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Spatio-Temporal Multi-Criteria Analysis – Conceptual Challenges and Application to Health Service Planning

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Abstract—Population health is influenced by many socioeconomic and demographic factors that may include levels of employment, income, education, ethnicity and age. For health planning and service delivery, it is important to take into account demographic trends over time. This temporal component is usually incoroporated into analyses by comparing multiple maps of variables at different points in time. In this study demographic variables with spatial and temporal components are used in a multi-criteria analysis within an interactive spatial decision support tool. We illustrate how the exploration of an area-based composite index over time can help analysts with identifying trends of increasing social deprivation and health-care needs. The paper focuses on the conceptual challenges of spatio-temporal multi-criteria analysis due to changing geographic boundaries, the standardization of variables across time, comparability of variables, and comparability of index scores.

Index Terms—Spatio-temporal, time, health service planning, multi-criteria analysis, geovisualization.

Introduction

The health of a population is highly influenced by social and economic factors [5]. These may include levels of employment, income, education, ethnicity and age [2]. Many studies have previously shown that certain neighbourhood characteristics may be indicators of poverty or low health status [11, 15]. In the study conducted by Odoi et al. [11] the importance of looking at multiple variables, as opposed to characterising neighbourhoods by one variable, was highlighted. Area-based composite indices (also called "area indices" or in the context of this paper "deprivation indices") are an effective way of incorporating multiple variables into an analysis by aggregating weighted indicators into an index. Such indices use GIS-based multi-criteria analysis (MCA) methods [9] and can be used for ranking and prioritizing of areas for the delivery of health and social services [10, 12, 13].

MCA enables researchers to work with a large number of decision alternatives, a large number of associated criteria (variables), and rules for data aggregation [9]. Jankowski et al. [7] incorporate MCA as a spatial decision support tool in CommonGIS, which provides interactive thematic map types, linked displays, and visualization of criterion maps and MCA outcomes. However, few researchers have investigated spatio-temporal decision-making problems that involve *multiple* spatial units, *multiple* variables, and *multiple* time periods.

The incorporation of demographic trends over multiple time periods to examine changes in composite indices over time poses conceptual challenges. In this paper we address the challenge of visualizing multiple variables and multiple time periods using MCA methods, such as the comparability of variables, changes in census tract (CT) geometry, and the comparability of indices through different standardization techniques.

1 Background

Sinton [cited by 8] and others [20, 1] identify space/location, time, and theme/attribute as the three dimensions of geospatial data. They further observe that frequently, space and/or time are considered the independent, or controlled, variable(s) while theme is the dependent, or measured, variable. Temporal variables add another dimension to spatial analysis [21]. Time does not only represent individual points in time, but may also refer to rates of change, causes of change, sequence of events, or the historical context of a spatial observation [4]. In the context of animated maps, Slocum et al. [16] distinguish between change of position, change of attribute, and the occurrence of events (appearance and disappearance of a phenomenon), and contrast these with the change in display of a fixed dataset (e.g. sequential display of symbol classes).

The City of Toronto is at the core of Canada's largest metropolitan area and is an ethnically diverse mix of 2.5 million people [3]. Between 2001 and 2006 the growth rate of the Canadian-born population was 4.6% while the foreign-born population increased by 14.1% and now make up one half of Toronto's inhabitants. Walks [19] examined socioeconomic trends in data for the City of Toronto between 1971 and 1991. He used static maps to show variables for different years and to analyze the change in spatial pattern of occupation, immigration and income variables. Using this method, static maps are put side-by-side in order to compare the same variable at different time periods. Similarly, Hulchanski [6] and the United Way [18] reported on spatio-temporal trends for the City of Toronto.

Hulchanski [6] analyzed sociodemographic data for the City of Toronto between 1970 and 2000. Neighbourhoods fall into one of three categories based on the socioeconomic characteristics of their residents, which is measured through a single variable: average individual income. The trend is a consolidation of low and high-income neighbourhoods (concentration) and an increase in very high-income and very low-income neighbourhoods (polarization) resulting in a diminishing middle class (from 66% of CTs in 1970 to 32% in 2000).

In 2004, the United Way released the Poverty by Postal Code report documenting the changing geography of neighbourhood poverty between 1981 and 2001 [18]. Using income and population data from Statistics Canada the report found that poor families are becoming increasingly concentrated in areas with high poverty rather than mixed-income communities. There has been a significant increase in the number of high-poverty neighbourhoods (since 1981) and these neighbourhoods are now concentrated in the inner suburbs rather than the inner city (geographical shift).

We propose to extend the latter two studies by combining multiple socio-demographic indicators into a composite deprivation index. By implementing this index in a geovisual research tool our objective is to address the conceptual challenges associated with

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spatio-temporal decision-making problems. In this case study we document the benefits and challenges for spatial decision support with MCA methods applied across different time periods.

2 Data and Methods

2.1 Data

The City of Toronto is divided into 527 CTs. The Canadian Census includes CTs as intermediate enumeration units in Census Metropolitan Areas (CMA) [17]. A CT usually represents 2,500 to 8,000 residents. Data acquired from Statistics Canada include ten variables that are present in the Census for the years 1981, 1991, and 2001 and serve as indicators of social deprivation (Table 1). The variables were standardized in relation to the Toronto CMA average for each respective year.

Table 1. Variables Consistent Across the Canadian Census Years 1981, 1991, and 2001.

Variable	Description
OVR65	% of the population that are over the age of 65 years
OWNED	% of dwellings that are owned
RENTED	% of dwellings that are rented
LPFAM	% of families that are long-parent families
IMMIG	% of the population that are immigrants
DWLVAL	Average dwelling value
TAVINC	Average personal income
UNEMRT	Unemployment rate
MTENG	% of the population whose mother tongue is English
MTOTH	% of the population whose mother tongue is neither English or French

Between 1981, 1991, and 2001, the CT boundaries for the City of Toronto changed. To make the data comparable across years, the 1981 and 1991 data were mapped to correspond with the 2001 CT boundaries using the point-in-polygon method, overlays, and spatial joins in ArcGIS. The result was a shapefile of the 2001 City of Toronto CT boundaries with the variables from the three time periods attached.

2.2 Methods

CommonGIS, and the analytic hierarchy process (AHP) were used to analyze spatio-temporal patterns of deprivation and the need for health-care services. The AHP was developed by Saaty [14] as a step-by-step process for dealing with complex decision problems involving large datasets. The steps of the AHP are to (1) break the problem into goals, objectives, attributes and alternatives, (2) derive a hierarchical weighting scheme of the criteria from either expert opinion or using a pairwise comparison matrix, and (3) output a ranking of alternatives based on the relative weights of the criteria [9]. We use the initial decomposition step in order to create separate area-based indices for the three Census years. The availability of the AHP method in CommonGIS then allows one to interactively blend one index into another for visual analysis of change. The screenshots produced for the Results section below are taken when full visual weight is given to the index scores of either of the three years.

Imperative to the AHP is the standardization of all criteria into comparable units [9]. We explored two standardization techniques available in CommonGIS and their effect on the overall ranking of neighbourhoods. The *maximum score procedure* and *score range procedure* both standardize values to a scale of 0.00 to 1.00. The *maximum score procedure* preserves proportionality by assigning the highest value a score of 1.00 and only a low score of 0.00 for the lowest value, if the lowest value that exists in the original distribution is itself 0.00. On the other hand, the *score range procedure* does not preserve proportionality because regardless of the original distribution of the criteria, the maximum and minimum score always assigned are 1.00 and 0.00.

Standardization also requires categorizing the variables as either benefit criteria or cost criteria. Benefit criteria are variables whose values should be maximized, while cost criteria should be minimized. In this case study indicators are standardized in the direction of positive contribution to neighbourhood well-being. For example home ownership, dwelling value, and personal income are benefit criteria, while unemployment, lone-parent households, or inability to speak English or French are cost criteria. For each year the overall maximum and minimum values across all three years are used to standardize all variables across time to the same scale. This results in three composite indices.

3 Results

A visual analysis of the average personal income variable across the Census years confirmed the general spatial patterns revealed by both Hulchanski [6] and the United Way [18]. The City of Toronto is characterised by a U shape or ring of deprived neighbourhoods around a wealthy core in its centre, just north of the central business district.

By viewing the maps side-by-side the spatial pattern of average personal income is evident. Figure 1 shows the average personal income for 1981 (a), 1991 (b) and 2001 (c). The concentration of CTs that have an average income more than 20% greater than the CMA average are concentrated in the core of the city (blue CTs). Census tracts whose average income is more than 20% below the CMA average are red. In 1981, these are concentrated in the downtown core of the city (Figure 1a). The white census tracts are those whose average is within a 20% range (above or below) the CMA average. Between 1981 and 2001 the three maps show a decrease in the number of these middle-income CTs, and an increase in both high- and low-income CTs. Of concern, is the fact that in 2001, large parts of the city are characterised by low income. Figure 1c also shows the polarization of very high and very low income neighbourhoods in Toronto (dark blue and dark red shades).

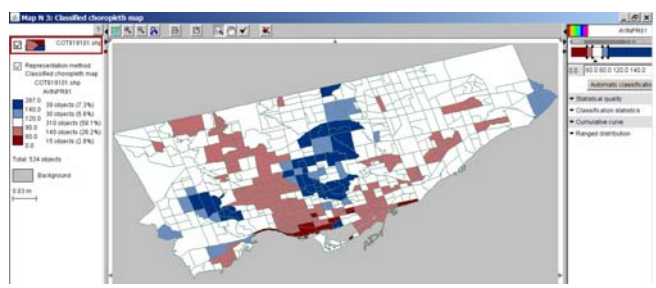

Fig. 1a. Average income in relation to the CMA average for 1981.

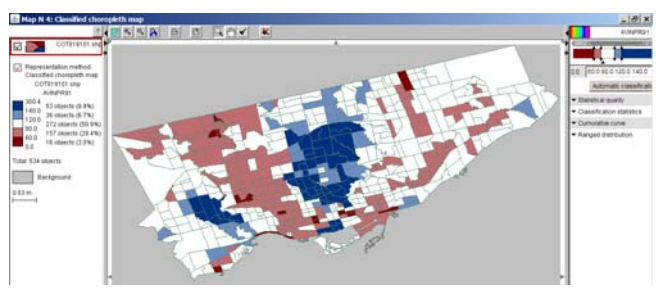

Fig.1b. Average income in relation to the CMA average for 1991.

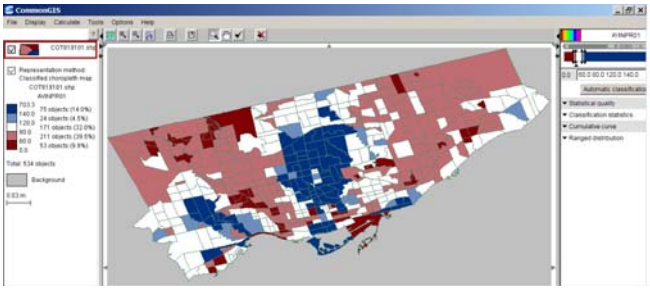

Fig.1c. Average income in relation to the CMA average for 2001.

Preliminary results of the composite deprivation indices show similar results (Figure 2). All variables were standardized using the *score range procedure*. Figure 2 maps the multi-criteria scores using the same class breaks for the three Census years. This allows for a visual examination of the scores across time.

Neighbourhoods that have consistently low deprivation (high scores) between 1981 and 2001 are located in the middle of the city as well as parts of the southwest and southeast (light and dark blue). Among these, the class with the least deprived areas (dark blue) grows over time, while the second class (light blue) shrinks considerably. At the other end of the deprivation scale, several areas develop into high-deprivation neighbourhoods (dark red) over time, and the two classes comprising the most deprived neighbourhoods start forming the above-mentioned U-shape around the centre of the city, although this pattern is less marked than when examining average personal income as the only variable. The decrease in the number of white-coloured CTs, CTs with mid range scores, identifies the shrinking middle/mixed income classes.

The general spatio-temporal trend of concentration and polarization of Toronto neighbourhoods with a diminishing middle class, diminishing mixed-income neighbourhoods and growing high income and low income areas [6, 18] is confirmed using an area-based composite deprivation index.

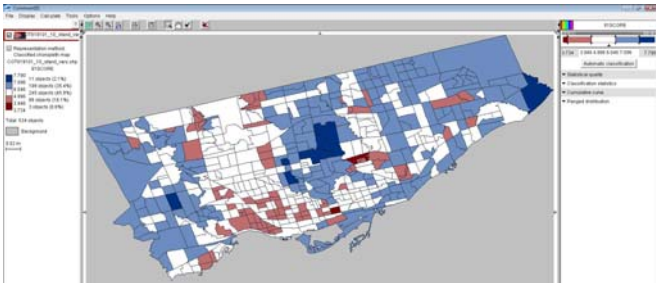

Fig.2a. Composite index of the average income in relation to the CMA average for 1981.

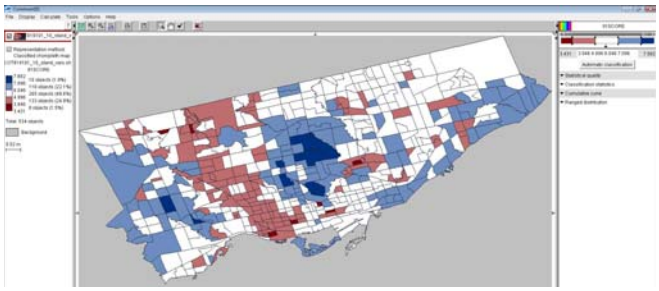

Fig.2b. Composite index of the average income in relation to the CMA average for 1991.

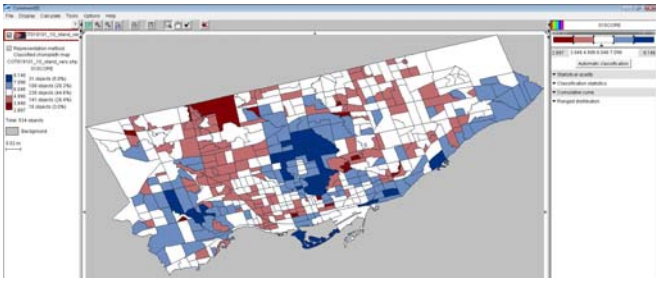

Fig.2c. Composite index of the average income in relation to the CMA average for 2001.

4 Conclusion

Variables are typically visualized across time on individual static maps [19]. The analyst is required to make comparisons across these maps. This technique is limiting because it tries to display a dynamic process (change in a variable over time) using a static medium. The continuity of the trend is broken up and harder to analyze [4].

Conceptually, the comparison of one variable across time periods is possible using only one dynamic map. Changes in CT geometry must be taken into consideration and mapping variables to one set of boundaries is important. The individual variables and the multi-criteria scores calculated from them can then be highlighted interactively across time periods.

Standardization is an important process for making the variables comparable across time. In the preliminary analysis the standardization step was calculated using the overall minimum and maximum values across all time periods ("joint standardization"). This produces standardized scores for each year on the same standardized scale and enables us to compare the aggregated scores of three composite indices directly with each other.

We have shown how variables can be computed into a composite index to visualize changing demographics over time. Further analysis of these indices will be conducted to better assess the applicability of using MCA for spatio-temporal problems. To make the deprivation index more accurate, weights could be applied to capture the relative importance of each variable in the index. An interesting challenge would arise if the value of the weights would vary over time. More generally, the effect of time on the various elements of spatial multi-criteria analysis has not been studied widely. We expect the use of an interactive geovisual tool, such as CommonGIS, to support both the development of a conceptual framework for spatio-temporal multi-criteria analysis and its application to real-world planning and policy making scenarios that involve prioritization and selection of locations for health-care or social service delivery.

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