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A GIS based spatially-explicit sensitivity and uncertainty analysis approach for multi-criteria decision analysis ☆

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ABSTRACT

GIS multicriteria decision analysis (MCDA) techniques are increasingly used in landslide susceptibility mapping for the prediction of future hazards, land use planning, as well as for hazard preparedness. However, the uncertainties associated with MCDA techniques are inevitable and model outcomes are open to multiple types of uncertainty. In this paper, we present a systematic approach to uncertainty and sensitivity analysis. We access the uncertainty of landslide susceptibility maps produced with GIS-MCDA techniques. A new spatially-explicit approach and Dempster–Shafer Theory (DST) are employed to assess the uncertainties associated with two MCDA techniques, namely Analytical Hierarchical Process (AHP) and Ordered Weighted Averaging (OWA) implemented in GIS. The methodology is composed of three different phases. First, weights are computed to express the relative importance of factors (criteria) for landslide susceptibility. Next, the uncertainty and sensitivity of landslide susceptibility is analyzed as a function of weights using Monte Carlo Simulation and Global Sensitivity Analysis. Finally, the results are validated using a landslide inventory database and by applying DST. The comparisons of the obtained landslide susceptibility maps of both MCDA techniques with known landslides show that the AHP outperforms OWA. However, the OWA-generated landslide susceptibility map shows lower uncertainty than the AHP-generated map. The results demonstrate that further improvement in the accuracy of GIS-based MCDA can be achieved by employing an integrated uncertainty–sensitivity analysis approach, in which the uncertainty of landslide susceptibility model is decomposed and attributed to model′s criteria weights.

1. Introduction

GIS based multicriteria decision analysis (MCDA) is primarily concerned with combining the information from several criteria to form a single index of evaluation (Chen et al., 2010a). The GIS-MCDA methods provide a framework for handling different views and compositions of the elements of a complex decision problem, and for organizing them into a hierarchical structure, as well as studying the relationships among the components of the problem (Malczewski, 2006). MCDA procedures utilizing geographical data consider the user′s preferences, manipulate the data, and combine preferences with the data according to specified decision rules (Malczewski, 2004; Rahman et al., 2012). MCDA involves techniques, which have received increased interest for their capabilities of solving spatial decision problems and supporting analysts in addressing complex problems involving conflicting criteria (Kordi and Brandt, 2012). The integration of MCDA techniques with GIS has considerably advanced the traditional data combination approaches for Landslide Susceptibility Mapping (LSM). In analyzing natural hazards with GIS-MCDA, the LSM is considered to be one of the important application in domains (Feizizadeh and Blaschke, 2013a). A number of direct and indirect models have been developed in order to assess landslide susceptibility, and these maps were produced by using deterministic and non-deterministic (probabilistic) models (Yilmaz, 2010). In creating a susceptibility map, the direct mapping method involves identifying regions susceptible to slope failure, by comparing detailed geological and geomorphological properties with those of landslide sites. The indirect mapping method integrates many factors and weighs the importance of different variables using subjective decision-making rules, based on the experience of the geoscientists involved (Lei and Jing-feng, 2006; Feizizadeh and Blaschke, 2013a). Among the proposed methods, GIS-MCDA provides a rich collection

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of techniques and procedures for structuring decision problems and designing, evaluating and prioritizing alternative decisions for LSM. Thus, GIS-MCDA methods are increasingly being used in LSM for the prediction of future hazards, decision making, as well as hazard mitigation plans (Feizizadeh and Blaschke, 2013a). However, due to the multiple approach nature of natural hazard modeling (e.g LSM) the problems related to natural hazards cannot usually be handled without considering inherent uncertainty (Nefeslioglu et al., 2013). Such uncertainties may have significant impacts on the results, which may sometimes lead to inaccurate outcomes and undesirable consequences (Feizizadeh and Blaschke, 2013b).

GIS-MCDA based LSM methods are often applied without any indication of error or confidence in the results (Feizizadeh and Blaschke, 2012; Feizizadeh et al., 2012; Feizizadeh and Blaschke, 2013a). The uncertainties associated with MCDA techniques applied to LSM are due to incomplete and inaccurate data on landslide contributing factors, rules governing how the input data are combined into landslide susceptibility values and parameters used in the combination rules (Ascough et al., 2008). In the context of GIS-MCDA uncertainty, there is a strong relationship between data uncertainty and parameter uncertainty, since model parameters are obtained directly from measured data, or indirectly by calibration (Ascough et al., 2008). Due to a potentially large number of parameters and the heterogeneity of data sources, the uncertainty of the results is difficult to quantify. Even small changes in data and parameter values may have a significant impact on the distribution of landslide susceptibility values. Therefore, MCDA techniques in general, and in the domain of hazard mapping in particular, should be thoroughly evaluated to ensure their robustness under a wide range of possible conditions, where robustness is defined as a minimal response of model outcome to changing inputs (Ligmann-Zielinska and Jankowski, 2012).

In an effort to address the uncertainty associated with data and parameters of GIS-MCDA we use a unified approach to uncertainty and sensitivity analysis, in which uncertainty analysis quantifies outcome variability, given model input uncertainties, followed by sensitivity analysis that subdivides this variability and apportions it to the uncertain inputs. Conceptually, uncertainty and sensitivity analysis represent two different, albeit complementary approaches to quantify the uncertainty of the model (Tenerelli and Carver, 2012). Uncertainty analysis: (a) helps to reduce uncertainties in how a MCDA method operates, and (b) parameterizes the stability of its outputs. This is typically achieved by introducing small changes to specific input parameters and evaluating the outcomes (Crosetto et al., 2000; Eastman, 2003). This process provides the possibility of measuring the level of confidence in decision making and in the decision maker (Chen et al., 2011). Uncertainty analysis aims to identify and quantify confidence intervals for a model output by assessing the response to uncertainties in the model inputs (Crosetto et al., 2000). Meanwhile sensitivity analysis technically explores the relationships between the inputs and the output of a modeling application (Chen et al., 2010b). Sensitivity analysis is the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation, and how the

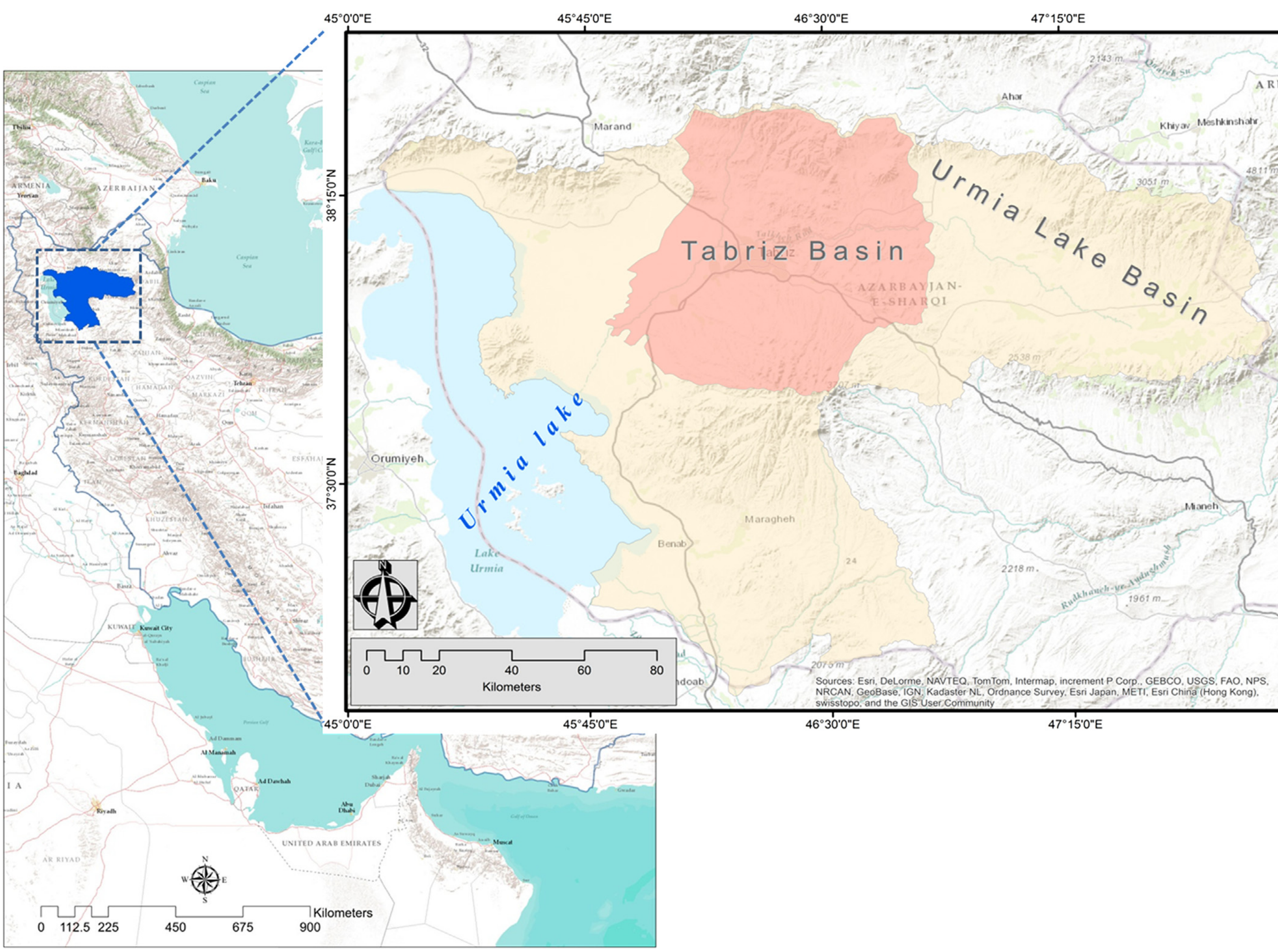

Fig. 1. Urmia lake basin (right).