Decision Support Systems for environmental management: a case study on wastewater from agriculture

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Abstract

Dealing with spatial decision problems means combining and transforming geographical data (input) into a resultant decision (output), interfacing a Geographical Information System (GIS) with Multi-Criteria Decision Analysis (MCDA) methods. The conventional MCDA approach assumes the spatial homogeneity of alternatives within the case study area, although it is often unrealistic. On the other side, GIS provides excellent data acquisition, storage, manipulation and analysis capabilities, but in the case of a value structure analysis this capability is lower. For these reasons, several studies in the last twenty years have given attention to MCDA-GIS integration and to the development of Spatial Decision Support Systems (SDSS). Hitherto, most of these applications are based only on a formal integration between the two approaches. In this paper, we propose a complete MCDA-GIS integration with a plurality of MCDA methodologies, grouped in a suite. More precisely, we considered an open-source GIS (GRASS GIS 6.4) and a modular package including five MCDA modules based on five different methodologies. The methods included are: ELECTRE I, Fuzzy set, REGIME analysis, Analytic Hierarchy Process and Dominance-based Rough Set Approach. Thanks to the modular nature of the package, it is possible to add new methods without modifying

the existing structure. To present the suite, we applied each module to the same case study, making comparisons. The strong points of the MCDA-GIS integration we developed are its open-source setting and the user friendly interface, both thanks to GRASS GIS, and the use of raster data. Moreover, our suite is a genuine case of perfect integration, where the spatial nature of criteria is always present.

Keywords:

GIS

Multicriteria analysis

GIS-MCDA integration

Spatial Decision Support Systems

Modular package.

1. Introduction

Several fields of research may benefit from the integrated use of geographical information systems (GIS) and Multi-criteria analysis (MCDA): environmental and land management issues, or territorial and urban analysis, just to give a few examples, face spatial multi-criteria decision problems. In a spatial multi-criteria decision problem, geographical data (input) is combined and transformed into a resultant decision (output) (Laskar, 2003; Malczewski, 1999; Malczewski, 2006). One method of dealing with this matter is to interface a Geographical Information System (GIS) with Multi-Criteria Decision Analysis (MCDA) methods (Drobne and Lisec, 1998; Malczewski, 2006).

MCDA methods are basic tools in the field of environmental valuation and management; environmental management is a multidimensional challenge, and MCDA is able to support decision-making, involving several different aspects to be taken into account at the same time. But MCDA methods cannot easily take into account the geographical dimension (Laskar, 2003). The conventional MCDA approach assumes the spatial homogeneity of alternatives within the case study area (Figuera et al., 2005), although this is often unrealistic, because evaluation criteria may vary across the space (Jankowski, 1995, Laskar, 2003). If alternatives have a geographical nature, classifying, ordering or choosing operations also depends on their spatial arrangement (Laskar, 2003), and both value judgments and geographical information are needed to define them (Laskar, 2003). Spatial MCDA problems are, for instance, location choice or land suitability (Geneletti and van Duren, 2008; Goncalves Gomes and Estellita Lins, 2002; Joerin et al., 2001; Johnson, 2005; Maniezzo et al., 1998; Ruiz et al., 2012; Sahnoun et al., 2012; Scheibe et al., 2006), as in the present application.

In a Spatial MCDA, geographical data (input maps) is combined and transformed into a decision (output maps) (Drobne and Lisec, 2009; Jankowski, 1995; Malczewski, 1999). Therefore, both the MCDA framework and GIS possibilities are required in spatial, multi-criteria evaluation, and their integration has become one of the most useful approaches in environmental management and planning (Chang et al., 2008; Chen et al., 2010, Papadopoulou-Vrynioti et al., 2013; Rahanaman et al., 2012; Zucca et al., 2008). Several studies over the last twenty years have thus focused on MCDA-GIS integration and on the development of Multi-criteria Spatial Decision Support Systems (MCSDDS) (Chakhar and Martel, 2003; Jankowski, 1995; Lidouh, 2013; Malczewski, 2006) as a fundamental instrument for managing the environment (Rahanaman et al., 2012; Zucca et al., 2008). Web GIS-MCDA applications have also been developing in very recent years (Bouroushaki and Malczewski, 2010a; Karnatak et al., 2007). Although several applications and examples of GIS-MCDA integration are found in the literature, there are fewer studies concerning the development of a theoretical framework (Chakhar and Mousseau, 2007; Chakhar and Mousseau, 2008).

The objective of this study is to present a new MCDA-GIS integration tool and its use in land management problems, as the land application of wastewater from agricultural activities. We developed a modular suite (*r.mcda*) based on different Multi-Criteria Decision Analysis methodologies in an open-source GIS (GRASS GIS 6.4) (Massei et al., 2012).

The paper is structured as follows: Section 2 describes the methodology; Section 3 presents the case study; Section 4 reports the results; Section 5 is the discussion. The paper ends with the main conclusions.

2. Methodology: MCDA-GIS integration

The multi-criteria spatial decision support system (MCSDSS) can be considered a specific part of the more general group of spatial decision support systems (SDSS) (Ascough et al., 2002). SDSSs have received a great deal of attention from researchers, since their usefulness in spatial decision problems has been clearly demonstrated (Crossland et al., 1995): SDSSs produce more efficient results in a shorter solution time.

An MCSDSS consists of three components (Ascough et al., 2002; Laskar, 2003; Malczewski, 2010): a geographical database and the relevant management systems, an MCDA model-based management system, and an interface.

According to certain authors (Chakhar and Martel, 2003; Laskar, 2003), it is possible to classify MCDA-GIS integration in three ways. The basic step is MCDA-GIS indirect integration: MCDA and GIS models are separated, and linked through an intermediate connection system, handled by the analyst. Each part has its own database and its own interface, which may affect their interaction. This procedure has the advantage of its low development cost, but the separation of MCDA and GIS parts makes it difficult to completely comprehend the spatial nature of the problem (Lidouh, 2013). Moreover, errors may occur during the transfer, due to the human element involved (Lidouh, 2013). There are some examples of this type of integration (Cavallo and Norese, 2001; Chang et al., 2008; Geneletti, 2004), where the complexity of the analysis is nevertheless quite high. The second type of system is represented by MCDA-GIS tools (Laskar, 2003), in which the multi-criteria component is integrated into the GIS system, but remains independent from a logical and functional point of view. In particular, the MCDA part has its own database, whereas the interface is the same. There is no need for an intermediate system, and the exchange data and analysis between the two parts are performed directly, which is a good step forward compared to indirect integration (Chakhar and Martel, 2003). It is a sort of one-directional integration (Malczewski, 2006), where one of the two softwares works as the main software. This type of integration is the one most successfully applied (Lidouh, 2013).

It is only at the third level, known as complete, or full MCDA-GIS integration (Greene et al., 2010; Laskar, 2003), that the two systems use the same interface and the same database. The MCDA model is activated inside the GIS software in the same way as any other analysis function (Chakhar and Martel, 2003). In a full-integration scheme, the user can access both the MCDA and the GIS tools at any time during analysis, and interaction is complete: it is possible to change the parameters and the methods, visualise results or the spatial elements (Lidouh, 2013), until the goal of the research is achieved.

As Lidouh reports (2013), some integration options are also possible in well-known commercial software, such as ArcGIS by ESRI (Lidouh, 2013). The weak point of the applications implemented in commercial software lies in the very nature of the products. In ArcGIS, for instance, the researcher cannot choose the algorithms he wishes to include, and he cannot improve them since ArcScripts closed down. Moreover, frontier methods are excluded, since preference is given to the most widely used and most well-known methods. In contrast, open-source options give more possibilities for developing new tools, even though there are few open components (Lidouh, 2013). The modular suite *r.mcd*, based on five different Multi-Criteria Decision Analysis methodologies presented in this paper, is developed in GRASS GIS 6.4 svn (Grass Development Team, 2002a, Grass Development Team, 2002b). As all geographical processing in GRASS GIS is carried out by separate modules, we developed our Multi-Criteria tools as modules. We chose GRASS GIS for our application because it is an advanced and well-known open-source GIS software (Frigeri et al., 2011), used for geospatial data management and analysis, image processing, graphics/maps production, spatial modelling and visualisation. Since its first release in 1982 (Frigeri et al., 2011),

GRASS GIS has been increasingly used by academic and commercial settings all around the world, as well as by many governmental agencies and environmental consulting companies, for a wide range of possible applications (Estalrich, 1998; Grass Development Team, 2002a; Grass Development Team, 2002b; Li et al., 2010; Massei et al., 2012; Neteler and Mitasova, 2008). Moreover, it is written in the C language, and its open libraries and GPL license make it possible to easily develop new modules (Estalrich, 1998; Grass Development Team, 2002a; Grass Development Team, 2002b; Neteler and Mitasova). In GRASS GIS, new modules can be added using the C language, Bash Shell and Python (Grass Development Team, 2002a; Grass Development Team, 2002b), and then they are available for all the users on the GRASS GIS repository. In our application we used the C and Python languages, and it will be possible to add new MCDA modules using these languages.

The great advantage of the *r.mcda* suite is the open nature of GRASS GIS. This allows a real improvement of the tool, because all GRASS GIS users can potentially modify the existing modules or perfect the algorithm applied. The possibility of adding new methods is also another great advantage, because it enables the scientific evolution of MCDA to be followed up. The presence of a wide range of methods enables the best algorithm to be applied for the specific problem. The selection of the right method for each problem is still an open question in the field (Guitouni and Martel, 1998; Roy and Slowinski, 2013; Zopounidis and Doumpos, 2002).

The methods used in the modules¹ are ELECTRE I (Roy 1991; 1997), Fuzzy set (Yager, 1977; 1988; 1993), REGIME (Hinloopen et al., 1986; Nijkamp and Hinloopen, 1990), Analytic Hierarchy Process (Saaty, 1977; Saaty, 1992) and Dominance-based Rough Set Approach (DRSA) (Greco et al., 2001). This last module in particular represents the first implementation of the DRSA in a geographical context.

The name of each module, based on GRASS GIS, is structured as follows: *r.mcda.[algorithm]*. Prefix *r* refers to raster data, *mcda* is the name of the suite, whereas the *[algorithm]* has to be substituted by the name of the MCDA method applied. For instance, the module corresponding to the ELECTRE I method is named *r.mcda.electre*, and so on. The modules use and process raster, and therefore the outputs are raster. The spatial nature of the data is always present in the multi-criteria process, because the basic unit of analysis is the single cell. This is not possible in the case of indirect integration.

Each criterion in all the modules is represented by a raster map (criterion map), which describes how the attribute is distributed in space. Each cell of the GRASS region stands for an alternative, and is described by means of the value assumed for the same cell the raster used as its criterion. The assignment of weights depends on the method applied.

More details about the methods applied in the case study can be found in sections 2.1 to 2.3.

2.1. *r.mcda.fuzzy*

This module is an implementation of the fuzzy multi-criteria classic algorithm proposed by Yager (1977; 1988; 1993) in a GRASS GIS environment. Judgements cannot be clearly defined in a fuzzy model, but they coincide with fuzzy subsets. A fuzzy subset is defined by non-numeric linguistic variables. The weighting process is expressed by linguistic modifiers, such as “much more” or “little more”. In the model, the affiliation degree for each alternative is valued as the degree of achievement of the goals. Different operators are possible to aggregate the objective. The MIN operator represents the intersection (AND) and requires all criteria to have been satisfied. Compensatory effects are not feasible. On the other hand, the MAX operator, representing the union (OR), allows compensation. The previous two operators are quite rigid: a compromise is the ordered weighted averaging (OWA) operator, which allows a judgement to be made for most of the criteria. The inputs required by the module are the list of the raster representing the criteria to be assessed in

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¹ All the modules are free to download from the GRASS GIS repository <https://svn.osgeo.org/grass/grass-addons/grass6/raster/mcda/>

the multi-criteria evaluation and the vector of linguistic modifiers to be assigned. The outputs are three different maps, which are the results of the intersection (or MIN), the union (or MAX) and the ordered weighted averaging (OWA) operators. Some Ordered Weighted Averaging (OWA) applications in spatial analysis have already been implemented (e.g. Bouroushaki and Malczewski, 2010a; Chang et al., 2008; Rahaman et al., 2012).

2.2.r.mcda.ahp

This module represents the implementation of the Analytical Hierarchy Process (AHP), as introduced by Saaty (1977), in GRASS GIS. The AHP is quite a popular decision tool, especially in engineering, science and economic applications (Bathrellos et al., 2012; Bathrellos et al., 2013; Figuera et al., 2005; Lidouh, 2013; Panagopoulos et al., 2012; Triantaphyllou, 2000). It is very popular, as it is highly flexible and can be applied by groups of decision makers. Moreover, the AHP is particularly suitable for spatial decision analysis with a large number of criteria (Lidouh, 2013), and it is one of the most popular MCDA methods for spatial problems (cf. Bottero et al., 2012; Farkas, 2009; Suarez-Vega, 2011).

The AHP is based on the general theory of the ratio scale measurement, based on mathematical and psychological foundations (Karnatak et al., 2007). The method is based on three principles: decomposition, comparative judgements and a synthesis of priorities (Saaty, 1977). Decomposition of the problem into hierarchy independent sub-problems makes it more understandable by capturing all the essential elements. The levels of the hierarchy may be expanded as needed; they represent the minimum objectives, criteria and alternatives. The comparative step is based on a pair-wise comparison of the decomposed elements, as regards their impact on the element above them in the hierarchy. This step establishes the priorities and weights. The weights are usually assigned using a nine-point scale, known as Saaty's scale (Saaty, 1977). In the final step, an analytic (numerical) synthesis is carried out. The priorities of alternatives are synthesised into an overall set of values indicating the relative importance of each factor at the lowest level of hierarchy (Laabiri, 1996).

The inputs required by *r.mcda.ahp* are the list of criteria maps and the table with pair-wise comparisons for each criterion. The criteria maps for this module have to be normalised on the same scale (Millet and Saaty, 2009). As for the other modules, every single cell of the GRASS region is considered as one of the possible alternatives to evaluate, and is described with the value assumed for the same cell used by the raster as criteria. Three outputs are produced by the *r.mcda.ahp* module: the eigenvalue, the eigenvector and the synthesis map. The eigenvalue and eigenvector represent the results of the decomposition and of the comparative judgements, whereas the synthesis map represents the final step, i.e. the analytic results.

2.3.r.mcda.roughset

Whereas all four methods described above can be considered the “classical tools” of MCDA, the 5th introduced in *r.mcda* can be considered as belonging to the frontiers of research. The Dominance-based Rough Set Approach (DRSA) (Greco et al., 2001; Greco et al., 2000) differs from the majority of the other MCDA methods, since it does not consider weights as representing the importance of the considered criteria. To fix the weights of the criteria, the DM is often asked to answer questions that require considerable cognitive effort, which reduces the reliability of the preferential information obtained in this way. Thus, the absence of weights constitutes a strong point of the DRSA. In the DRSA, the request for more or less direct information about the weights from the DM is replaced by the request for exemplary decisions in terms of the classification into predefined classes of some minimal units, well known to the DM. As a result of the application of the DRSA methodology, the DM is supplied with some “if..., then...” rules, explaining the exemplary decisions. These rules are then used to classify all the minimal units of the GIS. One advantage of the integration of DRSA with GIS is that the exemplary decisions require a lower cognitive burden with respect to the inputs required by other MCDA methods (e.g. weights of criteria). Furthermore, the decision rules and the results of their applications are easily

understandable, as they are expressed in a natural language. In the Dominance-based Rough Set Theory, there are three types of rules: certain, possible and ambiguous. The rules in the module are derived from a raster map, which includes a thematic key, essential for the analysis. The module produces both textual and graphical outputs, which represent the rules found.

Several algorithms are available to implement DRSA. One of the most well-known and widely used is the iterative algorithm DOMLEM (Greco et al., 2001), which is implemented in the *r.mcda.roughset* module. Other recent algorithms are the VC-DOMLEM (Blaszczynski et al., 2009; Greco et al., 2001; Greco et al., 2000; Zurawski, 2001), ALL RULES (Zurawski, 2001) and the Glance algorithm (Zurawski, 2001). Zurawski, 2001 made a comparison between several algorithms in terms of accuracy and found DOMLEM to be the most accurate, particularly in the case of large datasets. Thus, DOMLEM appears particularly suitable for GIS applications.

The *r.mcda.roughset* is also the first spatial implementation of the DRSA. None of the software packages available for DRSA applications enable spatial data to be managed (<https://idss.cs.put.poznan.pl/site/software.html>). However, one of the output text files (*.ifs extension) is compatible with 4emka2, Jamm and JMAF (Blaszczynski et al., 2009; Blaszczynski et al., 2010), which are three software packages developed by the Poznan University of Technology. Thus, it is possible to control the results produced by the module and to improve the analysis.

3. Case Study

The production of olive oil also involves the production of a great amount of olive mill wastewater (OMW), including liquid and solid parts (Paredes et al., 1999). OMW comes mainly from vegetable and operational water. The latter is one of the main environmental problems concerning the oil industry in Mediterranean basin (Paredes et al., 1999; Mechri et al., 2007). The production of wastewater is particularly relevant when using three-phase continuous centrifugation, which is the popular method (Saady et al., 2007). In Italy, OMW is not considered a waste, if applied under strict conditions to the land. Its incorrect application may cause the gradual accumulation of dangerous substances in the soil, while correct use may increase soil fertility (Mechri et al., 2007). The definition of suitable areas for land application is both an economic and an environmental management problem (Kalogerakis et al., 2013; Mechri et al., 2007). Moreover, it is a multidimensional, spatial issue, manageable thanks to an MCDA approach. Therefore, it could be considered a perfect example of a spatial multi-criteria analysis.

This study dealt with the need to classify the soil of the province of Perugia (central Italy – Fig.2) into classes of suitability for the land application of OMW. The potential area considered was agricultural land with a maximum slope of 15% and an elevation below 800 MASL. The selected area was classified into 5 homogeneous sets.

To analyse the issue, we used three different methods, all included in the *r.mcda* suite: the fuzzy set, AHP and DRSA. The fuzzy set was chosen because it produces two very different answers, which represent the interpretation of the sustainability paradigm (Daly and Cobb, 1990). AHP was also the most used MCDA method in spatial analysis (Rahman et al., 2012). The final method, the DRSA, is one of the most innovative in the family of MCDA and its application in a geographical context is still rare.

As Roy and Slowinski argued (2013), to select the best multicriteria methods, the analyst should consider which type of results the selected method produces, so as the type of elaboration of relevant answers asked by the decision maker solves. The type of results produced is a feature which distinguishes various MCDA methods (Roy and Slowinski, 2013). According to Roy and Slowinski (2013), the methods applied in the present study produced, as results, a numerical value (utility, score) assigned to each potential action (AHP), a set of ranked actions completely or partially ordered (DRSA), and the classification of each action into one or several categories which were defined a priori (DRSA, Fuzzy Set). All these types of results could be very useful in a problem such as land application of OWM. In this paper, some considerations on the comparison of the selected methods will be proposed, to better understand the pro and cons and which type of answers of DM it is possible to solve.

To evaluate the suitable areas for the land application of OMW, eight raster criteria were selected, as reported in Table 1. The criteria used are linked not only to the sensitivity of the alternatives to wastewater uses (ground vulnerability; altitude; slope) or to the intrinsic characteristics of the soil (hydraulic conductivity, crusting index; pH; organic matter), but also to economic considerations (distance from the olive press plant). Hydraulic conductivity and crusting index are presented grouped together because they both reduce the runoff risk, increasing the capability of the soil to receive the wastewater. The pH and organic matter criteria are also grouped together because both improve the soil purification and protective capacities. Each criterion has been standardised to between 0 and 1, where 1 is considered the most desirable value. It was then "weighted" using the SWING procedure (Hayashi, 1998). Table 1 also reports the normalised weights (column 3) of each criterion and the indication "gain" or "cost" referred to the criteria, which is a requirement of the DRSA approach. The criterion *ground water vulnerability* criterion is expressed in the application as a gain, because the lowest vulnerability class is the 5th. Nevertheless, Table 1 shows it as a cost, because the higher the vulnerability, the lower the suitability of the ground. Included in the fourth column are the functions used for the standardisation of the criteria, while column 5 gives the GRASS GIS string used for this standardization.

The DRSA module also needs a decision map as input, based on simulated or real decision data. In this case, the decision map is based on previous applications of wastewater in the area, including both professional applications and field experiments. The criteria in the decision map are classified only as gains or costs. Note that, in this case, no weight is used. The decision map can be created from the opinions of the DMs or from experimental data, as in this case.

4. Results

The graphic output of the three modules are presented in this section, whilst the different results are compared and considered in the discussion section. The red areas (class 1) in all the maps shown are the least suitable for wastewater applications; the blue areas are the most suitable.

The *r.mcda.ahp* output is shown in Figure 4. The module also produces the eigenvalue and the eigenvector, used to calculate the weight vector. The areas selected are quite a few, as clarified in the discussion.

The *r.mcda.fuzzy* module produces three outputs, each based on a different fuzzy operator. Figure 5 shows the result based on the intersection operator (OR) on the left, and the result based on the union operator (AND) on the right. The second is more conservative than the first, as we can see by comparing the best class of both right and left. The two maps are fairly contrasting, whereas the results of the OWA operator are intermediate (Fig. 6). Figure 6 reports the results of the OWA operator, representing the ordered weighted averaging operator. The OWA operator shows average results, compared to the union and the intersection operators (Fig. 6).

The *r.mcda.roughset* module produces several outputs, based on the classification rules produced. Figure 7 shows all the areas which can be classified as at least in class 2, 3, 4 or 5. All the rules that grade the alternatives in the same "at least" class are grouped in the same map. Figure 8 shows the areas classified at most in class 4, 3, 2, 1.

The module can also produce a synthesis map, which reports all the areas classified in the different classes, according to the "at least" and "at most" rules. However, this synthesis map is quite difficult to interpret, especially when several classes are present. Moreover, some rules can be obscured by others. Therefore, we preferred not to produce the synthesis map and reported all the "at least" and "at most" maps separately.

In addition to the raster maps, the *r.mcda.drsa* module also produces a text file, which reports all the rules generated. This application produces 201 rules. Table 2 gives some of those rules. The first column gives the progressive number of the rule, and then the conditions and the class assigned by them are given. The degree of complexity of the information varies across the rules. For instance, rule no. 4 is very short ("if the organic matter is equal to or less than 0.778 and the pH is equal to or less than 6.402, then the alternative is at most in class 1") in comparison to rule no. 201 ("if the crusting index is equal to or less than 0.656, and hydraulic conductivity is equal to or greater than

0.003, and the elevation is equal to or less than 414 MASL, and distance from the oil mill is equal to or less than 7534.840 m, and ground vulnerability is equal to or greater than 5, then the alternative is at least in class 5”). The text file allows the analysis of the rules. It makes it possible to understand which criterion is decisive for the attribution of alternatives in any particular group compared to another. In other words, it allows a perfect understanding of the results. The DRSA approach is a glass box, where all the results are traceable (Greco et al., 2001, Greco et al., 2000). Moreover, the presence of the rules file allows further processing, other than spatial.

5. Discussion

Each module produces its own results, which can be interpreted singularly or, in this application, in comparison with the others. Although results could seem similar, they give different answers to the same problem (Roy and Slowinski, 2013).

The results proposed by *r.mcda.ahp* are directly readable. The module produces a single synthetic map, which is also directly and easily readable by a non-expert user, as DMs often are. The map (Figure 4) represents the final classification of the area. The results proposed by *r.mcda.fuzzy* are more complex to interpret. Each of the three maps produced by the module has a very different meaning. The map based on the intersection operator, which can be associated with the logical AND, is found on the strong sustainability paradigm (Daly and Cobb, 1990). The intersection operator is the most conservative, as it minimises the values assumed by the criteria. On the other hand, the union operator, which can be associated with the logical OR, is based on the weak sustainability paradigm (Daly and Cobb, 1990), because it allows the compensation of bad performances. Although the two approaches are both useful, it could sometimes be difficult to interpret the opposing results. The OWA otherwise gives intermediate results, thanks to the use of an ordered weight. Nevertheless, it is always important to process all three maps, especially in the case of environmental evaluation, to provide the decision maker with a more complete framework. Moreover, the use of the three maps together enables different sustainability scenarios to be evaluated. In our opinion, the use of only one operator may give distorted solutions, whereas by using all three options, the DM can evaluate all three cases and choose the best according to his/her view on governance.

An accurate statistical analysis of the results is beyond the scope of this section, but it could be a future development of research. However, the qualitative analysis we carried out brings to light some interesting details. We used the software R within GRASS GIS, by means of the *spgrass* interface; Figures 9 and 10 and Table 3 give the results of the analysis.

Table 3 gives some univariate statistics regarding the frequency, while Figure 9 is the representation of such values. Table 3 gives the number of cells classified, the minimum, maximum and the average values assumed by them, and other statistical indices as the standard deviation or the variation index, which represent the ratio between standard deviation and the average.

The different behaviour of the fuzzy operators used can be analysed by histograms showing the distribution of the output frequency of the values assumed by each cell of the raster map, reported in Figure 9. The comparison between the histograms based on the AND/ OR operators clearly shows the different approach in terms of sustainability. The high frequency of cells close to the unit value (maximum preference condition) in the case of the OR operator is congruent with the approach of weak sustainability, whereas the opposite condition is found for the AND operator. In other words, the OR operator gives us a large number of cells which have the maximum preference values. The same cells are classified by the AND operator with values, which are always below 0.8. To confirm such a statement, one may refer to Table 3. The indices prove the different behaviour of the union and intersection operators, as well as the intermediate condition of the OWA operator. However, in this case, the OWA operator tends towards the highest levels of preference.

Using the same type of analysis, it is possible to evaluate the results produced by the AHP modules. The distribution of the cell values, in that case, appears to be more balanced. The histogram assumes a Gaussian shape trend, with the average value close to 0.5 and the mode value which almost coincides with the latter.

Figure 10 represents a Scatterplot Matrix, which allows a quick, visual comparison to be made of processing, built up using the results produced by the `r.macda.ahp` and `r.mcda.fuzzy` modules. A Scatterplot Matrix is a squared table, where the correlation of the column-row represents the scatterplot between the raster output maps. Modules appear in the same order on the rows and on the columns; namely:

1. `r.mcda.ahp`;
2. `r.mcda.fuzzy` (intersection);
3. `r.mcda.fuzzy` (OWA);
4. `r.mcda.fuzzy` (union).

Scatterplot results used in the scatter analysis are reported on the main diagonal, with the names of the method applied. Looking at Figure 10, the absence of coordination between the results produced by the union and intersection operators and the other modules is quite clear. This is due to the intrinsic characteristics of the two methods, which base evaluation on the best or worst case. This problem is overcome by the OWA operator. In general, there is a certain degree of correlation between the results obtained by the different methods, although with a difference in the degree of scattering.

As regards the DRSA module, we preferred not to compare its results with the others, because the `r.mcda.roughset` is quite different from a methodological point of view. The dominance-based rough set theory (DRSA) required an a priori knowledge of the decision areas, but it overcame the problematic phase of weighting. On the contrary, the other methods do not need such knowledge, although all of them require a weighting phase. It is clear, therefore, that a comparison between DRSA and the other methods could be particularly complex.

The output produced by `r.mcda.roughset` is also quite complex to understand, due to the many levels of information given. Although it is possible to produce a synthesis map based on all the rules, the analysis of the separate results could be more interesting and readable. The maps reported in the case study include all the areas that satisfied the rules to be at least or at most in certain classes. Therefore, the maps are not related to one single class. For instance, the first map on the left in Figure 8 includes all the areas that, according to the rules, can be classified at least in class 2; therefore, we are sure that each area in the map is in class 2, 3, 4 or 5, but not in class 1. The separation of the rules allows for checking concealed effects among them. As a matter of fact, the spatial arrangement of the rules may cause a part of them to be covered. It is of course possible to extract the data of a single class, and all the related maps can be prepared by considering the preference of the DMs. The module produces a text file to provide a better understanding of the maps. The text file gives all the rules each map produces. It enables the construction of the maps to be understood in detail. Moreover, the file is very useful for doing a cross-check with the classical, non-spatial approach.

Although the module is based on the minimal algorithm (DOLEM), in some cases the geographical nature of the processing produces redundant rules. Moreover, the `.rls` and `.isf` file can be used for analysis with different algorithms, which the `r.mcda.roughset` does not allow. Thanks to another module (`r.in.drsa`), such non spatial results can be imported into the module.

The results of the analysis made with the `r.mcda.drsa` appear more complex when compared with the other two, and to some extent they are. However, the more accurate and numerous outputs enable further processing. A more detailed knowledge of reality is a great advantage, although it requires a greater effort by the analyst to support the DMs.

6. Conclusions

The main aim of this paper was to present a new MCDA-GIS integration tool and its potential. Although GIS-MCDA integration is at present an interesting and well-developed field of research, there are few examples of perfect or almost perfect integration using existing GIS software. Applications are more commonly based on a formal integration of the two approaches. There is generally a better integration if SDSS are considered. The disadvantages of SDSS are linked to the number of users and to the peculiarity of the tool. Moreover, in our opinion, the possibility of a geographical tool in spatial analysis is greater than that of a SDSS.

Our application is a contribution towards this. We developed five GRASS modules that enable five different MCDA methods to be implemented: the REGIME, the Fuzzy, the ELECTRE I, the AHP and the Dominance-based Rough Set Approach (DRSA). One of the main advantages of our application over previous applications is the presence of a community which leaves room for improvement of the suite.

The presence of several modules is also an advantage. The selection of the right method to be applied in each problem is still an open question in the field, so the presence of different modules in the same suite makes it possible to better deal with the matter. In our application, we tried to analyse the same case study by means of three modules, as comparative studies based on different methods are considered helpful to better understand the application potentiality of MCDA algorithms. In this case, it was done to explain the reasons, whereas it is very important in real life applications to choose the best method for the case study.

Another advantage over other MCDA-GIS integrations is the development in GRASS GIS 6.4. GRASS is a well-known, widely used, open-source software. The number of potential users for the suite is higher than in the case of owner software. In our opinion, it is better to integrate MCDA in an already well-known GIS software than to develop Spatial Decision Support Systems. First and foremost, there is a large number of potential users, who already know the geographical software. In addition, there are greater possibilities of being able to add non-MCDA-based processing to the results by using, for instance, GRASS GIS. Finally, there is a large number of geographical tools present in GRASS GIS. A complete GRASS GIS tool needs good tools both for the MCDA and for a geographical analysis.

The case study presented here helped us understand some peculiar characteristics of MCDA-GIS integration. First of all, although we used a very easy case, the results did not always completely agree with one another, whereas they did relate to each other to a certain degree. As expected, fuzzy union and intersections gave different results from the others. Integration requires not only the MCDA, but also the geographical part.

In future, we would like to improve some of the mathematical aspects of the modules by adding, for instance, other operators to the r.mcda.fuzzy module, such as the t-norm and t-conorm, which are generalisations of the minimum and maximum operators. We would like also to work on the DRSA module, because we think it is the most powerful for territorial and environmental evaluation. In particular, it would be interesting to introduce other algorithms, such as the V-DOLEM. A more accurate analysis from a statistical point of view is required, to improve the comparison between the MCDA tools.

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Table 1 Criteria: meaning, weighting and standardization

Criteria		Weighting	Standardization	Grass Gis commands used for standardization
Capability to receive wastewater avoiding runoff risk	Hydraulic conductivity [Saxton et al., 2006]	0.8 Gain		r.mapcalc 'hydraulicConductivity_norm=if(slope<15 && elevation<800 && Soil>0, hydraulicConductivity/0.03413,null())'
	Crusting index (CI = (1.5Zf + 0.5Zc)/(C+10M)) [Calzolari et al., 2009]	0.8 Cost		r.mapcalc 'CrustingIndex_norm=if(slope<15 && elevation<800 && Soil>0,((14.7566071213427-CrustingIndex)/(14.7566071213427))*0.8,null())'
Soil purification and protective capacity	pH (opt.7)	0.5 Gain if pH<7 Cost if pH>7		r.mapcalc 'pH_norm=if(slope<15 && elevation<800,(exp((2.71828),-(exp((pH-7),2))))*0.5,null())'
	Organic matter	0.5 Gain		r.mapcalc 'OrganicMatter_norm=if(slope<15 && elevation<800 && Soil>0,(OrganicMatter /35.51937)*0.5,null())'
Ground water vulnerability (PTCP tav A.1.4)		1 Cost*		r.mapcalc 'vulnerability_norm=if(slope<15 && elevation<800 && Soil>0,((vulnerability)/6.0*1),null())'
Altitude (0 - 800 m) (DEM ASTER 30m)		0.4 Cost		r.mapcalc 'elevation_norm=if(slope<15 && elevation<800 && Soil>0,((800.0-elevation)/800.0*0.4),null())'
Slope (0- 15%) (DEM ASTER 30m)		0.8 Cost		r.mapcalc 'slope_norm=if(slope<15 && elevation<800 && Soil>0,((15-slope)/(15))*0.8,null())'
Distance from the olive press plants		0.6 Cost		r.mapcalc 'distance_norm=if(slope<15 && elevation<800 && Soil>0,((63489.6767961233-distance)/(63489.6767961233))*0.6,null())'

Table 2: DRSA rules. In Table 2 few examples of the rules among the 201 produced by the module are reported.

ID Rules	Condition	& Condition	& Condition	& Condition	Classification
4	OrganicMatter<= 0.778	& pH_acid<=6.402			Then Class at_most, 1
67	OrganicMatter<= 1.936	& Distance>=4681.719	& pH_basic>=7.582	& HydraylicConductivity<= 0.005	Then Class at_most, 2
92	CrustingInde>=1.100	& Distance>=4798.526	& HydraylicConductivity<= 0.006		Then Class at_most, 3
106	Elevation>=486.000	& Distance>=4798.526	& pH_basic>=8.062		Then Class at_most, 4
134	Slope<=13.676	& HydraylicConductivity>= 0.003	& CrustingIndex<= 1.110		Then Class at_least, 2
151	Distance<=4375.109	& OrganicMatter>= 3.021	& pH_basic<=7.994		Then Class at_least, 3
189	OrganicMatter>= 3.557	& Distance<= 7944.309	& Elevation<=346.000		Then Class at_least, 4
201	CrustingInde<=0.656	& HydraylicConductivity>= 0.003	& Elevation<=414.000	& Vulnerability>= 5.000	Then Class at_least, 5

Table 3: Basic statistics for the OR, AND and OWA operators and for the AHP module.

AHP univariate statistics n: 612149 minimum: 0.310844 maximum: 0.747831 range: 0.436986 mean: 0.51706 mean of absolute values: 0.51706 standard deviation: 0.0626742 variance: 0.00392806 variation coefficient: 12.1213 % sum: 316517.546993785	<i>Fuzzy intersection univariate statistics</i> n: 612005 minimum: 0 maximum: 0.967482 range: 0.967482 mean: 0.65778 mean of absolute values: 0.65778 standard deviation: 0.115281 variance: 0.0132897 variation coefficient: 17.5258 % sum: 402564.611175082
Fuzzy union univariate statistics n: 612005 minimum: 0.951925 maximum: 1 range: 0.0480752 mean: 0.995036 mean of absolute values: 0.995036 standard deviation: 0.0031565 variance: 9.9635e-06 variation coefficient: 0.317225 % sum: 608967.045147665	Fuzzy OWA univariate statistics n: 609476 minimum: 0.750897 maximum: 1.07507 range: 0.324175 mean: 0.965809 mean of absolute values: 0.965809 standard deviation: 0.0279385 variance: 0.000780558 variation coefficient: 2.89275 % sum: 588637.663073554

Figure 1 represents a Decision flowchart for spatial multicriteria analysis, proposed by [40]. In the flowchart GIS and MCDA parts are clearly tightly bound.

Figure 2: Case study area. The area considered in the analysis consists in all the agricultural ground with an inclination lower than 15% (Datum Roma40 - EPSG 3004).

Figure 3: Umbria region main characteristics and localization of olive mills (Datum Roma40 - EPSG 3004).

Figure 4: visual output of the `r.mcda.ahp` module; it reports the spatial distribution of AHP results. The worst class is the n. 1, while the n. 5 represents the most suitable area for the wastewater application (Datum Roma40 - EPSG 3004).

Figure 5: reports on the left the results of the intersection operator, while on the right the results of the union one (Datum Roma40 - EPSG 3004).

Figure 6: The map of the OWA operation in r.mcda.fuzzy presents intermediate results in comparison to the other two fuzzy operators. This is due to the computational characteristic of the OWA operator, that is an ordered average (Datum Roma40 - EPSG 3004).

Figure 7: at least areas. Starting from the high-left corner, the areas that are classified at least in class 2, 3, 4 or 5 are reported (Datum Roma40 - EPSG 3004).

Figure 8: at most areas. Starting from the high-left corner, the areas that are classified at most in class 4, 3, 2 or 1 are reported (Datum Roma40 - EPSG 3004).

AHP histogram

Intersection (Fuzzy AND) histogram

Figure 9: Histograms about the distribution of the output frequency the values assumed by each cell of the raster map for the OR, AND and OWA operators and for the AHP module.

Figure 10: Scatterplot Matrix was produced to compare the results obtained by modules `r.mcda.ahp` e `r.mcda.fuzzy` (all the operators). On the main diagonal the methods applied.