Sensitivity and Uncertainty Analysis Approach for GIS-MCDA Based Economic Vulnerability Assessment

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Abstract

This research aims to employ a novel methodology for modelling uncertainty in the GIS environment. The spatially explicit sensitivity and uncertainty analysis was applied on Multicriteria Decision Analysis (MCDA) for an economic vulnerability assessment within the Salzach Basin. The main objective of this research is to demonstrate how a unified approach of uncertainty and sensitivity analysis can be applied to minimize the associated uncertainty within an economic vulnerability assessment. In order to achieve this objective, the following methodology, composed four steps, was applied: (1) computation of criteria weights using Analytic Hierarchy Process (AHP); (2) Monte Carlo Simulation was applied for computing the uncertainties associated with AHP weights; (3) the Global Sensitivity Analysis (GSA) was employed in the form of the model-independent method of output variance decomposition, in which the variability of vulnerability maps is apportioned to every criterion weight, generating one first-order (S) and one total-effect (ST) sensitivity index map per criterion weight; and (4) an Ordered Weighted Averaging method was applied for producing vulnerability maps. The results of this research demonstrated the robustness of spatially explicit GSA for minimizing the uncertainty associated with GIS-MCDA models. According to the achieved results, we conclude that applying the variance based GSA leads to a spatial and statistical assessment of the importance of each input factor on the outcome of the GIS-MCDA method, which allows us to introduce and recommend GIS based GSA as a useful methodology for minimizing uncertainty of GIS-MCDA.

1 Introduction

The capability of Multicriteria Decision Analysis (MCDA), when integrated with GIS, makes GIS-based MCDA one of the most useful and robust methods for spatial decision making (CHEN et al. 2011). MCDA procedures utilizing geographical data consider the user's preferences, manipulate the data, and combine preferences with the data according to specified decision rules (FEIZIZADEH & BLASCHKE 2014). Since GIS-MCDA deals with numerous criteria, it is increasingly recognized that MCDA's outcomes are prone to the inherent uncertainties related to the MCDA process (FEIZIZADEH et al. 2012, 2014a). The principal sources of GIS-MCDA uncertainty are due to errors and variability in model

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choice, system understanding, weighting factors, data used, and human judgment (CROSETTO et al. 2000). Conceptually, uncertainty and sensitivity analysis represent two different, albeit complementary approaches to quantify the uncertainty of the model (FEIZIZADEH & BLASCHKE 2014). 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 (EASTMAN 2003). One specific approach to uncertainty analysis applicable to MCDA is to gain a sense of error or uncertainty in the predictions, given the uncertainty in the criterion weights (BENKE & PELIZARO 2010, FEIZIZADEH & BLASCHKE 2014). It is believed that it is essential to handle GIS-MCDA errors and uncertainty in decision-making, particularly when decisions are based on probabilistic ranges rather than on deterministic results (TENERELLI & CARVER 2012, FEIZIZADEH et al. 2014a). MCDA uncertainty analysis embraces issues beyond traditional risk definitions. These broader issues include the propagation of errors in predictive environmental models (OBERKAMPF et al. 2004, BENKE & PELIZARO 2010). Such issues require an analysis of probability distributions, rather than a risk specification based on a single imprecise probability or consequence (BENKE & PELIZARO 2010). In this research we started from the hypothesis that GIS-MCDA uncertainty analysis provides a possibility of increasing the level of confidence in the GIS-MCDA methodology. We aim to investigate if uncertainty in the results can be reduced by applying sensitivity and uncertainty analysis to the GIS-MCDA methodology when employed for an Economic Vulnerability Assessment (EVA) in Salzach basin, Salzburg, Austria.

2 Methods

The research methodology is based on spatially explicit sensitivity and uncertainty analysis of GIS-MCDA for EVA within the Salzach basin. The mean objective of this research was to demonstrate how a unified approach of uncertainty and sensitivity analysis can be applied to minimize the associated uncertainty within EVA. In order to achieve this objective, the methodology is composed of four steps, including a) computing criteria weights using Analytic Hierarchy Process (AHP), b) applying Monte Carlo Simulation (MCS) for computing the uncertainty of the AHP weights, c) running Global Sensitivity Analysis (GSA), and c) employing the Ordered Weighted Averaging (OWA) method for producing vulnerability maps.

2.1 Assessing the Criteria Weights Through AHP

The Analytic Hierarchy Process (AHP) method (SAATY 1977) is a well-known means of the multicriteria technique, which has been incorporated into GIS-based MCDA. The AHP method reduces the complexity of a decision problem to a sequence of pairwise comparisons, which are synthesized in a ratio matrix that provides a clear rationale for ordering the decision alternatives from the most to the least desirable. The development of AHP pairwise comparison is based on the rating of relative preferences for two criteria at a time. Each comparison is a two-part question, determining which criterion is more important and to what extent, using a scale with values from the set: {1/9, 1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 1/2, 1, 2, 3, 4, 5, 6, 7, 8, 9} (FEIZIZADEH & BLASCHKE 2013a). The values range from 1/9 representing the least important (than), to 1 for equal importance, and to 9 for the most important (than), covering all the values in the set. Since human judgment can violate the transitivity rule, and thus cause an inconsistency, the consistency ratio (CR) is computed to check the consistency of the conducted comparisons. In case of high inconsistency the most inconsistent judgments can be revised (GORSEVSKI et al. 2006). After the weights are determined through the pairwise comparison method, the resulting evaluation scores are used to order the decision alternatives from the most to the least desirable, followed by an aggregation criterion technique (GORSEVSKI et al. 2006). Because of its simplicity and robustness in obtaining weights and integrating heterogeneous data, the AHP has been used in a wide variety of applications, including multi-attribute decision-making, total quality management, suitability analysis, resource allocation, conflict management, and design and engineering (GORSEVSKI et al. 2006). Within this research we used the AHP pairwise comparison procedure to obtain criteria and sub-criteria weights based on a hierarchy process (see table 1 for weights of criteria of each dimension). In AHP, the CR is computed in order to check the consistency of the conducted comparisons (GORSEVSKI et al. 2006). Based on (SAATY 1977), if the CR < 0.10 then the pairwise comparison matrix has an acceptable consistency and the weight values are valid and can be utilized. Otherwise, if the CR ≥ 0.10 then the pairwise comparisons lack consistency and the matrix needs to be adjusted and the element values should be modified (FEIZIZADEH & BLASCHKE 2013b). Table 1 shows the AHP's pairwise matrix for economic dimension of EVA.

Table 1: The AHP's pairwise matrix for the economic dimension of EVA

Criteria for VA dimensions	1	2	3	4	5	6	7	8	Eigen values
Economic									
(1) Company size	1								0.1326
(2) Employees by sector	3	1							0.1243
(3) Land use/cover	2	3	1						0.1097
(4) Eco-Services	6	4	3	1					0.1741
(5) Transport networks	4	5	5	6	1				0.4593
Consistency ratio: 0.057									

2.2 Implementation of AHP-Monte Carlo Simulation

The AHP is indeed considered the best method of criteria weighting that has been introduced to GIS-MCDA so far. However, since the pairwise comparison of criteria is based on expert opinions, AHP is open to subjectivity in making the comparison judgements (FEIZIZADEH et al. 2014a, FEIZIZADEH & BLASCHKE 2014). One specific approach to uncertainty analysis applicable to MCDA is to gain a sense of error or uncertainty in the predictions, given the uncertainty in the criterion weights (BENKE & PELIZARO 2010). The uncertainty of weights lies in the subjective expert or stakeholder judgement of the relative importance of different attributes, given the range of their impacts (CHEN et al. 2011). FEIZIZADEH et al (2014a) implemented the GIS-MCDA based AHP-Monte Carlo Simulation (MCS) as an effort to deal with subjectivity in criterion weights contributing to potential uncertainty of model outcomes. Relevant studies have also suggested integrating the MCS with conventional AHP in order to enhance the screening capability when there is a need to identify a reliable decision alternative (model outcome) (e.g. BENKE & PELIZARO 2010, FEIZIZADEH et al. 2012, FEIZIZADEH & BLASCHKE 2013a). The AHP-MCS approach takes the probabilistic characterization of the pairwise comparisons into account. This approach is based on the association with probability distributions, which is sufficient to confirm that one alternative is preferred to another (in the sense of maximizing expected utility), provided that certain constraints on the underlying utility function are satisfied. Sampling-based uncertainty analysis, via MCS approaches, plays a central role in this characterisation and quantifi-

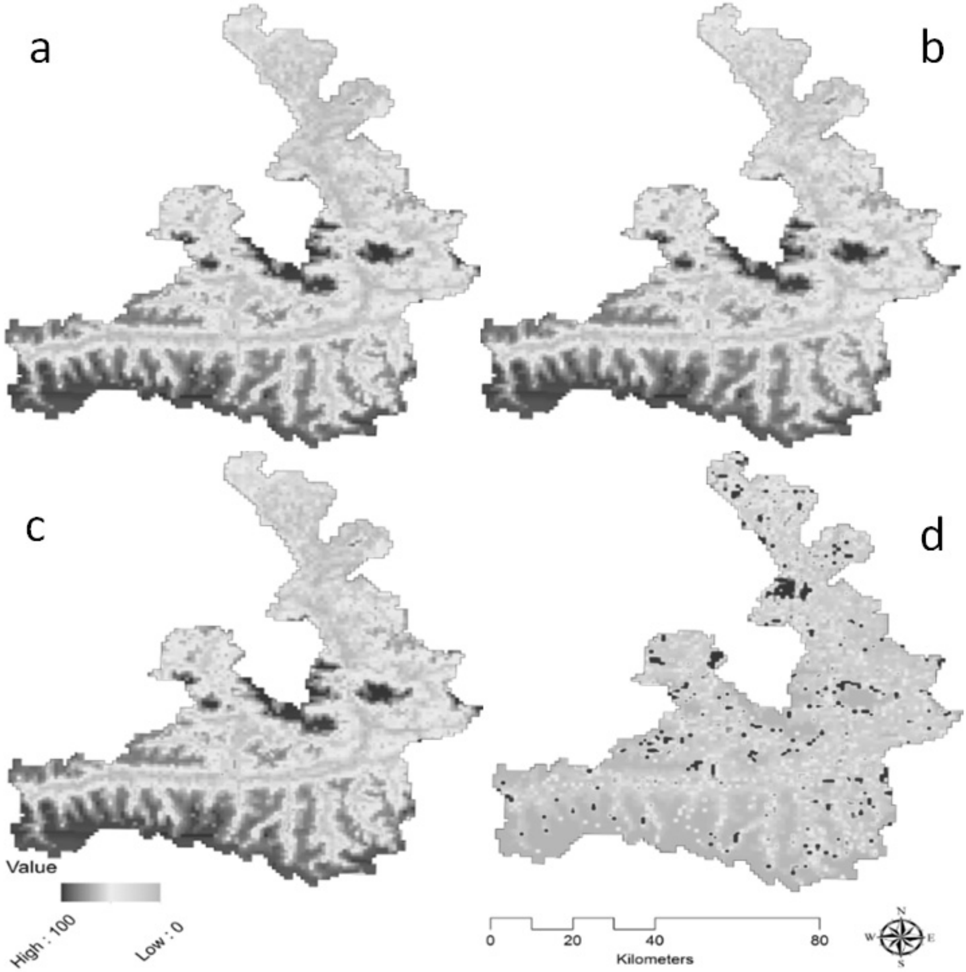

Fig. 1: Results of AHP-MCS for EVA: a) minimum rank, b) maximum rank, c) average rank, and d) standard deviation rank

cation of uncertainty (HELTON 2004), since the uncertainty of attribute values and weights can be represented as a probability distribution or a confidence interval (CHEN et al. 2011).

In our approach we use the MCS to carry out the uncertainty analysis associated with AHP weights. For this to happen, our research methodology makes use of the concept of AHP-MCS, where we take into account the criteria weights derived from the AHP pairwise matrix for the uncertainty analysis using MCS. We performed AHP-MCS to model the error propagation from the input data to the model output. Our AHP-MCS process included three steps: a) using the AHP based criteria weights as reference weights of MCS; b) running the simulation N times: practically the number of simulations (N) vary from 100 to 10000 according to the computational load; and c) analysing the results, producing statistics by mapping the spatial distribution of the computed errors including: the minimum rank, maximum rank, average rank and standard deviation of rank. Figure 1a-d presents the results of AHP-MCS for the EVA.

2.3 Variance-Based Global Sensitivity Analysis

The variance-based method of Global Sensitivity Analysis (GSA) developed by SOBOL (2001) is a very popular approach for uncertainty analysis (TODRI et al. 2014). GSA subdivides the variability and apportions it to the uncertain inputs. The GSA approach can recognize the contribution of the input variables to uncertainty of the model output response, by which the priority level of the input variables can be determined in experiments or research. Accordingly, the order determined by the importance of model input variables can help to better define the unknown parameters, as well as to reduce the uncertain scope of response and to get an acceptable uncertain response range (FEIZIZADEH et al. 2014a). In this context, GSA reveals input variables, which are important in determining the outcome variability, and in particularly for establishing the variance of agent disutility, as well as the uncertainty of pattern fragmentation (LIGMANN-ZIELINSKA & JANKOWSKI 2010). The goal of variance-based GSA is to quantitatively determine the weights that have the most influence on ranking. Variance based GSA aims to generate two sensitivity measures: first order (S), and total effect (ST) sensitivity indices. The S estimates the individual contribution of each input parameter to the output variance. While the ST measures the total contribution of a single input factor. The total effects are used to identify non-important variables, which can then be fixed at their nominal values to reduce model complexity (SOBOL 2001, TODRI et al. 2014). In the particular context reported in this paper, the goal of ST is to find the criterion weights that have the most influence on vulnerability. S is defined as a fractional, first-order (linear) contribution of a given criterion weight to the variance of the vulnerability scores calculated for a given pixel. Analysts use S to look for influential criterion weights that, if fixed independently, would most reduce the variance of the vulnerability. This is to say, weights with relatively high S values have the most impact on the variability of vulnerability assessments. No established threshold for the S values exists. Values for all criterion weights have to be analysed and their importance is determined based on their relative magnitudes (SALTELLI et al. 2004, LIGMANN-ZIELINSKA & JANKOWSKI 2014). In the exercise of applying GSA for VA, within the first step, we selected the AHP weight as the reference ranking (see table 1). We also used maximum weights for the criteria, which are assessed based on the importance of each criterion in the AHP pairwise matrix. The results of variance based GSA are presented in table 2.

Table 2: Results of GSA for three dimensions of EVA

Factor	S	ST	S %	ST %
Company size	0.71	0.774	71	65.7
Transport networks	0.031	0.041	3.1	3.5
Economy Sector	0.008	0.004	0.8	0.3
Ecosystem Services	0.182	0.148	18.8	12
Land use/cover	0.126	0.218	12.6	18.5

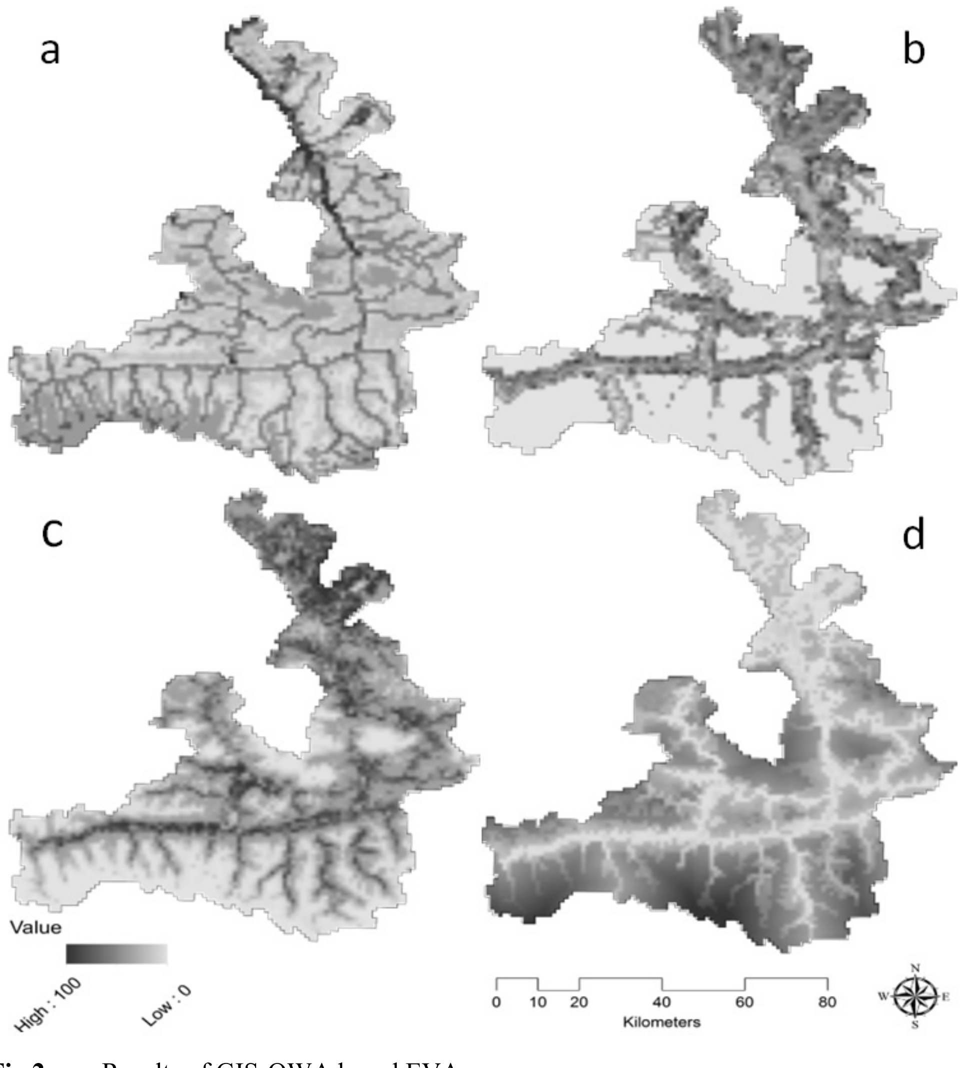

Fig 2: Results of GIS-OWA based EVA

2.4 GIS based Ordered Weighted Averaging

Ordered Weighted Averaging (OWA) is one the well-known GIS-MCDA operators introduced by YAGER (1988). OWA is a class of multicriteria operators, which was given quantifier-guided aggregation. OWA is a method involving two sets of weights, including criterion importance weights and order weights (MALCZEWSKI 2006, FEIZIZADEH et al. 2012). An importance weight is assigned to a given criterion (attribute) for all locations in a study area to indicate its relative importance (according to the decision-maker's preferences) in the set of criteria. The order weights are associated with the criterion values on a location-by-location (object-by-object) basis. They are assigned to a location's attribute values in decreasing order without considering which attribute the value comes from. The order weights are central to the OWA combination procedures. OWA provides a tool for generating a wide range of decision strategies in a decision strategy space, by applying a set of order weights to criteria that are ranked in ascending order on a pixel-by-pixel basis. The number of order weights is equal to the number of criteria, and must sum to one. The position of a set of order weights can be identified in a decision strategy space based on the concepts of trade-off and risk (YAGER 1988). Trade-off indicates the degree to which a low standardized value on one layer can be compensated for by a highly standardized value on other considered criteria. Risk refers to how much each criterion affects the final solution (MALCZEWSKI 2006, FEIZIZADEH et al. 2012). Within this research, the OWA approach was employed to produce vulnerability maps, based on the weights derived from the GSA. Figure 2 depicts the results of EVA for three dimensions according to OWA-GSA.

3 Conclusion and Outlook

In this paper, GIS based spatially explicit Global Sensitivity Analysis (GSA) was presented with particular consideration of the influences of uncertainty criteria on Economic Vulnerability Assessment (EVA). It was presented in order to quantify the significant factor that influenced EVA. This study demonstrated that the systematic exploration of the multivariate input space provided by GSA is critical to identifying and understanding the dominant processes affecting the EVA. Based on the results, we conclude that GSA is a tool that can help analyse, design and improve processes. GSA leads to an assessment of the robustness of weights; accordingly it helps to identify the process behaviour and/or helps to identify the most important process stages that affect a given process variable (model output). With this information it is possible to redesign or change an operational condition to improve process performance. We conclude that using the variance based GSA leads to a spatial and statistical assessment of the importance of each input factor for the outcome of the GIS-MCDA method. Based on the results achieved from current research, our future research will include the application of a spatially-explicit reliability model for spatial sensitivity and uncertainty analysis associated with AHP and Fuzzy-AHP. It should be noted that despite these shortcomings the AHP has been widely used for practical applications and integrated with other methodologies such as fuzzy sets to represent human judgments and capture their inconsistencies (FEIZIZADEH et al. 2014b).

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