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An interactive method to select a set of sustainable urban development indicators

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ABSTRACT

The paper proposes a method for selecting a set of sustainable development indicators which can be used for various sustainability-related tasks, such as assessment of current condition, measure of progress toward specific goals of sustainable development, in general, and sustainable urban development, in particular. The method is based on variable clustering, selecting cluster representative, and multivariate linear regression in combination with experts and stakeholders' input in an interactive process. The small set of indicators derived from the proposed method was able to account for a significant amount of information from the initial indicator set while effectively assisting stakeholders in making informed decision based on objective quantitative information and meeting their preference simultaneously.

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1. Introduction

Conceptually sustainable development (SD) is development that strikes a balance between the needs of the present generation and those of future generations (United Nations, 1987). In an urban setting, sustainable urban development (SUD) can be defined a process of synergetic integration, interaction, and co-evolution among the economic, social, physical and environmental subsystems making up a city which guarantees a non-decreasing level of wellbeing for the city population in the long term while maintaining a balance with the surrounding areas as well as contributing to reducing the harmful effects on the biosphere (Camagni, 1998). Sustainable development indicators (SDIs), which reflect key trends in the environment, social systems, economy, human wellbeing, and quality of life, have been seen as major and effective tools in measuring progress toward SD goals. Therefore to have a representative set of SDIs for gauging SD, in general, and SUD, in particular, is of significant importance. In that context, this paper is to introduce a method for selecting a representative set of SDIs that can be used for SUD-related tasks (e.g., assessment of current condition, measure of progress toward specific SUD goals).

2. Background

Generally there are two main approaches in developing and/or selecting SDIs (Spohn, 2004). With the top-down approach, experts and researchers define the overall structure for achieving the sustainability and subsequently break them down into set of indicators. In contrast, the bottom-up approach requires systematic participation of various stakeholders to understand the framework as well as the key sustainable development indicators. However, with the growing trend in the integration of science, policy-making, and stakeholders' involvement, the distinction between the two approaches has been increasingly blurred in SUD efforts (McCool and Stankey, 2004). In that context, a suitable method to select SDIs should be able to facilitate the participation of diverse participants from science, policy makers, and the public. In general, the process of developing or selecting SDIs includes some common key steps as follows:

- Define urban sustainability: concept and characteristics of SUD (e.g., inter-/intra-generational equity, efficiency, individual well-being, etc.), its dimensions (e.g., social, economic, and environmental) and relationship/connections among them (e.g., driving force-state-response).
- Define indicator selection/development criteria: e.g., scientifically valid, representative, responsive relevant to the needs of stakeholders, comparable to thresholds or targets, cost-effective, etc. (MacLaren, 1996).

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• Select or develop indicators: identify indicators, evaluate indicators, and select indicators.

In this paper we focuses on the last step of the selecting SDI process. Readers interested in the two first steps are referred to other studies, such as those by MacLaren (1996), Huang et al. (1998), Cornforth (1999), Westfall and Clarke (2001), McCool and Stankey (2004), Reed et al. (2006), Donnelly et al. (2007), Niemeijer and de Groot (2008), Munier (2011), and Rosales (2011). With the rapid development of geospatial technologies (e.g., remote sensing, Geographic Information System) and increasing interest in SD, numerous SDIs have been created and made available to the public by various organizations and agencies. Some examples are the United Nations' Millennium Development Goals Indicators (United Nations, 2015), the EU Sustainable Development Strategy's Sustainable Development Indicators (EU, 2013), USA's Partnership for Sustainable Communities (EPA, 2014), and the Canadian Sustainability Indicators Network (Pintér et al., 2005).

There is a practical difficulty in working with a large number of indicators. Hence to be able to produce a manageable set of representative indicators addressing key components of SD in general and SUD in particular is not only desirable but also crucial to the success of a SD project or effort. Munier (2011) presented a methodology based on the concept of entropy (i.e., quantity of information in a dataset) and linear programming for choosing a set of sustainability indicators for SUD assessment purposes. Recatalá and Sacristán (2014) used principal component analysis to select a minimum indicator set useful to evaluate natural resources quality at municipality level as a basis for assessing environmental impacts from land use development projects. Visvaldis et al. (2013) argued that it is crucial to have the participation of stakeholders comprehensively in the indicator selection process. In similar fashion, Uhlmann et al. (2014) suggested that the process to select indicators is an exercise itself including expert input and inclusive dialog as well as learning focused on adaptation to the local context. This paper is to introduce a method of selecting indicators that is able to integrate objective quantitative analysis with participatory dialog and input from stakeholders in the process of selecting SDIs. The method is based on variable clustering, selecting cluster representative, and multivariate linear regression in combination with experts and stakeholders' input in an interactive process.

3. Methodology

3.1. Clustering analysis

The term "clustering" embraces various different approaches, such as crisp clustering, fuzzy clustering (Bezdek and Pal, 1992), and mixture model-based clustering (McLahlan and Basford, 1987). In this paper, we focus on clustering methods for partitioning an unclassified data (or variable) set into a set of clusters with similar characteristics, e.g., K-means clustering and hierarchical clustering. Although the general course of clustering is to maximize within-cluster similarity and/or between-cluster dissimilarity, various proximity measures (e.g., Euclidean, city-block, and Mahalanobis distances) and various distance criteria (within-cluster: average, nearest neighbor, and centroid distances; between-cluster: single, complete, average, and centroid linkages) exist, causing clustering results on the same data set to vary from one analysis to another. A thorough discussion on proximity measures and clustering distance criteria can be found in various multivariate statistical textbooks, such as those of Jobson (1992) and Rencher (1995).

There are two main ways to cluster data: partitive and hierarchical approaches. K-means cluster analysis is a typical partitive clustering technique in which the data set is divided directly into a predefined number of clusters (e.g., the clustering process does not depend upon previously found clusters). This method implicitly assumes spherical shapes of the clusters. In the hierarchical clustering approach, the data set is organized into a hierarchical clustering tree (dendrogram) via either top-down (divisive) or bottom-up (agglomerative) algorithms. Between the two, agglomerative procedures are more commonly used than the divisive ones. The dendrogram can be used to study the data structure and to determine the number of clusters. With the dendrogram, it is guaranteed that a sub-cluster belongs completely to a larger cluster. This feature is not always true with the K-means clustering and other partitive approaches.

The "best" clustering (e.g., the number of clusters) among different clustering results can be selected by using some type of validity index such as those in Milligan and Cooper (1985) and Bezdek (1998). Some common validity indices include the Davies–Bouldin index (Davies and Bouldin, 1979) and the average Silhouette width (Rousseeuw, 1987). More on stopping rules and ways of finding out the "best" number of cluster can be found in McCune and Grace (2002). In the context of selecting SDIs, stakeholders can explore and determine the maximum number of clusters based on their preference (e.g., the number of indicators, i.e., cluster representatives, to be included).

3.2. Selecting indicators

The SDIs to be selected are cluster representatives derived from cluster analysis. To select an indicator as cluster representative, we use the "$1-R^2$ ratio" that is defined as:

$$1-R^2\ \text{ratio} = (1-R^2_{\text{own cluster}})/(1-R^2_{\text{closest cluster}}) \tag{1}$$

Intuitively a cluster representative should be as closely correlated to member of its own cluster (i.e., $1-R^2_{\text{own cluster}} \to 0$) and uncorrelated to those in the nearest cluster (i.e., $1-R^2_{\text{closest cluster}} \to 1$). Hence the rule of thumb is to choose the variable with the minimum $1-R^2$ ratio as the cluster representative.

Complementary to the rule of minimum $1-R^2$ ratio, stakeholder's knowledge and input can be utilized in the process. For example, an alternative indicator that might have a better intuitive interpretation to stakeholder or be more compatible with SDIs collected in the surrounding areas can be selected instead of the cluster representative. Furthermore, stakeholders could decide to have more than one indicator per cluster for some specific reasons, for example, balancing the number of indicators representing different components of SUD (e.g., social, economic, and environmental). In other words, clustering and cluster representative analysis should be treated as diagnostic means rather than a rigid procedure. In that context, the selecting indicator procedure proposed in this paper is an integration of objective quantitative analysis, experts' knowledge, and stakeholders' input.

3.3. Multivariate linear regression (MLR)

MLR is an approach for modeling the relationship between a dependent variable and multiple explanatory variables (Draper and Smith, 1998). More details on MLR's theoretical foundation and its applications can be found in Christensen (2001), Myers et al. (2002), and McCulloch et al. (2008). We use MLR in the proposed method as simply an informative tool to determine how much variance of the whole set of SDIs can be explained by the selected SDI set. To be more specific, if a SDI is included in the selected SDI set, all of its variance (=1) is considered being accounted for. For an

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