

# GIS-based multiple criteria decision analysis and optimization for land suitability evaluation

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## Abstract

The purpose of our paper is twofold: (1) to overview and systematize the techniques and methods for spatial multiple criteria decision making; and (2) to demonstrate the approach of integrating GIS, multiple criteria analysis, and Compromise Programming (CP) for land suitability evaluation. The CP method is implemented in the ARC/INFO environment as an AML-program and it is tested for two research areas, one in Győr (Hungary) and another nearby Dresden (Germany). After an introduction, a short review of MCDM is given in section 2. The section 3 describes the CP methodology. The section 4 deals with the integration of MCA, CP, and GIS as well as application results.

## 1 Introduction

Systematic procedures of multiple criteria decision making (MCDM) have been researched and developed for several decades primarily in the fields of management science, operations research, public administration, and military science (e.g. Raiffa 1968; Zeleny 1973; Saaty 1980 & 2001; Openshaw & Whitehead 1982; Churgin & Peschel 1989; Romero & Rehman 1989; Nijkamp, Rietveld & Voogd 1990; Keeney 1992; Eisenführ & Weber 1994; Czeranka 1997; Laux 1998; Malczewski 1999). It is widely accepted that MCDM can be divided into two categories: multiple attribute decision making (MADM) and multiple objective decision making (MODM). MADM is often referred to as multiple criteria analysis (MCA) or multiple criteria evaluation (Jankowski 1995; Nijkamp, Rietveld & Voogd 1990), while MODM is viewed as a natural extension of mathematical programming, where multiple objectives are considered simultaneously. The MCA can be conceived of as an extension of conventional evaluation methods. For example, cost-benefit analysis, with its reliance on market prices has been replaced by a much broader set of discrete MCA methods where prices or weights may also reflect different priorities. Linear programming, as another example, only deals with one objective function. In the context of MCA it is replaced by optimization methods for multiple, conflicting objective functions (Steuer 1986). In doing so the original concept of optimality has been replaced by the concept of Pareto-optimality (or efficiency), leading to much broader sets of alternatives which are in principle acceptable (Janssen & Rietveld 1990).

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The class of decision problems which interests spatial planners typically involves a set of geographically defined alternatives. The alternatives are geographically defined in the sense that results of the analysis or decisions depend on their spatial arrangement (Malczewski 1999, 90). Compared to the conventional MCDM, spatial multiple criteria decision analysis (SMCDA) requires both data on criterion values and the geographical locations of alternatives. Thus, two considerations are of paramount importance for SMCDA: (1) the GIS component (e. g., data acquisition, storage, retrieval, manipulation, and analysis capability); and (2) the MCDM analysis component (e. g., aggregation of spatial data and decision maker's preferences into discrete decision alternatives). Consequently, the terms GIS-based multiple criteria decision analysis and spatial multiple criteria analysis will be used interchangeably (Malczewski 1999, 90). The combination of GIS capabilities with MCDM techniques provides the decision maker with support in all stages of decision making, that is, in the intelligence, design, and choice phases of the decision making process (see Jankowski 1995; Janssen & Rietveld 1990; Malczewski 1999, 91).

The German Leibniz Institute of Ecological and Regional Development (IÖR), Dresden and the Hungarian VÁTI Hungarian Public Non-profit Company for Regional Development and Town Planning, Budapest are highly involved in national and European scaled land use research and development on a local and regional level, respectively. In this field MODM is an important issue, and multiple criteria evaluation (MCE) is a popular approach to decision analysis in the GIS environment. In a joint project researchers of both institutes aim to develop new methodological possibilities for a comprehensive patch based land use optimization dedicated to the practical demands of spatial planning. As one aspect of land use optimization the project focus the interactions between land utilisations and the environment. Therefore on the basis of Compromise Programming (CP) as an already high developed multiple criteria method the suitability of this method for land use optimization considering ecological aspects is investigated. The results should be used for a further development of the method.

## **2 Spatial multiple criteria decision analysis – an overview of the methodology**

### **2.1 Framework for GIS-based multiple criteria decision analysis**

SMCDA can be conceived of a process that combines and transforms geographical data (input maps) into a resultant decision (output map) (see Figure 1). The MCDM procedures define a relationship between the input maps and the output map.

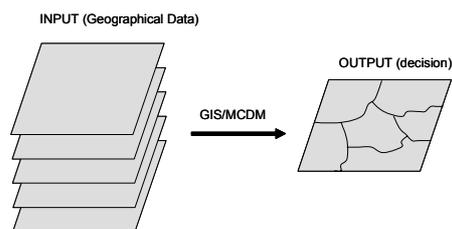


Figure 1: Spatial multiple criteria decision analysis: input-output perspective  
(based on Malczewski 1999)

Figure 2 presents a three-stage hierarchy of intelligence, design, and choice to represent the decision making process. In the intelligence phase, data are acquired, processed, and exploratory data analysis is performed. The design phase usually involves formal modeling/GIS interaction in order to develop a solution set spatial decision alternatives. The integration of decision analytical techniques and GIS functions is important for supporting the design phase. The choice phase involves selecting a particular alternative from those available. In this phase, decision rules are used to evaluate and rank alternatives. The three stages of decision making do not necessarily follow a linear path from intelligence, to design, and to choice.

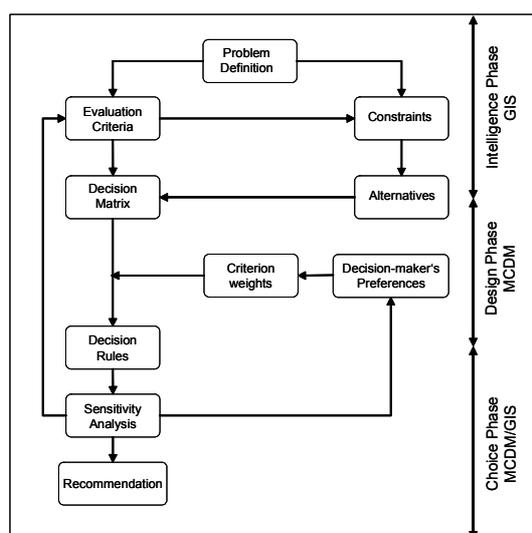


Figure 2: Framework for spatial multiple criteria decision analysis  
(based on Malczewski 1999, modified)

### Problem definition

The decision problem is a perceived difference between the desired and existing states of a system. It is a gap between the desired and existing states as viewed by a decision maker. The GIS capabilities for data storage, management, manipulation, and analysis offer major support in this stage.

### Evaluation criteria

This step involves specifying (1) a comprehensive set of objectives that reflects all concerns relevant to the decision problem, and (2) measures for achieving those objectives. The evaluation criteria are associated with geographical entities and

relationships between entities and therefore can be represented in the form of maps (thematic map or data layer in GIS terminology). The GIS is used to generate inputs to SMCDAs.

### Criterion weights

The preferences of decision makers are typically expressed in terms of the weights of relative importance assigned to the evaluation criteria under consideration. The derivation of weights is a central step of the evaluation and decision process. A number of criterion weighting procedures have been proposed in the multiple criteria decision literature. Some of the most popular procedures are discussed in the chapter 2.2.

### Recommendation

This step should be based on the ranking of alternatives and sensitivity analysis. It may involve the description of the best alternative or group of alternatives considered candidates for implementation. Visualization techniques (e. g. Hasse-Diagram technique, see Brüggemann et al. 2001) are of major importance in presenting and communicating the results to decision makers.

## 2.2 Some methods to estimating weights

### Ranking methods

Every criterion under consideration is arranged in the order of the decision maker's preference. Either straight ranking (the most important = 1, second important = 2, etc.) or inverse ranking (the least important = 1, next least important = 2, etc.) can be used. After this step, several procedures for generating numerical weights from rank-order information are available (e. g. rank sum, rank reciprocal, and rank exponent methods, see Malczewski 1999, 178). *Rank sum weights* are calculated as following:

$$w_j = \frac{n - r_j + 1}{\sum_{k=1}^n (n - r_k - 1)} \quad (2.1)$$

where  $w_j$  is the normalised weight for the  $j$ -th criterion,  $n$  is the number of criteria under consideration, and  $r_j$  is the rank position of the criterion.

*Rank reciprocal weights* are calculated according to the following formula:

$$w_j = \frac{1 / r_j}{\sum_{k=1}^n 1 / r_k} \quad (2.2)$$

The *Rank exponent method* calculates the weights as following:

$$w_j = \frac{(n - r_j + 1)^p}{\sum_{k=1}^n (n - r_k + 1)^p} \quad (2.3)$$

This method has several interesting properties. For  $p = 0$  equation (2.3) assigns equal weights to the criteria. For  $p = 1$  the method results in rank sum weights. As  $p$  increases, normalised weights gets steeper and steeper.

### Rating methods

The rating methods are used rather frequently in spatial planning. The decision maker is asked to estimate weights on the basis of a predetermined scales, e. g. a scale of 0 to 100 can be used. The decision maker have to assign to each criterion a number of points  $x$  with  $0 \leq x \leq 100$  (point allocation approach), where 0 indicates that the criterion can be ignored and 100 represents the situation where only one criterion need be considered in a given decision situation. There exist several way of standardizing objectives (see Churgin & Peschel 1989, 67; Nijkamp, Rietveld & Voogd 1990, 42), for example:

$$q_j = \frac{x_j}{\max\{x_1, x_2, \dots, x_n\}} \quad (2.4)$$

or

$$q_j = \frac{x_j - \min\{x_1, x_2, \dots, x_n\}}{\max\{x_1, x_2, \dots, x_n\} - \min\{x_1, x_2, \dots, x_n\}} \quad (2.5)$$

An alternative to the point allocation approach is a ratio estimation procedure (see Malczewski 1999, 181). According to the result identified by one of the ranking methods, a score of 100 is assigned to the most important criterion. Proportionately smaller scores are given to criteria lower in the order. In contrary to the point allocation method, the score assigned to the least important criterion is taken as an anchor point for calculating the ratios

$$q_j = \frac{x_j}{\min\{x_1, x_2, \dots, x_n\}} \quad (2.6)$$

By normalising of  $q_j$ , one obtains the weight  $w_j$ . One way of doing this is to divide each  $q_j$  by the total sum.

### Pairwise comparison methods

These methods are based on a pairwise comparison of criteria. The best known method is the *analytic hierarchy process* (AHP), originally developed by Saaty 1980. Several modifications of this method have been suggested. The method has proved to be one of the more widely applied MCA methods, see, for example, Saaty & Varga 2001 for a collection of selected applications in economic, social, political, and technological areas. It is important to note that the group AHP method has been extended to a fuzzy decision environment (see Xiang et al. 1992). For each pair of criteria, the decision maker is required to respond to a pairwise comparison question asking the relative importance of the two. Responses are gathered in verbal form and subsequently codified on a nine-point intensity scale, as follows:

Intensity of Importance	Definition
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extreme importance

Table 1: Scale for pairwise comparison (Source: Saaty & Vargas 2001, 6)

After the development of the pairwise comparison matrix  $A = (a_{ij})$  ( $i, j = 1(1)n$ ), we can compute the criterion weights as follows (see Saaty 1980, 49-51; Saaty 2001, 26-38): (1) sum the values in each column of the matrix  $a_{ij}$ ; (2) divide each element in the matrix by its column total (the resulting matrix  $b_{ij}$  ( $i, j = 1(1)n$ ) is the normalised pairwise comparison matrix); and (3) compute the average of the elements in each row of the normalised matrix. These averages can be used as an estimate of the relative weights  $w_i$  ( $i = 1(1)n$ ) of the criteria being compared.

$$w_i = \frac{\sum_{j=1}^n b_{ij}}{n} \quad (i = 1(1)n) \quad (2.7)$$

The next step is the estimate of the consistency ratio. In this step we have to investigate if the comparisons are consistent. It involves the following operations (see Saaty 1980, 21): (1) determine the consistency vector by component-wise dividing the vector  $Aw$  (matrix  $A$  times vector  $w$ ) by the vector  $w$ ; (2) determine the average value  $\lambda$  of the consistency vector; (3) calculate the consistency index  $CI$

$$CI = \frac{\lambda - n}{n - 1} \quad (2.8)$$

The quantity  $CI$  provides a measure of departure from consistency. The ratio of  $CI$  to the average random index ( $RI$ ) for the same order  $n$  is called the consistency ratio ( $CR$ ):

$$CR = \frac{CI}{RI} \quad (2.9)$$

(for the meaning and generating of RI see Saaty 1980, 21). If  $CR < 0.1$ , the ratio indicates a reasonable level of consistency in the pairwise comparison. If  $CR \geq 0.1$ , one should reconsider and revise the values in the pairwise comparison matrix and repeat the procedure.

### 3 The Compromise Programming Method

The Compromise Programming (CP) was first suggested by Zeleny (1973) as a method for solving multiple objective programming (MOP) problems. It has been used in a wide range of problems involving MOP and MCDM frameworks, especially in the context of natural resource use. CP has been applied to regional and landscape planning (e. g. Grabaum & Meyer 1997, Nijkamp et al. 1990, Ferencsik 2000), to water resources development (e. g. Gnauck 1996), and to the selection of construction systems (e. g. Karni & Werczberger 1995). Today, MCAD has been moving from optimization methods to more interactive decision support tools. Thus the CP and especially the combination of CP with Fuzzy modeling allow various sources of uncertainty and are intended to provide a flexible form of group decision support (Bender & Simonovic 2000).

The use of mathematical programming for dealing with decision making problems is based on a similar theoretical structure. Feasible solutions are those that satisfy the constraints of the problem. These feasible decisions are ordered according to a given criterion, referred to as the objective function, representing the preferences of the decision maker (DM). The optimum solution is found from the feasible set using some mathematical procedure, such as Simplex for instance, to find the highest possible value for the objective function. Notwithstanding the fact that this paradigm is logically sound, it does not faithfully reflect the real life decision situation. The DM is usually not interested in ordering the feasible set according to just a single criterion but seems to be striving to find an optimal compromise amongst several objectives. (Romero & Rehman 1989, 4)

The basic idea of CP is to identify solutions which are closest to the ideal point as determined by some measure of distance, accepting the basic postulate that the decision maker prefers solutions as close as possible with respect to the ideal (Zeleny's axiom of choice, Zeleny 1973). Since the ideal solution is infeasible, because of the inherent conflict of multiple objectives, it is necessary to look for compromise solutions. For that distances between each solution and the ideal point need to be calculated. To avoid a meaningless summation of values with different units and solutions biased towards those objectives that can achieve larger values, the normalization of the degrees is necessary. Thus the degree of closeness  $d_j$  between the  $j$ -th objective and its ideal is given by

$$d_j = \frac{|z_j^* - z_j(x)|}{|z_j^* - z_{*j}|} \quad (3.1)$$

Thereby  $x$  is a vector,  $z_j^*$  is the ideal value for the  $j$ -th objective, and  $z_j$  is the anti-ideal or nadir point for this objective. To measure the distance between each solution and the ideal point, compromise programming uses the family of  $L_p$  metrics and attempts to minimize the distance from the ideal solution (e. g. see Zeleny 1982, 322; Romero & Rehman 1989, 90; Ehrgott 2000, 90)

$$L_p(w) = \left[ \sum_{j=1}^n w_j^p \left| \frac{z_j^* - z_j(x)}{z_j^* - z_{*j}} \right|^p \right]^{1/p} \rightarrow \min! \quad (3.2)$$

That means that any point  $z(x) = (z_1(x), z_2(x), \dots, z_n(x))$  is a compromise solution if it minimizes  $L_p(w)$  for some choice of weights  $w_i > 0$ ,  $w_1 + w_2 + \dots + w_n = 1$ , and  $p \geq 1$  ( $p$  is a natural number).  $L_p(w) \rightarrow \min$  has been denoted by Ehrgott 2000, 92, the weighted compromise programming problems. It is general practice to calculate  $L_p(w)$  for  $p = 1$  (the city-block norm),  $p = 2$  (the Euclidean norm), and  $p = \infty$  (the maximum norm). The parameter  $p$  reflects the importance of the maximal deviation from the ideal point. For  $p = 1$  all deviations are weighted equally; for  $p = 2$  each deviation is weighted in proportion to its magnitude. The larger the deviation, the larger is the weight. For the case of  $p = \infty$ , we have a min-max-problem, that is, the compromise solution minimizes the maximum difference between the ideal point and the solution with respect to all objectives. The figure 3 illustrates the set of three compromise solutions for  $p = 1$ ,  $p = 2$ , and  $p = \infty$ .

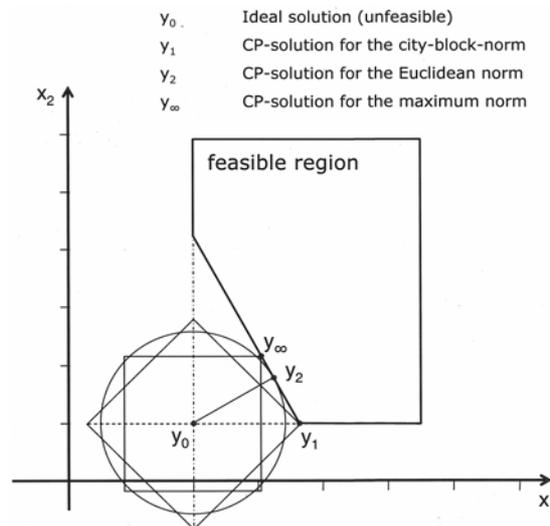


Figure 3: The set of three compromise solutions

## 4 Implementation of spatial multiple criteria evaluation of land suitability and compromise programming in GIS and application

### 4.1 Linking of MCA and CP to GIS

The rapid development of GIS has enabled the combination or integration of different methods and models. Linking of MCA-methods and optimization to GIS helps to create power tools in environmental and geographical sciences. The GIS itself becomes an integral part of methods and models by providing both the mapped variables and the processing environment. A discussion about the integration of mathematical methods and models in GIS can be found in Think (2002).

In order to combine the methodological investigations and development with the aim of applicability for spatial development, our research is referred to a special problem of sustainable land use. Because of its meaning for the EU accession states and for Eastern Germany as well as for a lot of international agglomerations the urban sprawl phenomenon is chosen. To deal with this process on a concrete level two case studies were launched, one in Hungary and one in Germany. They consider parts of the agglomeration Győr (HU) and Dresden (GE). According to the characteristics of suburbanization we have defined 8 land utilisation types (LUT): (LUT 1) Residential settlement, (LUT 2) Non-residential settlement, (LUT 3) Cropping – high input, (LUT 4) Cropping – low input, (LUT 5) Horticulture production (fruit trees, vineyard), (LUT 6) Agriculture with protection function, (LUT 7) Natural area, and (LUT 8) Forest area.

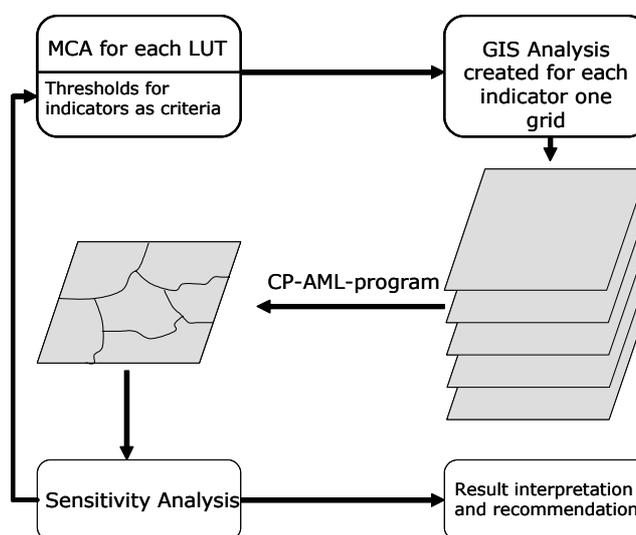


Figure 4: The workflow to linking of MCA, GIS, and Compromise Programming

	LUT1 Residential settlement	LUT2 Non-residential settlement	LUT3 Cropping – high input	LUT4 Cropping – low input	LUT5 Horticulture production	LUT6 Agriculture w. protec. func.	LUT7 Natural area	LUT8 Forest
Indicator1 Distance to existing settlement	D	D						
Indicator 2 Accessibility of railway station	D	D						
Indicator 3 Accessibility of major road	D	D						
Indicator 4 Distance to natiral areas	P	P	P	P	P	D	D	
Indicator 5 Distance to surface water	P	P	P	P	P	D	D	
Indicator 6 Soil fertility	P	P	D	D	D	D		D
Indicator 7 Zones of fresh water resource	P	P	P	P	P	D	D	
Indicator 8 Naturalness	P	P	P	P	P	D	D	
Indicator 9 Slope			D	D				D
Indicator 10 Erosions risk			P	P		D		D
Indicator 11 Risk of deflation			P	P		D		
Indicator 12 Groundwater pollution	P	P	P	P	P	D	D	
Indicator 13 Aspect					D			
Indicator 14 Risk of flooding	P	P	P	P	P	P	D	
Indicator 15 Fragmentation	P	P					D	
Indicator 16 Potential biotope network							D	D
Sum	11	11	10	10	8	9	8	4

Table 2: matrix of 8 LUT and 16 indicators (D: demand, P: pressure)

To ecological evaluation of land use options, we developed a set of 16 indicators as criteria (see table 2). It is important to distinguish between demand and pressure indicators. The pressure indicators (criteria) are to be minimized, the demand indicators to be maximized (for normalized indicators, demand: best = 1, worst = 0; pressure: best = 0, worst = 1). The suitability of each location in the study area (e. g. a grid cell in the digital database) for a specific land utilisation type can be

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determined by considering some of the 16 indicators. Each criterion is represented as a data map layer in form of a grid (see figure 4).

In this paper we should not detailed report about the estimation of the thresholds for the 16 indicators, although this working step is important and consumes so much time (see also figure 4). Examples of GIS-based development of grids for indicators can be found in Walz (2001).

Using the Arc Macro Language (AML) of ARC/INFO (ArcGIS) we developed an AML-program for the Compromise Programming and methods to estimating of weights as described in sections 2.2 and 3. To demonstrate the utility of the CP methodology as a practical multiple criteria decision analysis tool, two case studies were considered: Dresden and Győr.

#### **4.2 Application result for the case study Dresden**

The research area is situated in the southeast of Dresden, capital of the Saxony State, in the transition zone between the Elbe Valley and the eastern “Erzgebirge“ Mountains. It consists of five communities named Bannewitz, Kreischa, Dohna, Heidenau and Pirna. With an area of nearly 150 square kilometers and approximately 80.000 inhabitants (SMU 1994; Statistisches Landesamt des Freistaates Sachsen 2001) the research area is part of the suburbanisation belt around the saxonian regional capital. During the last fifty years the areas for settlement and industry in the five communities increased about 50 and 80 percent while the agricultural land decreased nearly 40 percent. This is why this region was selected as a test area.

The land suitability maps resulting from our AML-Program “CP-grid-calculation.aml” to the database of the research area in Dresden, with equally weights, are presented in figure 5. For each LUT, we have calculated CP-results for  $p = 1$ ,  $p = 2$ , and  $p = 10$  (represented for  $p = \infty$ ). A value of zero resulted from CP-grid-calculation.aml represents cells of ideal suitability for the considered land use type in all maps. The scores for the worst cells, however, range e. g. for the case of LUT 1 from 0.845 ( $p = 1$ ) to 0.112 ( $p = 10$ ), with an intermediate value of 0.272 for  $p = 2$ . This variation in range of suitability scores is a result of the different distance metrics and invalidates intermap comparisons on an interval scale. For this reason, each map has been discretized into five land suitability classes defined at ordinal levels (with equispaced intervals), which removes the effect of different data ranges and permits comparisons between the three maps for each LUT. The maps in the figure 5 reveal the sharpe contrast between  $p = 1$  and  $p = 10$ , between total compensation (that means decrease of one unit of one criterion can be totally compensated by an equivalent gain on any other criterion; this is basically equivalent to a weighted linear additive model) and total non-compensation. The case of  $p = 2$  presents partial compensation.

The histograms on the number of cells with different distances to the ideal solution (figure 6) reveal a largely lop-sided distribution amongst suitability classes to the left for the case of  $p = 1$ , and to the right for the case of  $p = 10$ .

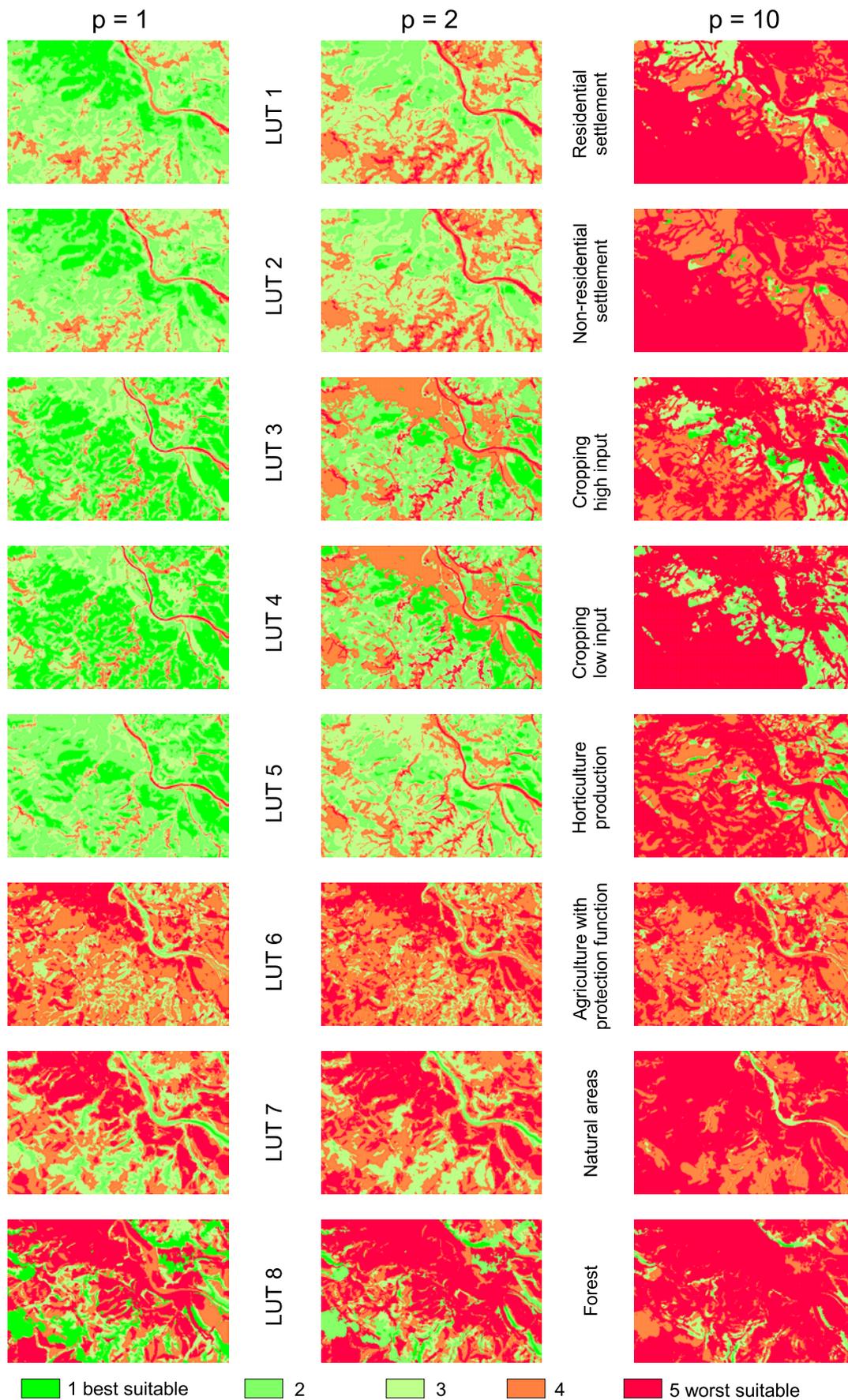


Figure 5: CP-result for the research area in Dresden

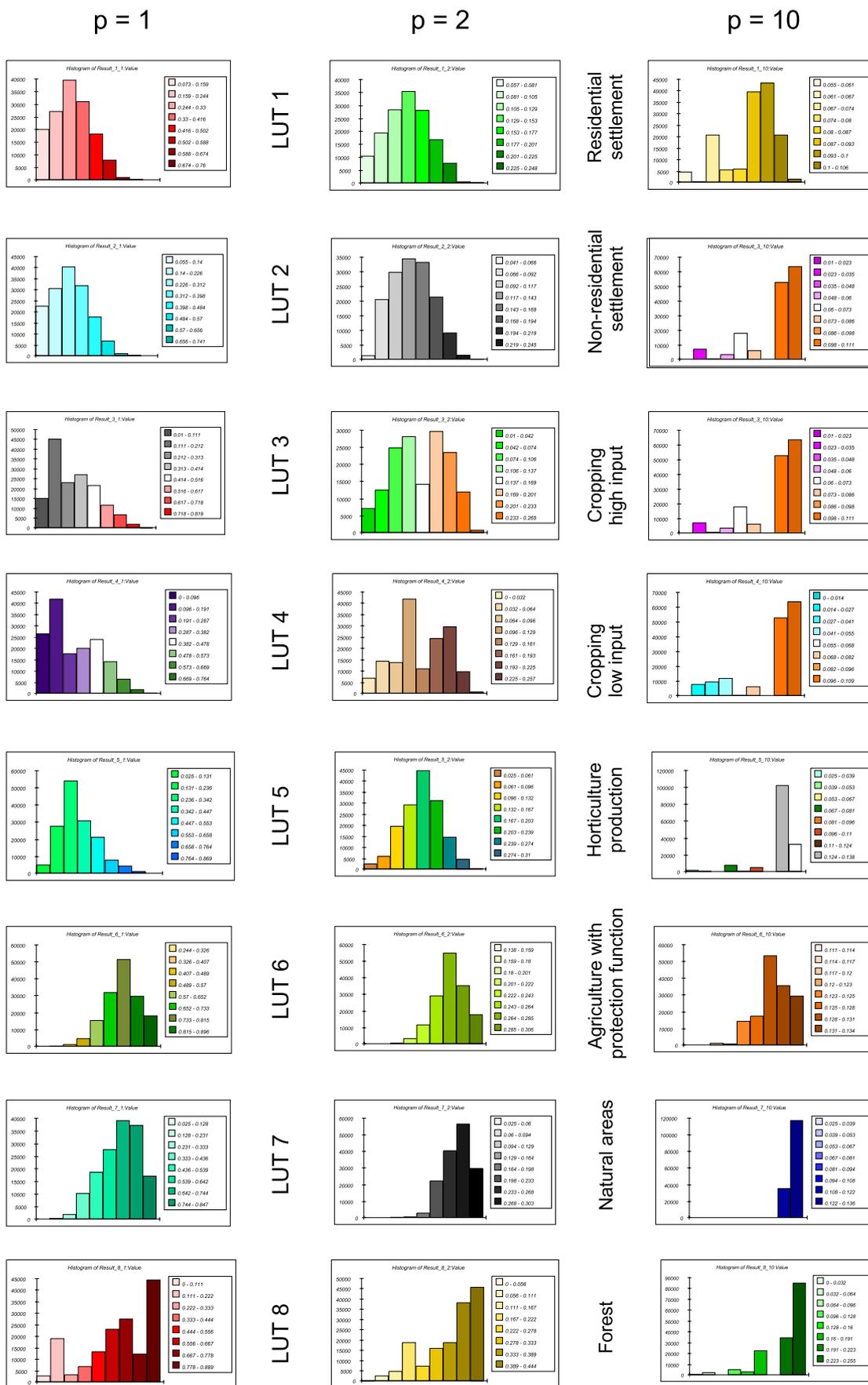


Figure 6: Histograms on the distribution of cells with different distance classes to the ideal point

### **4.3 Application result for the case study Győr**

The town Győr is situated in the west part of Hungary. It is a significant traffic and commercial centre of the region, its inhabitants exceed the 127,000. Győr has a traditional industrial background (e.g. vehicle industry), while in the surrounding settlement the agricultural activity is notable. Győr and its agglomeration is in the suburbanization phase. A significant movement is detectable from the city centre towards the surrounding settlement. According to a comprehensive research has made by VÁTI, the agglomeration ring is made up of 35 settlements. From these 10 were chosen because of unique land use demand (e.g. main road construction) and values (e.g. world heritage site). The settlements are: Gönyű, Nagyszentjános, Pér, Töltéstava, Győrújbarát, Nyúl, Écs, Pannonhalma, Györság and Bönyréta. Total area of studied area is about 307 square kilometers.

For reasons of space the results were not included in this paper. They are available upon request from the authors.

## **5 Conclusions and future research**

MCDM seems to be applicable to GIS-based land suitability analysis. CP makes it possible to investigate alternative strategies for data aggregation and their consequences. These results suggest the potential usefulness of GIS-based MCDM for other problems of land suitability analysis. Using the developed AML-program we can create a set of CP-solutions for site selection for the 8 land utilisation types. Thus we can generate several alternatives for decision support.

Three conclusions that need to be assessed at this point. First, there is the definition of thresholds for the indicators, a further investigation about the choice of threshold level should be carried out; second, the problem of dependence of the results on the ordinal definition of suitability classes should be investigated; because the largely lop-sided distribution amongst suitability classes to the left for the case of  $p = 1$ , and to the right for the case of  $p = 10$  (figure 6), another way to selection of the best suitable class is adequate, e.g. the first 10 percent of the distribution; third, the theoretical framework underlying the CP at first sight seems quite simple, but the concept of a displaced ideal (see figure 3) is a powerful paradigm competing with the traditional concept of optimality.

In the ongoing work, we will use a Fuzzy-Software-Tool developed by Wieland (2004) in order to merge the classical Compromise Programming and Fuzzy-Modeling and to create a Fuzzy Compromise Programming Environment.

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