the basis of 140 geographic units, to which demographic and socio-economic variables can be attached. The 140 neighbourhood boundaries stored in Shapefile format are 422 kB large, while a sample data table with 14 variables from the City’s Wellbeing Toronto tool for each of the 140 neighbourhoods occupies a mere 13 kB in comma-separated format. However, complexity arises when such data are used in analytical processing. The degrees of freedom in analytical models result in numerous possible solutions, if input parameters are uncertain. This is the case in MCDA, where parameters such as criterion weights depend on decision makers’ preferences and different input settings will result in different outcomes. The potential of geographic visualization for exploring decision space, attribute space, and parameter space in MCDA simultaneously was first suggested by Armstrong et al. (1992), Church et al. (1992), and later comprehensively illustrated by Jankowski et al. (2001).

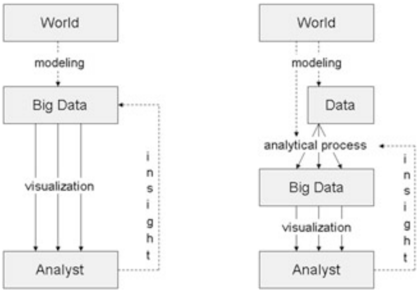

Fig. 11.1 (Geo)visualization used to gain insight from large datasets (*left*) or from analytical processes applied to not-so-large data (*right*) (*Source* modified from Rinner 2007)

The diagram in Fig. 11.1 contrasts the 'traditional' use of geovisualization to explore large datasets ('big data', left column) from its use to explore the complex output of an analytical process, which was applied to any dataset, large or small (right column). In the first case, geovisualization is used to support the development of hypotheses about the real-world phenomena represented by a large dataset. In the second case, geovisualization is used to gain insight into the effects of parameter settings in an analytical process, such as an MCDA model. Rinner (2007) also relates this application of geovisualization techniques to the emerging research fields of visual analytics (Thomas and Wong 2004) and geovisual analytics (Andrienko et al. 2007).

The two approaches illustrated in Fig. 11.1 can also be associated with the geovisualization of MCDA input and MCDA results, respectively. The geovisualization of MCDA input uses human-map interaction to manipulate graphical displays of 'raw' input data, including criterion values and model parameters (such as local weights). In contrast, the geovisualization of MCDA results refers to the interactive graphical display of evaluation scores or a derived ranking of alternatives, which changes with the analyst's modification of model parameters. The remainder of this chapter presents concepts, tools, and applications for geovisualization of both, MCDA input and MCDA results.

11.3 Geovisualization of MCDA Input

The elements of GIS-MCDA introduced in Chap. 2 include the decision makers, criteria, and alternatives (see Sect. 2.2). This formal framework also includes the decision makers' preferences regarding value scaling, criterion weighting, and combination rule (see Sect. 2.3). Most of these components can have spatial dimensions (Rinner and Heppleston 2006) and be visualized geographically, as outlined in the following sections.

11.3.1 Visualizing Decision Alternatives

Geovisualization, as introduced in this chapter, implies that an analyst works with cartographic displays interactively. This requires systematic changes of data or display parameters. In the case of MCDA elements, maps can be used to view the spatial distribution of decision alternatives, and the way in which constraints reduce the set of alternatives (see Sect. 2.2.3.1). For example, the analyst could initially view point locations of alternatives (vector model) or a gridded area of interest (raster model), in conjunction with a basic reference map, and then successively add constraints and view the diminishing set of feasible alternatives. This would help identify thresholds where constraints are becoming too narrow by not leaving a sufficiently large set of feasible alternatives to choose from. An implementation of this interactive approach is available with the 'dynamic query' tool in the CommonGIS software mentioned earlier (Andrienko and Andrienko 2001). However, this form of geovisualization is limited to manipulating the presence or absence of decision alternatives, since we have not included characteristics of these locations in the display yet.

11.3.2 Visualizing Criteria

The evaluation criteria in the form of criterion outcomes assigned to decision alternatives are perhaps the most common element of GIS-MCDA to be explored with geovisualization tools. The criteria are represented in a decision matrix (vector model) or through a set of criterion maps (raster model). Here, geovisualization occurs through interactive thematic mapping, where the data can be viewed from multiple perspectives using different map symbologies and zoom levels, allowing the focusing on, or highlighting of, data subsets, and linking different map displays so that the analyst can take advantage of the full scope of map-centred data exploration methods. Within CommonGIS, Andrienko and Andrienko (2001) introduce interactive visual tools to support MCDA, including 'utility signs'. These thematic map symbols include standardized bar charts and pie charts, which represent the relative performance of decision alternatives on multiple, weighted criteria. For example, a frame around bar charts indicates the maximum performance in the decision matrix, while the width of the bars increases with the corresponding criterion weight. An example with three criteria is shown in Fig. 11.2 (Rinner and Malczewski 2002).

Another mapping technique to visualize evaluation criteria is 'small multiples'. Multiple small single-criterion maps allow the analyst to examine the spatial association between criteria. In CommonGIS, this approach is further supported through dynamic linking of the small multiples, which ensures that objects highlighted or selected on one map are highlighted or selected on all other maps. Griffin et al. (2006) presented an interesting study of small multiples compared to animated

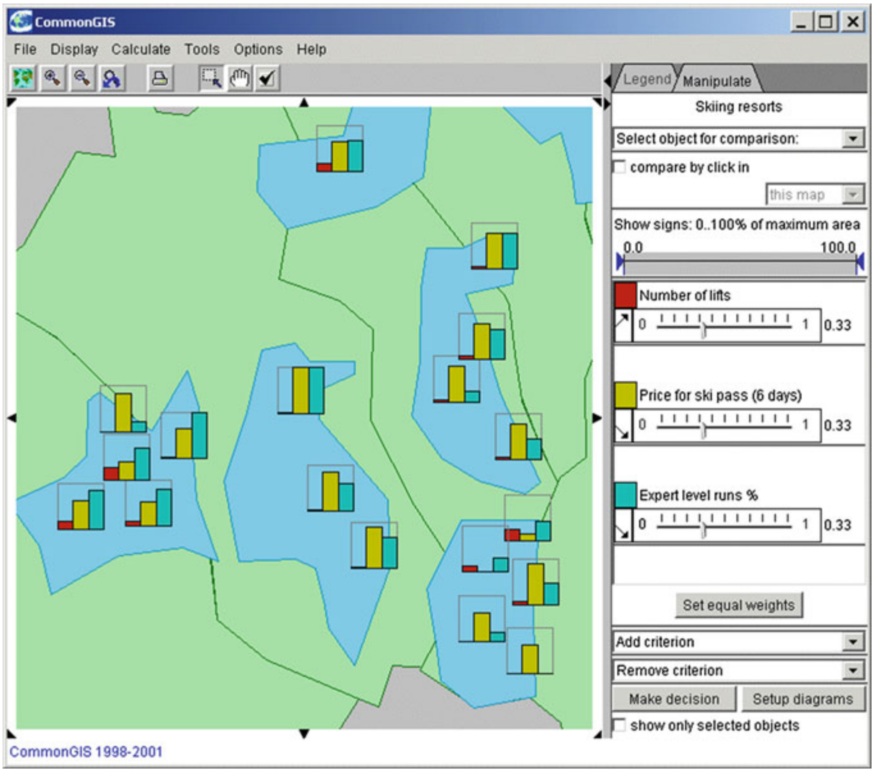

Fig. 11.2 The use of interactive standardized bar charts to visualize criterion values (*Source* Rinner and Malczewski 2002, Fig. 4, used with permission)

maps, and found that animated maps were more effective for cluster identification than static small multiples. However, the interactive small multiples available in select geovisualization software, such as CommonGIS, may overcome the limitations of static small multiples.

11.3.3 Visualizing Scaled Values and Criterion Weights

A basic GIS-MCDA concept that can benefit from geovisualization is the value scaling (or criterion standardization) process (see Sect. 2.3.1). For example, Young et al. (2010) explored the effects of switching between different value functions (standardization procedures) by mapping the corresponding standardized values on interactive maps in CommonGIS. Specifically, two approaches for the scaling of cost criteria using the maximum-score procedure were compared, which resulted in considerable differences in scaled criterion values, although these did not significantly change the MCDA results. An additional example for visually exploring value scaling is provided as part of the case study in Sect. 11.5.

Geovisualization can also be applied to another key concept of GIS-MCDA: criterion importance weighting (see Sect. 2.3.2). While criterion weights are usually globally defined, Malczewski (2011) proposed local weighted linear combination (LWLC) with locally varying weights (see Sect. 2.3.2.2). These local weights can be mapped in order to understand the LWLC procedure (Malczewski 2011; Carter and Rinner 2014). Geovisualization principles could be applied to compare the spatial patterns of multiple sets of local weights. An example of visually exploring local weights is provided in the case study in Sect. 11.5.

11.4 Geovisualization of MCDA Results

11.4.1 Visualizing Combination Rules and Parameters

Results of a multicriteria analysis typically take the form of evaluation scores and ranks for decision alternatives. In the context of a geovisual approach to MCDA, these results are understood to be tentative and subject to adjustment and fine-tuning (Rinner 2007). Interactive changes of the cartographic display are not only triggered by the analyst's manipulation of map symbology, but more importantly, by iterations of the MCDA process with different input and processing parameters. The effects of changes to any of the parameters discussed in the previous section (alternatives, criteria, scaled values, and weights) can in principle be explored using geovisualization. Additionally, the choice of a combination rule, and the parameters that are specific to each rule, can be explored using interactive maps. This map-centred exploration of tentative MCDA results can provide feedback into the MCDA process as outlined in Fig. 11.1.

Jankowski et al. (2001) provide one of the most comprehensive studies using geovisualization of MCDA results. These authors developed tools within the CommonGIS platform that help analysts explore decision space (geography) along with criterion space (attributes). The integrated geovisualization offers interactive map manipulation, linked displays, and immediate response when changing map symbols, map classification, or criterion weights in an ideal point analysis (see Sect. 4.4).

Rinner and Malczewski (2002) and Malczewski and Rinner (2005) extended this research to include the geovisualization of decision making strategies defined by the ordered weighted averaging (OWA) operator and equally implemented within CommonGIS (see Sect. 4.2.3). An example from Malczewski and Rinner (2005) is shown in Fig. 11.3, in which the rankings of neighbourhood quality of life using two distinct combination rules are compared in geographic space (i.e., map) and MCDA result space (i.e., classified scatter plot).

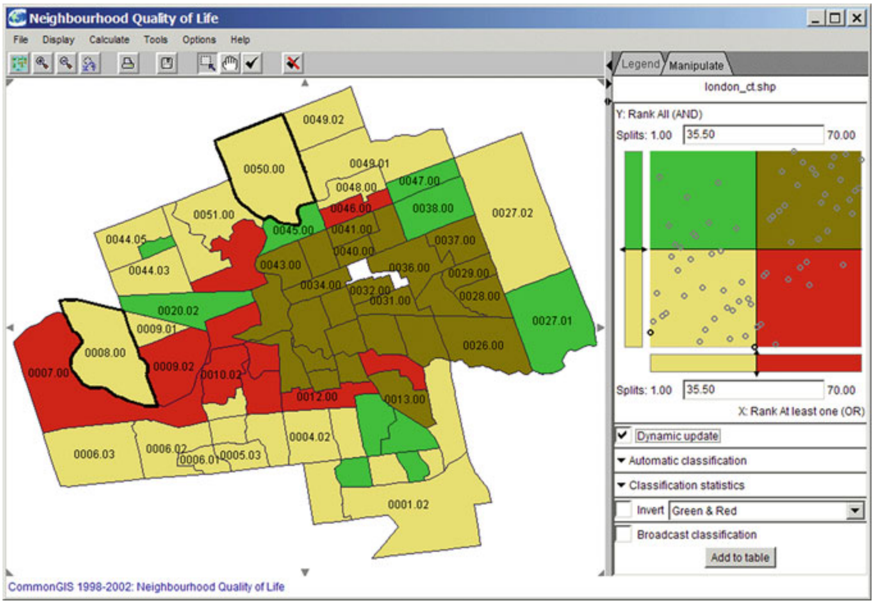

Fig. 11.3 Comparison of neighbourhood quality of life rankings under two distinct MCDA combination rules, using a map (*left*) and linked scatterplot (*right*) in CommonGIS (*Source* Malczewski and Rinner 2005, Fig. 5a, used with permission)

Rinner and Taranu (2006) added an implementation of the AHP method (see Sect. 4.3.1) to CommonGIS, and illustrated how analysts could interactively explore the effects of changes in the criterion hierarchy and weighting on tentative MCDA results. The geovisualization of the effects of modifying combination rules and their parameters is further illustrated in the case study in Sect. 11.5.

11.4.2 Visualizing Model Sensitivity

To deal with uncertainties in GIS-MCDA, it is recommended to conduct sensitivity analyses on model input factors (see Sect. 7.5). Sensitivity analysis changes the input parameters and examines the resulting effects on MCDA results, much like geovisualization. However, while geovisualization leaves it to the analyst to visually assess the effects, sensitivity analysis provides quantitative measures of effects. In fact, geovisualization, as presented in Fig. 11.1, could itself be labelled as 'visual sensitivity analysis'. In addition, geovisualization can assist with quantitative sensitivity analysis.

While sensitivity analysis is commonly conducted using global (i.e. spatially invariant parameters), recent work by Ligmann-Zielinska and Jankowski (2008) and others adds spatiality to a framework for sensitivity analysis in GIS-based

MCDA (see Sect. 7.5.2 for details). The authors argue that spatial criteria and spatial weights should be explicitly considered in sensitivity analysis within MCDA. Similar to the introduction of local weights, spatially explicit sensitivity analysis opens the door to the application of geovisualization. For example, the visual exploration of spatial patterns in MCDA outcome sensitivity could yield important insight into sources of uncertainty in a given GIS-MCDA problem.

11.5 Case Study: Geovisualization in Spatial Decision Support

In this section, a case study is used to illustrate the principles of geovisualization of MCDA inputs and results, including the effects of modifying MCDA model parameters. A deprivation index is a composite measure of socio-economic status, attempting to identify socially disadvantaged areas. In this case study, a sample deprivation index was composed of nine variables aggregated to the 140 social planning neighbourhoods for the City of Toronto, Canada. The variables were retrieved through the Wellbeing Toronto tool and include:

(a) Average household income after taxes (Canadian $)
(b) Gini coefficient
(c) Proportion of rented dwellings
(d) Proportion of seniors living alone
(e) Proportion of children living in low income homes
(f) Proportion with no high school education
(g) Proportion of unemployed persons
(h) Rate of teen (age 15–19) pregnancy
(i) Rate of deaths that occurred before the age of 75

The geovisualization tool used in this case study is MCDA4ArcMap (Rinner and Voss 2013). MCDA4ArcMap is an add-in for the commercial ArcGIS software. It includes functions for loading a data layer, selecting attributes as decision criteria, choosing a decision rule and standardization technique, and assigning criterion ‘directions’ and weights. The decision rules available in the tool include the WLC, LWLC, and OWA methods (see Sect. 4.2). The standardization, or value scaling, techniques available include score-range transformation and maximum-score procedures (see Sect. 2.3.1). The MCDA4ArcMap tool also includes an interactive mapping dialog that supports classified and unclassed choropleth mapping of criteria and MCDA scores with ad hoc changes to the map’s colour scheme, classification method, and number of classes.

The interactive thematic mapping function is first used to explore the nine case study criteria individually. Figure 11.4 shows the MCDA4ArcMap user interface to explore the household income indicator. Figure 11.5 shows screenshots of the additional eight quintile maps. In an interactive session, these maps show the

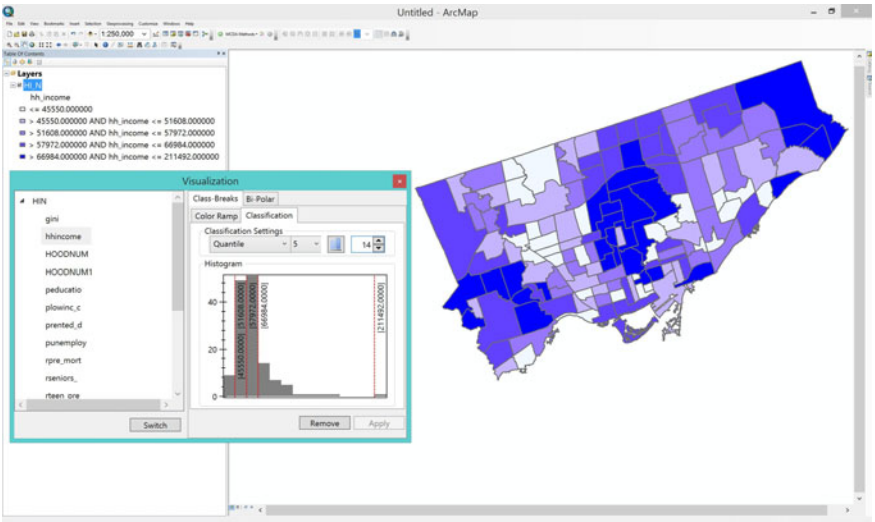

Fig. 11.4 Screenshot of the MCDA4ArcMap tools used to visualize MCDA input data (criterion values)

analyst that the spatial patterns of most of the criteria are similar, with lower values in the centre of the city and toward the southwest and northeast, and higher values arranged in a U-shaped pattern around the centre. However, all criteria have somewhat different spatial distributions, providing locally different contributions to the composite deprivation index. The most distinct pattern is shown in the proportion of seniors living alone, where some of the high (problematic) values coincide with the wealthy neighbourhoods in the centre of the City.

These deprivation indicators were combined using the OWA and LWLC methods (see Sect. 4.2). Figure 11.6 shows the OWA dialog window, along with screenshots of the MCDA results, using the seven predefined values of the alpha parameter of the OWA method. The quintile maps suggest that the variation of outcomes is relatively stable, since the general spatial pattern of higher deprivation in neighbourhoods to the west and east of the centre of the City persists from one end of the parameter range to the other.

A different finding emerges from the exploration of the LWLC parameters. Figure 11.7 shows the LWLC tool with the parameters that can be changed by the user. Figure 11.8 shows screenshots of the MCDA results using four different settings for the k parameter in the nearest-neighbour definition of the LWLC method. A high number of nearest neighbours (k = 15) yields a spatial pattern of deprivation that is similar to the pattern observed using the OWA method. However, the smaller the parameter and processing window become, the more distinct the pattern that emerges. For example, a few neighbourhoods in the centre of Toronto show greater deprivation, as they are directly compared with the adjacent wealthy neighbourhoods.

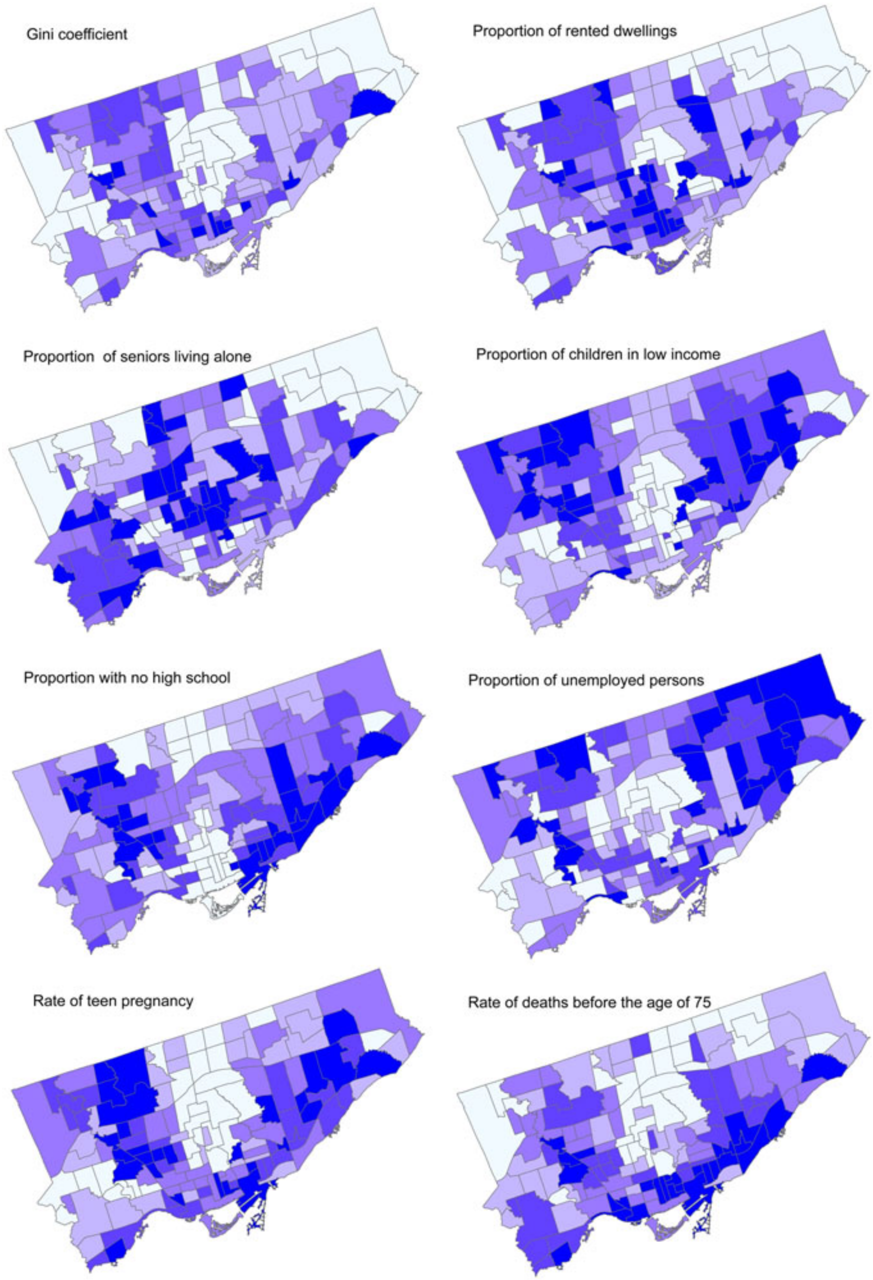

Fig. 11.5 Screenshots of maps of additional input data (criterion values) from the MCDA4ArcMap tool

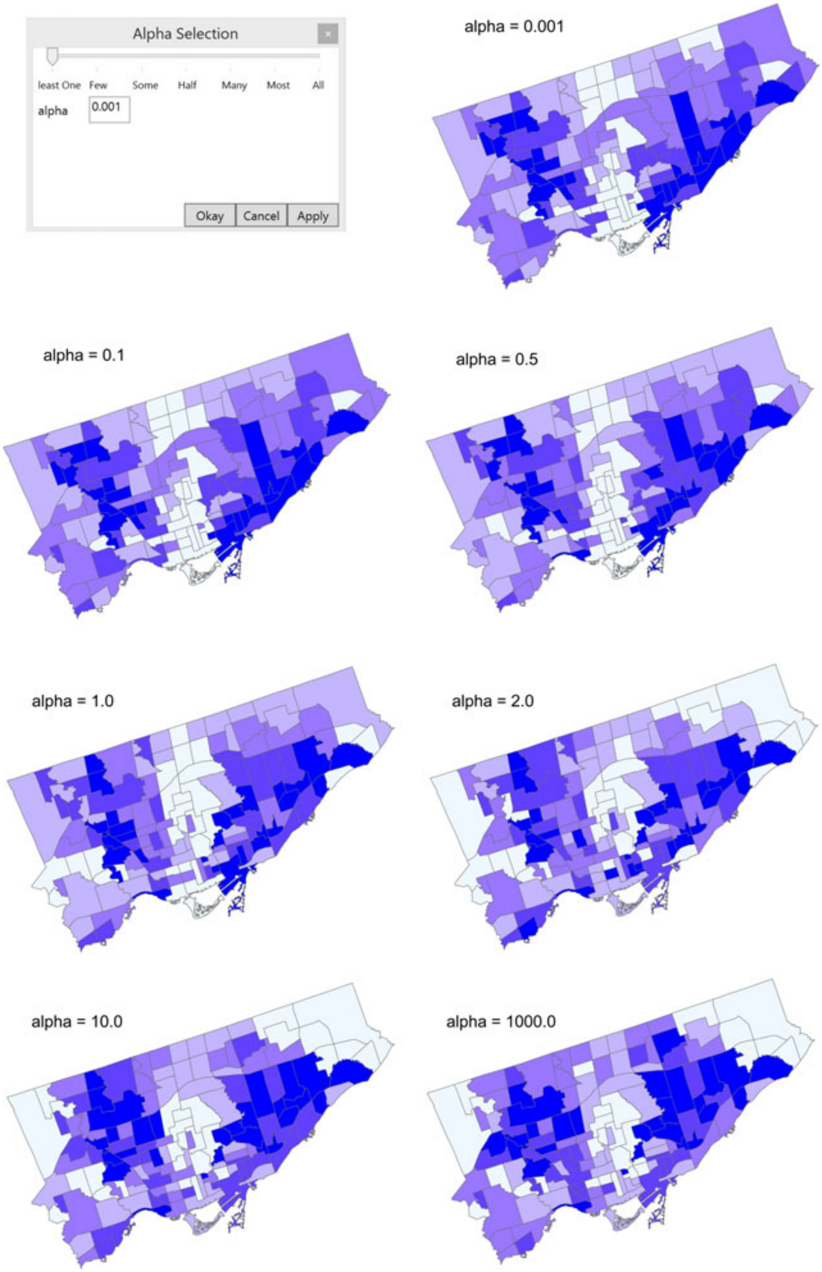

Fig. 11.6 Screenshots of the OWA tool and maps of deprivation index (MCDA result) using seven different settings of the alpha parameter

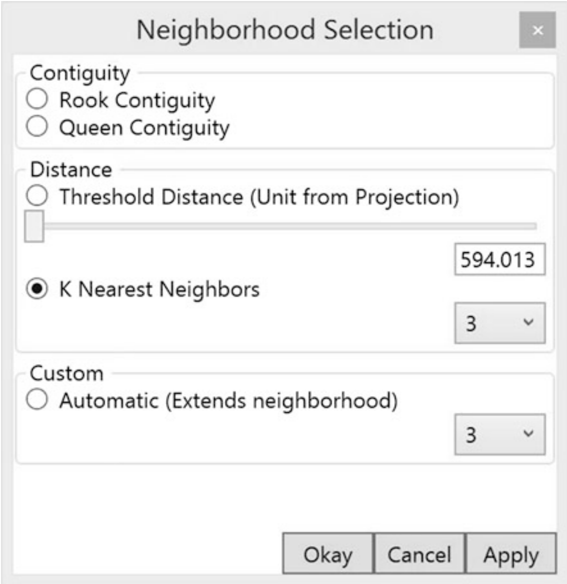

Fig. 11.7 Screenshots of the MCDA parameters to be set in the LWLC tool

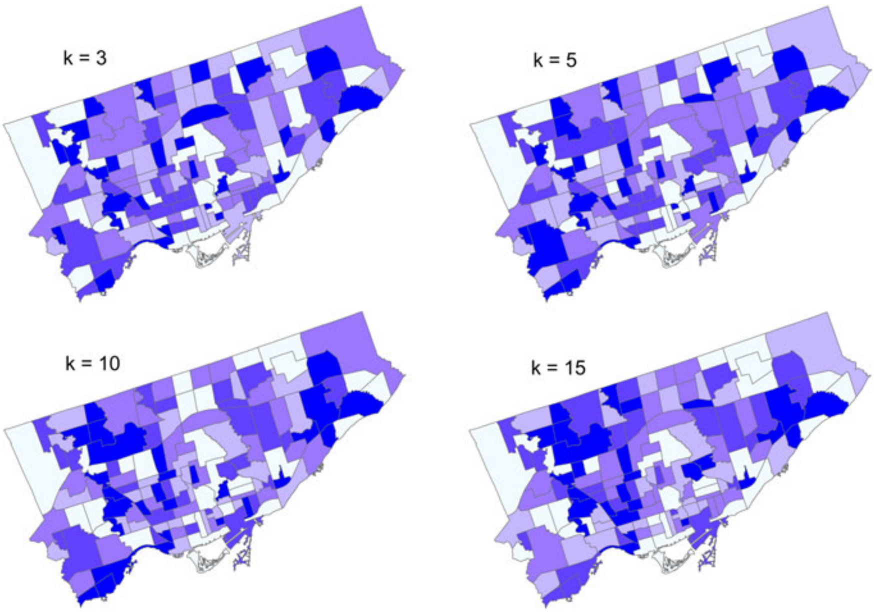

Fig. 11.8 Screenshots of deprivation index (MCDA result) using four different settings of the *k*-nearest neighbour definition in the LWLC tool

In a similar fashion, the MCDA4ArcMap tool allows the analyst to explore other model parameters such as the standardization (value scaling) technique, the criterion weighting in the WLC and other methods, and alternate neighbourhood definitions in the LWLC method. In addition, visual comparison of the MCDA results across the different methods can be conducted. Thereby, the analyst will gain insight into the options for modeling deprivation, enabling an informed decision with respect to the creation of the composite index.

11.6 Conclusion

This chapter's case study illustrates the benefits of combining principles of geovisualization with MCDA techniques. The interactive exploration of thematic maps of MCDA input and MCDA results allows the analyst to better understand the decision problem, generate working hypotheses about spatial relationships between criteria, and conduct sensitivity analysis to examine the impact of gradual parameter changes in the MCDA approach. These benefits grow as geospatial datasets become increasingly large and pervasive across numerous fields of government and business operations.

The visual analysis approach, however, also comes with limitations. Most notably, visual examination of spatial patterns on maps is imprecise and relies on the analyst's experience and impartiality. While maps in data analysis and decision making can effectively support reasoning, the reliance on maps alone is often found to be unsatisfactory by quantitative analysts. In a group decision making scenario, Jankowski and Nyerges (2001) found that maps were used to present results of analysis rather than in the problem formulation stages. In contrast, Andrienko et al. (2003) determined that maps, combined with interactive tools, worked well in a collaborative site selection role-play.

The workflow shown in Fig. 11.9 illustrates the use of MCDA techniques and maps in the project described in Sect. 10.4 (see also Toronto Public Health 2011). Decision support was aimed at prioritizing hot weather outreach, as well as planning for longer-term climate change adaptation. Maps of individual exposure and sensitivity indicators, and of composite indices, allowed analysts, outreach managers, and research consultants at Toronto Public Health to assess the spatial distribution of potential heat vulnerability across city neighbourhoods (Toronto Public Health 2011). This map-centred analysis supported a first reduction of the set of decision alternatives (neighbourhoods) to those with the highest potential vulnerability (e.g., highest quintile).

The bottom half of Fig. 11.9 shows how geovisualization of MCDA input and results was integrated in a broader analytical and decision making process. First, adaptation maps were created by overlaying hot weather response facilities, such as cooling centres, with the indicator and index maps. These adaptation maps give the public health agency an indication of accessibility of facilities by people living in the most vulnerable areas. Furthermore, three different 'lenses' were applied to the

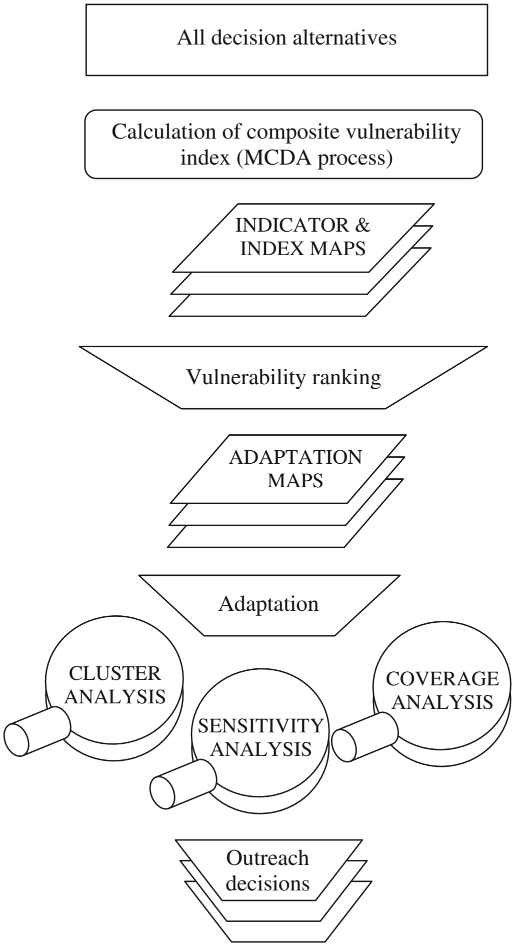

Fig. 11.9 Workflow for heat vulnerability assessment and decision support using maps of MCDA input and result (*Source* modified from Toronto Public Health 2011)

results, as indicated by the magnifying glasses near the bottom of Fig. 11.9. Cluster analysis was used to identify local clusters of heat vulnerability across multiple neighbourhood boundaries; sensitivity analysis was proposed as a way to assess the stability of the heat vulnerability index under changes to the indicator weights; and coverage analysis provided a way to combine the heat vulnerability index, which was based on normalized indicators such as proportions and rates, with raw-count data for populations of interest. All of the additional steps in this workflow were supported by maps showing descriptive statistics or analytical results, thereby confirming the importance of geovisualization and map-centred MCDA in this public planning and decision making case study.

Ultimately, the role of interactive maps and MCDA in public and private sector planning and decision making has yet to be determined. However, the status of MCDA as an established analytical modeling technique, and of geovisualization as an increasingly popular approach to data analysis, will create sustained interest in combining these technologies. The emerging 'big data' phenomenon will further increase this interest, as growing databases provide the necessary input for MCDA and geovisualization facilitates making sense of the results.

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