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The Effect of Standardization in Multicriteria Decision Analysis on Health Policy Outcomes

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Abstract. Health planners and epidemiologists have begun to use spatial analysis and Geographic Information Systems (GIS) to explore socioeconomic inequalities that can affect population health. In particular, the use of area-based composite indices, also known as deprivation indices, has been effective at incorporating multiple indicators into an analysis. We used GIS-based Multicriteria Decision Analysis (MCDA) to create a weighted index of health service need, and explored the standardization step in MCDA within a geovisualization environment. In a neighbourhood prioritization scenario for the City of Toronto, we implemented an MCDA using two common standardization techniques and three methods for standardizing cost criteria. We compared the resulting scores and rankings of neighbourhoods, and show that standardization is an important consideration in the data analysis process. We conclude with an assessment of the appropriateness of using one technique over the other as well as the potential effect on decision-making related to health policy.

Keywords: Multicriteria Decision Analysis, health policy, indicator standardization.

1 Introduction

There has been a growing trend by health planners and practitioners to include geography in the analyses of health and socioeconomic inequality and disparity (Boulos 2004). Recent studies have focused on identifying the dimensions of neighbourhoods that have an influence on health (Odoi et al. 2005; Schuurman et al. 2008). Neighbourhoods may be characterized by the age structure of residents, income and employment status, ethnicity, family structure, or dwelling type. In a study conducted by Odoi et al. (2005) the importance of characterising neighbourhoods by multiple variables, as opposed to one variable, was highlighted. Area-based composite indices (also called area indices or deprivation indices) are an effective way of incorporating multiple variables into an analysis by aggregating weighted indicators into a single index value for each neighbourhood.

Area-based indices have been used to investigate mental health, the allocation of resources, and factors influencing childhood development (Matheson et al. 2006; Breslin et al. 2007; Oliver et al. 2007). Although certain individual characteristics contribute to a person's mental health, neighbourhood indicators are also important for identifying social influences (Matheson et al. 2006). Oliver et al. (2007) focus on

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young children and neighbourhood characteristics affecting wellbeing and childhood development, while Bell et al. (2007) have constructed place-specific composite measures that account for material wealth, housing, family status, demographics, mobility, education, employment, and cultural identity.

Geographic Information Systems (GIS) and spatial analysis are already important tools for health system planning and policy making (McLafferty 2003). The most common applications of GIS have been in epidemiology (disease mapping) and in healthcare delivery (Boulos 2004). Area-based indices have been created using GIS-based Multicriteria Decision Analysis (MCDA) methods for the ranking and prioritization of areas for the delivery of health and social services (Malczewski and Rinner 2005; Rinner and Taranu 2006). Geovisualization can be used to visualize criterion maps and maps of the outcomes of MCDA methods. For example, Jankowski et al. (2001) promote high interactivity, linked views, map representations of criteria, decision outcomes and analytical models to increase the utility of geovisualization for MCDA. They used CommonGIS as an exploratory, interactive tool enhanced with MCDA methods (Andrienko and Andrienko 1999; Jankowski et al. 2001; Rinner and Malczewski 2002), which has been used to evaluate non-medical determinants of health and assess urban quality of life (Rinner and Taranu 2006; Rinner 2007). This evidence-based approach to health planning can aid in policy development, health service management and delivery, and cost reduction (Boulos 2004).

For decision scenarios with many criteria, GIS-based MCDA is a useful technique (Malczewski 1999). The AHP method was developed by Saaty (1980) to address the issue that many complex decision making scenarios lacked a formal methodology to aid in the decision process (Bhushan and Rai 2007). This method takes into account expert experience, intuition, and opinion, and uses mathematical and statistical principles to derive a ranking of alternatives for decision makers.

In this chapter we present a case study of neighbourhood prioritization in the City of Toronto, for a community health centre that provides health and social services to recent immigrants. The AHP method implemented in CommonGIS was used to organize neighbourhood characteristics that were standardized using two linear scale transformations: the *maximum score procedure* and the *score range procedure*. The resulting rankings of neighbourhoods and criterion scores were compared. The next section describes the methods, and is followed by a summary of the case study and a discussion of the implications of standardization in MCDA on health policy outcomes.

2 Methods

The AHP method simplifies the decision problem by organizing large sets of variables and alternatives. In doing so, the complex decision problem is broken down into more comprehensible parts. Firstly, the decision problem is divided into goals, objectives, sub objectives and attributes. The goal is at the top of the hierarchy while sub objectives are towards the bottom. By decomposing the problem the decision maker can more easily grasp the scope and depth of the problem. Secondly, based on expert opinion and the literature, a weighting scheme for the hierarchy is derived, since not

all criteria have equal influence on a decision problem. Lastly, a ranking of alternatives is calculated based on the criterion values and weights in the hierarchy.

As part of the AHP, all variables must be standardized into the same numeric range. Variables are considered benefit criteria if the more desirable values are the higher values. Conversely, cost criteria are variables in which the more desirable values are the lower values.

To investigate the effect of standardization, two linear scale transformations were used. The *maximum score procedure* for benefit criteria was calculated as $x'_{ij} = x_{ij} / x_j^{max}$, and for cost criteria as $x'_{ij} = 1- (x_{ij} / x_j^{max})$, where x'_{ij} is the standardized score, x_{ij} is the original value and x_j^{max} is the maximum value of the respective variable. This can produce scores between 0.0 and 1.0. For benefit criteria the scores are anchored at 1.0, while those for cost criteria are anchored at 0.0.

Hwang and Yoon (1981) and Malczewski (1999) use $x'_{ij} = x_j^{min} / x_{ij}$, where x_j^{min} is the minimum value for the respective variable, to calculate cost criteria because it anchors the cost scores at 1.0. This makes the cost scores more comparable with the benefit scores.

The *score range procedure* does not preserve proportionality since the highest and lowest scores are always 1.0 and 0.0. For benefit criteria $x'_{ij} = (x_{ij} – x_j^{min}) / (x_j^{max} – x_j^{min})$, and for cost criteria, $x'_{ij} = (x_j^{max} - x_{ij}) / (x_j^{max} – x_j^{min})$.

In the following case study, we assessed the two different standardization methods with the three options for the standardization of cost criteria. Although Hwang and Yoon (1981) and Malczewski (1999) emphasize that when both benefit and cost criteria are included in an analysis, both sets of scores should be anchored at 1.0, they did not assess the differences between using the two cost calculations. Thus, we derived three AHP rankings that handle cost criteria differently: using the *maximum score procedure* anchored at 0.0, the *maximum score procedure* anchored at 1.0, and the *score range procedure*.

3 Case Study

Community Health Centres (CHCs) provide comprehensive inter-disciplinary primary health care ensuring access for underserved and marginalized groups. CHCs also aim to improve the health of their local community as a whole through community development, promoting supportive environments and partnerships to influence determinants of health such as poverty, employment, and housing.

We have collaborated with a CHC that provides clinical, settlement and outreach services to immigrants and refugees living across the City of Toronto. In order to be responsive to changing settlement patterns and to focus on disadvantaged newcomers living in underserved areas, the CHC needs to prioritize neighbourhoods based on health and social indicators.

Toronto is situated on the northwest shore of Lake Ontario. It has an ethnically diverse population of 2.5 million people, of which 50% were born outside Canada, and 47% identify themselves as a visible minority (City of Toronto 2010a). Between 2001 and 2006 the growth rate of the Canadian born population was 4.6% while the foreign born population increased by 14.1%.

For social planning and policy purposes the City of Toronto aggregated Statistics Canada census tracts (CTs) to form 140 neighbourhoods (City of Toronto 2010b). These are areas of 7,000 to 10,000 people that share similar socioeconomic characteristics. The neighbourhood boundaries are frequently used for mapping social variables and underserved areas to aid in the planning of health and social services across the city. The neighbourhoods are an appropriate unit of analysis because they are defined by natural boundaries that encompass multiple CTs with similar socioeconomic characteristics (City of Toronto 2010b).

Variables from the 2006 Canadian Census were used that fell into one of two categories: either the variable was important for identifying the distribution of recent immigrants in the city; or the variable represented important demographic information about neighbourhoods. In total, 23 variables were chosen from the following themes: education and employment, income, dwellings and households, and citizenship, immigration and language. Of these, two were cost criteria: *equity rate*, and *participation rate* (in the labour force). *Equity rate* was constructed as a ratio of neighbourhood median income compared to the city median income.

3.1 Analysis of Benefit and Cost Criterion Scores

The following analysis consists of a comparison of benefit scores, followed by a comparison of cost scores. For the cost scores, the *score range procedure* scores are compared separately to each of the *maximum score procedure* cost scores.

The *score range* and *maximum score procedures* each includes a benefit criterion calculation. The difference between the scores of these two transformations vanishes when variables include original values of 0.0. This ensures that 0.0 is the lowest standardized score for both methods. While a few variables had the exact same scores, others had slight differences. The histograms of standardized scores showed that the frequency differed the most for the lower original values (low standardized scores).

In contrast, variables that do not have the value 0.0 in their range are more likely to have larger differences in standardized scores between methods. Standardized scores appeared to be higher using the *maximum score procedure* compared to the *score range procedure* and the smaller original values were affected the most.

Using the original cost criteria calculation for the *maximum score procedure* the most desirable score falls between 0.0 and 1.0. The most desirable cost score will only be 1.0 if the smallest original value is 0.0. Thus, these *maximum score* cost scores are anchored at 0.0.

For *equity rate*, this calculation produced a result that was similar to the *score range* cost scores (Figure 1). The cost scores using the *score range procedure* ranged from 0.0 to 1.0, whereas the *maximum score procedure* ranged from 0.0 to 0.77. For *participation rate*, the *score range* distribution ranges from 0.0 to 1.0 whereas the *maximum score* distribution ranges from 0.0 to 0.34.

In contrast to the above cost scores, the following compares scores anchored at 1.0. This approach anchors the standardized scores at 1.0 regardless of whether or not the value 0.0 exists in the original distribution. The original low values have greater cost

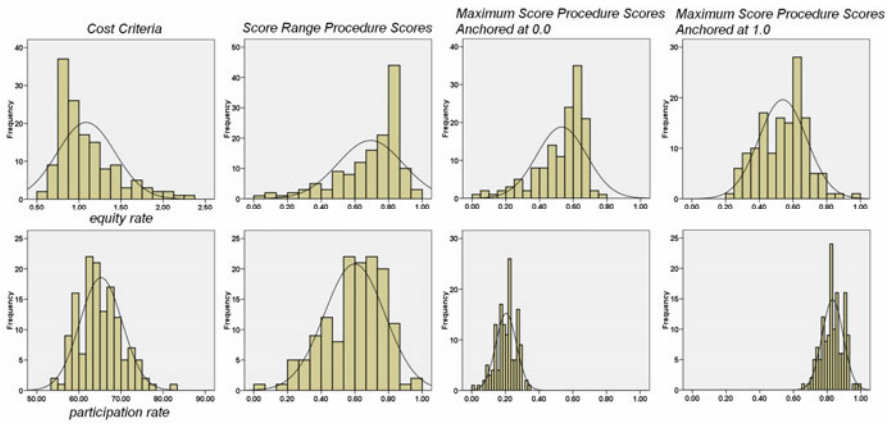

Fig. 1. Histograms of cost criteria standardized using the *score range procedure*, and the *maximum score procedures* (row 1 is for *equity rate*, row 2 is for *participation rate*).

scores using the *maximum score procedure* compared to the *score range procedure* (similar to the difference between standardization procedures for benefit criteria) because only the *score range procedure* guarantees a low cost score of 0.0.

For scores anchored at 1.0, *equity rate* has a standardized *score range* distribution from 0.0 to 1.0 whereas the *maximum score* values range from 0.23 to 1.0 (Figure 1). *Participation rate* has a *maximum score* distribution from 0.66 to 1.0 compared to the range of 0.0 to 1.0 using the *score range procedure*.

Overall, we found that the *maximum score* cost scores were significantly different from the *score range* cost scores. While the *score range procedure* scores are consistently standardized between the range of 0.0 and 1.0, the range of the *maximum score procedure* scores depends on the cost criteria calculation and the original data distribution. Depending on which cost criterion calculation is used the *maximum score procedure* scores are either lower (anchored at 0.0) or higher (anchored at 1.0).

This trend is exemplified in Figure 2. For each neighbourhood, a trio of bars represents the different cost scores calculated for *participation rate.* The left most bars represent the *score range* cost scores, the middle bars represent the *maximum score* cost scores anchored at 1.0, and the right most bars represent the *maximum score* cost scores anchored at 0.0. When anchored at 1.0, the *maximum score* bars are taller than the *score range* bars, and when anchored at 0.0, the *maximum score* bars are shorter than the *score range* bars.

3.2 Comparison of Neighbourhood Rankings

Three different rankings of Toronto neighbourhoods resulted from using the *score range procedure* and the *maximum score procedure* with different cost criterion calculations. The two *maximum score* cost calculations produced slightly different rankings of neighbourhoods.

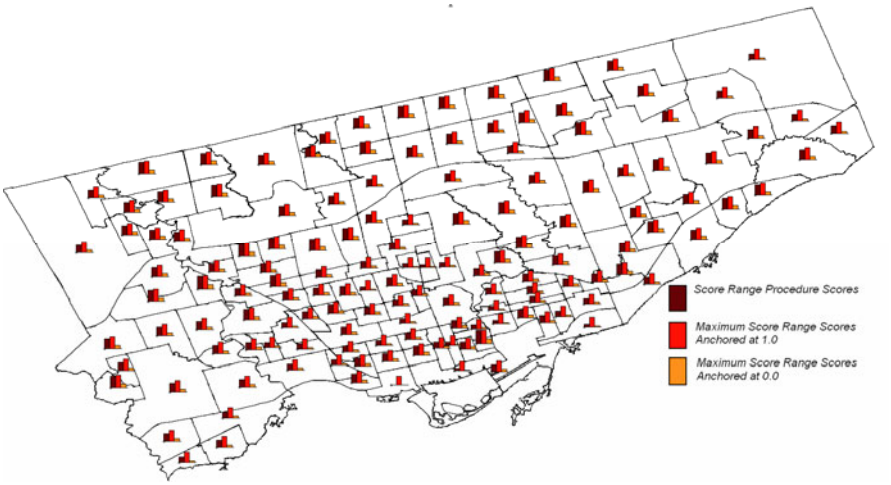

Fig. 2. A comparison of cost criteria scores for *participation rate* using the *score range procedure* and the *maximum score procedure* anchored at 1.0, and anchored at 0.0.

The ranking produced by the *score range procedure* was the most different among the three options. Some neighbourhood ranks differed up to 14 positions. The two *maximum score procedure* rankings only had rank differences up to three positions. Most of these were "flips" where two neighbourhoods would swap positions. For example, Neighbourhood #78 and Neighbourhood #115 were ranked 16 and 17, respectively, when anchored at 1.0. When anchored at 0.0, Neighbourhood #78 was ranked 17 and Neighbourhood #115 ranked 16.

The average change in position of neighbourhoods was calculated by summing the rank changes of all neighbourhoods multiplied by the corresponding count of neighbourhoods, and dividing the sum by the total count of neighbourhoods. The average change in position between the *score range procedure* and each of the *maximum score procedures* was 2.9 positions. Between the two *maximum score procedures* the average change in position was 0.47. These findings show that the *maximum score procedure* rankings are more similar to each other than to the *score range procedure* ranking.

4 Discussion and Conclusion

In this case study the effect of standardization parameters on the ranking resulting from MCDA was small. A manual inspection of the top ten neighbourhoods revealed that each standardization technique resulted in the same top eight neighbourhoods. The neighbourhood ranked 9th using the *score range procedure* was ranked 10th using the *maximum score procedure*, and the last ranked neighbourhood differed in each case. These differences were noted as acceptable by staff at the collaborating community health centre.

The *maximum score procedure* resulted in higher scores for benefit criteria compared to the other procedure. For cost criteria, the *maximum score procedure* scores

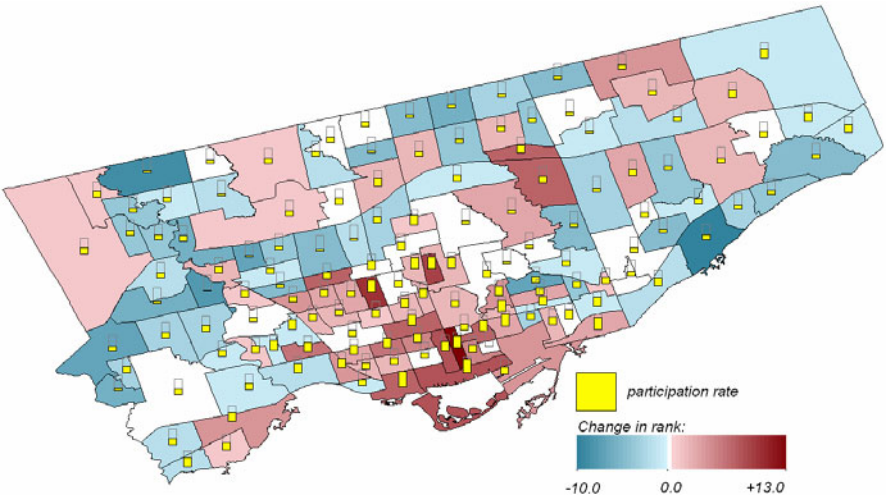

Fig. 3. Change in ranks using different standardizations. Bars represent the original *participation rate* values and the choropleth map represents increases (red) and decreases (blue) in rank when moving from *score range procedure* to *maximum score procedure* anchored at 1.0.

were lower than the *score range procedure* scores if anchored at 0.0, and higher if anchored at 1.0. The difference in ranks between the two *maximum score procedure* cost calculations was negligible. Similar to benefit criteria, cost scores anchored at 1.0 were more appropriate to use, as recommended by Hwang and Yoon (1970) and Malczewski (1997). Even though the cost scores are anchored at 1.0, the *maximum score procedure* ranked neighbourhoods higher than the *score range procedure* when the original value is high (Figure 3). This is due to the fact that the lowest standardized score is not necessarily 0.0. When only the standardization of *participation rate* changes in the composite index from the *score range procedure* to the *maximum score procedure* neighbourhoods with high original values increase in rank closer to 1 (red neighbourhoods).

Based on the analysis of this specific case study we cannot recommend the use of one linear scale transformation over another. Both performed equally well, and in addition to standardization the outcomes are affected by original data distributions, the criterion weights, and other factors. Since we did not find guidelines for choosing among different standardization methods in the literature, we recommend that analysts perform manual inspections. Examining the distribution of the original variables as well as score and rank distributions is necessary to compare scores between standardization techniques. Ultimately, the analyst should have a deep understanding of the decision problem, the data representing it, and the possible interpretations of MCDA results. Different standardization techniques may yield slightly different results and manual inspections will help to determine which result is consistent with other sources of information.

When MCDA is used in health policy development data analysts need to be sensitive to the context and policy implications of its application. Some tasks may be exploratory and focused more on general trends while other tasks may be more sensitive

to rankings. Scenarios involving the prioritization of areas for funding or service delivery will be more sensitive to differences in rank. In such cases, it is advisable to produce multiple results using different standardizations for comparison. Through manual inspection, one set of rankings may stand out to the decision makers, or a combined approach may be taken where the decision makers manually merge the results of more than one ranking. Analysts should also assess whether the characteristics of available standardization techniques such as their anchor point correspond with substantial aspects of the decision problem at hand.

Although it is impossible to perform error-free GIS analyses, it is important to be aware of, and to acknowledge factors that may affect the final result (Boulos 2004). It is hoped that health analysts and policy makers will use spatial MCDA for planning service delivery, policy making or implementation, but the added complexity in the data processing and analysis of spatial MCDA still warrants that a decision-aider specialized in these methods be available.

The use of intelligent spatial data analysis, such as spatial MCDA, along with geographic visualization can support complex decision-making for health policy development. Variables can be drawn from those commonly used by decision makers or created from data sets relevant to the decision-making requirements. The approach engages stakeholders as it uses concepts that resonate with their decision-making preferences and enables them to explore policy options by changing MCDA parameters. The analysis tools should be flexible, adaptable and easily allow for the comparison of different methods and changes in the selection of variables. In addition, they should provide interactive visualizations of criterion maps and decision outcomes with linked views that promote group decision mapping and consensus-building among stakeholders.

While the desired result is an effective and suitable policy outcome, decision-making is rarely straightforward. Spatial MCDA can provide technical support to data analysts, and an efficient and effective means of visualization to decision makers. By recommending the use of quantitative and visual analysis we hope to enable transparent and sustainable health policy decision-making.

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