

# Informed Spatial Decision Making Using Coordinated Views

Natalia Andrienko and Gennady Andrienko  
*Spatial Decision Support Team*  
*Fraunhofer Institute AIS*  
*Schloss Birlinghoven, 53754 Sankt Augustin, Germany*  
*<http://www.ais.fraunhofer.de/SPADE>*  
*[gennady.andrienko@ais.fraunhofer.de](mailto:gennady.andrienko@ais.fraunhofer.de)*

## Abstract

*According to a commonly accepted view, the process of decision making comprises three major phases: intelligence (situation analysis and problem recognition), design (finding possible variants of problem solution), and choice (evaluation of the options and selection of the most appropriate ones). It is widely recognised that exploratory data visualisation is very helpful during the first phase of the decision making process while the other phases require different software tools. In particular, the choice phase is typically supported by various computational methods that find appropriate trade-offs among multiple conflicting criteria taking into account user-specified priorities. Visualisation plays a limited role: in the best case, it is used to represent the final results of the computations. We argue that conscious, well-substantiated choice requires a more extensive use of exploratory visualisation facilities, which need to be properly coordinated with the computational multi-criteria decision support methods. Extremely important is a high degree of user interactivity, which allows the user to probe the robustness and quality of computationally-derived solutions. We suggest several mechanisms for linking and coordinating visual exploratory tools with two types of computational methods differing in the sort of output they produce. We demonstrate the use of this dynamic link with an example of a real spatially-related decision problem.*

**Keywords:** multi-criteria decision support, data visualisation, geographic visualisation, display coordination, exploratory data analysis

## 1. Introduction

Decision making is one of people's usual activities since situations that require making decisions constantly arise in their everyday life. Very often, however, the dimensionality and complexity of decision problems reach far beyond human's capabilities while the cost of a poor decision may be rather high. Therefore, there is a need in software support to the decision making process, and, in response, a wide variety of software tools, from tools for building graphs and charts to expert systems and intelligent agents, are offered as decision support systems. The reason for this variety is the compound, multi-faceted nature of the decision making process.

The most widely accepted generalisation of the decision-making process was introduced by Simon [25], who divided the process into three major phases: intelligence, design, and choice. The intelligence phase involves data collection, integration, pre-processing, and exploration with the aim to identify the problems or opportunities. During the design phase, one looks for a set of possible solutions to the problem(s) identified in the intelligence phase and analyses the options thus found. During the choice phase, the options are evaluated and analysed in relation to others, and a particular option or a set of options is selected. Typically, a decision-maker must account for multiple, often conflicting, evaluation criteria, and the final decision results from an explicit or implicit trade-off. At any point in the decision-making process, it may be necessary to loop back to an earlier phase.

Malczewski [20] mentions the software tools that can support the decision process at the different stages. Techniques of exploratory data analysis, or EDA, play a major role in the intelligence phase. For determining the set of alternatives in the design phase, formal models are typically used. The phase of choice is supported by an array of computational methods developed within the research field called multi-criteria decision-making, or MCDM.

The concept of EDA emerged in statistics. John Tukey [29] introduced it as a counterbalance to the traditional statistical techniques of checking a priori selected hypotheses. The goal of EDA is to survey previously unknown data and to arrive at plausible hypotheses concerning relationships, patterns, and trends hidden inside the data volumes. Techniques of EDA are mostly based on data visualisation, that is, graphical representation of data that can help in revealing important traits and relationships [7]. A high degree of user interactivity is a general requirement to graphical displays used for exploratory data analysis. A taxonomy of techniques for interactive manipulation of graphical displays can be found in [4].

It is commonly recognised that comprehensive data investigation requires multiple complementary displays exposing various aspects of the data. Multiple views need to be linked so that the information contained in individual views can be integrated into a coherent image of the data as a whole [5]. The most common method of linking is the identical marking of corresponding parts of multiple displays, for example, with the same colour or some other form of highlighting. Usually highlighting is applied to objects interactively selected by the user in one of the displays. This technique originates from the so-called “scatterplot brushing” operation suggested by Newton [22] and is often traditionally called “brushing”. An overview of currently existing methods for display linking is proposed in [24].

Over the past decade, the notion of EDA has spread from statistics to cartography. Cartographers have recognised the demand for new software supporting the use of interactive, dynamically alterable thematic maps and facilitating “visual thinking” about spatially referenced data [18] [19]. Linking of a map display with various kinds of statistical graphs was suggested as a primary instrument of the exploratory analysis of spatially referenced data [21] [17] [27] [8] [30] [9].

We argue that linked displays may be supportive not only during the intelligence phase of the decision-making process but also in the stage of choice. They can aptly complement and enhance the existing mathematics-based, computational MCDM support techniques.

Surveys of the existing MCDM methods can be found in [10] and [28]. For supporting decision making in a spatial context, for example, for choosing locations, most researchers suggest integration of the MCDM support methods with geographical information systems (GIS) [14] [6] [12] [20]. A GIS is used as a source of data for the MCDM methods and a means of displaying the results. For example, in the prototype described in [13], evaluation scores assigned to spatially distributed options by one of the MCDM methods are shown on a map by circles of differing sizes. We find, however, that this kind of interaction is very limited and insufficient for making informed, well substantiated decisions in a spatial context.

We see two major problems. First, besides the geographical space, a decision maker needs to see how the solution found by a MCDM algorithm is positioned in the attribute space and where it is with respect to the remaining options. On this basis, the decision maker can check whether this solution corresponds to her/his expectations and whether the trade-off involved is admissible. Otherwise, the decision maker would have to blindly accept the output of a “black box”, while bearing the full responsibility for the decision to be made. Second, the decision maker needs to test the robustness of the solution with respect to minor changes of input parameters. For example, some MCDM support methods ask the user to specify so-called weights for the decision criteria to express the relative importance of the criteria. If changing the weight of some criterion from 0.33 to 0.35 results in the MCDM method proposing a different solution, this means that the previous solution might not be really optimal. In such a case, careful consideration of options with close ranking is necessary, probably, with the involvement of additional criteria.

The necessity of testing the sensitivity of possible solutions to parameter variation is pertinent to many areas rather than unique for multi-criteria decision-making. Thus, Spence [26] considers sensitivity analysis using an engineering problem as an example. Here the task of the designer is to study the influence of parameter variation upon artefact characteristics and performance. This sort of analysis needs to be supported by a highly interactive visualisation tool, such as the Influence Explorer [30], which is applied to outputs of a simulation model [26]. A decision maker also needs a tool able to dynamically react to user’s variation of inputs of a MCDM method by immediately visualising the consequences of the changes made. Such a degree of user interactivity and reactivity is not achieved in the known GIS-MCDM combinations.

In the remainder of the paper, we describe our solution to these two problems based on an integration of computational MCDM support methods with interactive exploratory visualisation tools, in which multiple coordinated views play an important role. We would like to stress that our innovation is this integration rather than invention of any new MCDM techniques. We consider two representative MCDM methods, which differ in the type of produced output and, hence, require different mechanisms for linking to the visualisation tools. The integration is shown by an example of a particular decision problem. All the techniques described are implemented in the software system CommonGIS designed to support exploratory data analysis and decision-making in a spatial context.

## 2. Display coordination in CommonGIS

CommonGIS offers an array of data visualisation techniques facilitating exploratory analysis of spatially referenced data, including highly interactive maps [2] and various statistical graphs: dot plot, frequency histogram, scatter plot, scatterplot matrix, parallel coordinate plot, etc. Multiple displays can be simultaneously present on the screen providing an opportunity to view data from various perspectives. All the displays are dynamically linked in many different ways. Besides the tools for EDA, CommonGIS offers a range of spatial decision support facilities. Some of them are described in [3].

CommonGIS has a configurable, extensible component-based architecture. It contains a large number of components realising various methods of data visualisation or computational procedures. The components are independent of each other: adding or removing any component does not affect the other components. The components are coordinated through various types of events. The following types of events play the most important role in the coordination between the MCDM-related components and the data visualisation components of the system:

- object selection;
- object classification;
- attribute change;
- query change.

Object selection events are used for simultaneous highlighting of corresponding objects in multiple displays present on the screen. There are two types of highlighting, transient and durable. The transient highlighting occurs when the mouse cursor is positioned on a graphical element representing some object or a group of objects in one of the displays and lasts until the cursor moves away. The integration between the MCDM and visualisation components involves the durable highlighting. From now on, we shall only refer to this type of highlighting.

Objects to be durably highlighted can be selected directly by the user who clicks on a corresponding graphical element in some display or drags a frame to enclose several elements. Another possibility is indirect object selection originating from a computational component (in particular, a MCDM component) as a way to represent its results. Durably highlighted objects are marked by black boundaries or, in some displays, black painting. They remain highlighted until the user explicitly deselects them (by clicking on an object-free area of any display or pressing a special button) or until another object set is indirectly selected.

Object classification events may originate from a map or another graphical display where the objects are in some way divided into groups (classes), and a particular colour is assigned to each class. Typically, the user can interactively change the classes by manipulating this map or display. The user interface for object classification includes a checkbox "Broadcast classification". When the checkbox is selected, the classes and their colours are propagated to all non-cartographical displays by means of classification events. In response, these displays paint their graphical elements in the corresponding class colours. Classification events are generated when the user selects or deselects this checkbox and when she/he interactively changes the classes while the checkbox is in the "selected" state. As a result, object colouring simultaneously changes in all displays.

Attribute change events are generated when values of some thematic attribute(s) associated with objects change. This is particularly pertinent to attributes resulting from computations. Some computational components of CommonGIS produce new attributes, which can be then visualised like the data originally loaded in the system. Furthermore, the computational components may be interactive and allow the user to change the parameters of the computations. When the user manipulates the parameters, the tool re-computes the values of the attributes it has produced earlier and notifies other components about the change. In response, all components visualising these attributes are updated (in particular, redrawn) to take into account the new values.

All displays in CommonGIS synchronously react to changing conditions in the Dynamic Query tool [1] by removing objects that do not satisfy the current conditions. This is realised by means of query change events. In decision-making, Dynamic Query allows the user to disregard inappropriate options and concentrate on options with suitable characteristics. For example, in selecting a house to buy, the user may wish to exclude too small or too expensive houses from the consideration.

Let us now briefly describe the internal mechanisms of these four types of coordination.

Selection and classification events are managed by an internal component called system's core. The core registers receivers of these types of events, i.e. all components that can react to the events. When, working with some system component, the user performs an operation that can be treated as object selection or indirectly results in object selection, this component sends an event to the core, and the core propagates it to all registered event receivers. Analogously, when classes change in a component performing object classification or the user selects or deselects the checkbox "Broadcast

classification”, the component notifies the core about the change, and the core propagates this event to all registered receivers of this type of event.

Irrespective of the source of an event, all components that receive it react to it in their specific ways. Selection events usually result in (durable) object highlighting, which occurs in multiple displays in parallel. However, other results of selection are also possible, for example, appearance of a list of object characteristics in a special subwindow called “Object view”. Chart maps (e.g. maps with bar charts or pie charts) may be set to the mode of drawing charts only for currently selected objects. In this mode, upon receiving an object selection event, a map removes the charts of the objects that are no more selected and draws the charts for the selected ones.

A typical result of classification events is using the colours assigned to the classes for painting display elements corresponding to the objects classified. Examples of other possible results are grouping rows in a table view and (re)computing various statistics for the classes in some components.

Attribute change events are managed by “internal tables”, that is, internal components storing attribute data. Several internal tables may exist simultaneously. Every component representing data from some table or using these data for other purposes is registered as a receiver of data change events from this table. Such events may originate from components that produce new attributes or change values of the existing attributes. The table propagates the events to all registered receivers. A receiver should check whether the change affects it. For example, when a map display receives a notification about some attribute having been changed, but this attribute is not currently represented on the map, no reaction to the event is needed.

The most common reaction to attribute change events is redrawing of the displays representing the attribute(s) that have been changed. Some components may re-compute statistics or re-order their elements, like, for example, rows in a table view.

When the user interactively changes query conditions in the Dynamic Query device, it generates query change events and requests the corresponding internal table to propagate the events among the registered listeners of this table. Typically, all displays react by hiding the objects that do not satisfy the current conditions.

Besides these general event types, there may be some special events being only relevant to particular components. For example, relevant for a bar chart map is an event of selecting particular attribute values. In response to the event, the map uses bar heights to represent the differences between the attribute values for each object and the selected values.

### **3. Decision support in CommonGIS**

In this section, we describe how computational techniques supporting multi-criteria decision-making are integrated with interactive visualisation components of CommonGIS. We consider two types of MCDM techniques, according to the output they produce.

#### **3.1. General notes about numeric MCDM support methods**

Most MCDM support methods require decision criteria to be represented as numeric attributes. In order to use a qualitative attribute as a decision criterion, one needs to specify an order of preference among its values and encode the values by numbers, for example, 1, 2, 3, ....

Two different types of criteria are possible: benefit criteria and cost criteria. If higher attribute values make an option better (more appropriate), this attribute is a benefit criterion. If higher attribute values are less desirable (less appropriate) than lower ones, this is a cost criterion.

CommonGIS includes several MCDM methods differing in the type of output they produce:

- a subset of options approximating a user-specified goal, i.e. a desired combination of values of the criteria;
- overall ranking of options according to selected criteria and priorities.

The former type of methods will be further referred to as goal approximation methods and the latter as option ranking methods.

Criteria may have different relative importance for a decision maker. The relative importance of criteria can be specified, for example, through so-called weights of the criteria. The weights are real numbers between 0 and 1. The sum of the weights of all criteria used in the decision-making process must be equal to 1. The weight 0 means that the corresponding criterion is of no importance for the decision maker. Criteria weights may be specified by the user directly or indirectly, for example, by ranking the criteria according to their relative importance. Some MCDM support methods do not use criteria weights.

The rationale for combining computational MCDM methods with visualisation tools is two-fold. First, cartographic representation of computation results is crucial for appropriate decision-making in spatial context. A map allows the user to see where the options are, what is around, and other important spatial information. Second, visualisation can greatly help the user in comprehension of computation results. The user can better understand why this or that option has (or has not) been found suitable and what trade-offs are involved in the proposed solution. Furthermore, the user can check what happens when she/he changes any of computation parameters, for example, criteria weights or the desired value combination. Only if the computed solution is justifiable (complies with user's expectations) and sufficiently robust, the user can take it as a basis for her/his decision.

### 3.2. Example decision problem

As an example, we use a real-world decision problem of ranking Idaho counties according to the need for funding the primary health care services. The problem is considered in detail in [13]; here we give a short summary.

Due to numerous geographic and access barriers, the delivery of primary health care services throughout the state of Idaho is complicated. Idaho has one of the lowest physician-to-population ratios in the USA. Recruiting health professionals to Idaho's remote areas and to regions in the state with substantial portions of low-income/undeserved persons is a constant challenge. The decision problem is how to distribute limited funds in order to help the state counties attract health care professionals through repaying their education loans.

There are ten evaluation criteria (attributes) to be taken into account in making the decision about the distribution of the funds:

1. <i>Estimated Number of Unaccounted Primary Care Visits.</i> This criterion serves as an indicator of unmet demand for primary care medical services due to the unavailability of providers within the 15-mile travel distance constraint.
2. <i>Burden on On-Call Providers.</i> Expresses the number of hours on call for each provider.
3. <i>Availability of Obstetrical Care.</i> It is expressed by the number of providers offering obstetrical delivery services in each county.
4. <i>Availability of Emergency Medical Services.</i> The criterion values are calculated dividing the sum of ambulances and quick response units by the number of population in each county
5. <i>Percent of Population Receiving Medicaid / Medicare.</i> It is the percent of population in each county who utilize Medicaid or Medicare medical insurance.
6. <i>Low Birth Weight Rate.</i> It is the percent of low weight births per each county averaged from a multi-year interval.
7. <i>Poverty Rate of Population.</i> The criterion values are based on census poverty rates by county.
8. <i>Proximity of a Hospital to the Population.</i> The criterion values are calculated based on the nationally accepted standard for the maximum travel distance of 35 miles to a hospital in rural areas. The number of individuals residing outside each hospital influence zone (35-mile radius) is calculated for each county.
9. <i>Emergency Room Visits.</i> The criterion values are based on annually collected hospital emergency room visit data.
10. <i>Fertility Rate.</i> County wide average fertility rates.

### 3.3. Integration of goal approximation methods

Working with a goal approximation MCDM method, the user specifies a goal, i.e. a desired combination of criteria values, and receives a subset of options with characteristics close to the goal. Hence, the result of such a method is a certain group of objects. CommonGIS uses the object selection mechanism for showing these objects on a map and other displays present on the screen. This process is schematically shown in Figure 1. The MCDM tool produces an object selection event, which includes the subset of objects (options) resulting from the computations, and sends it to the system's core. The core propagates the event among all registered listeners of this type of event, in particular, all visualisation components. These components react to the event by highlighting the corresponding graphical elements or/and in other, component-specific ways. If the user changes the input parameters of the tool (to test the robustness of the solution), it performs the computations again, produces another set of options, and generates a new object selection event. The core propagates the new event to all components, and they change the highlighting. With this coordination mechanism, the visualisation components do not need to be directly linked to the computational components and even do not need to know about their existence. Hence, the components remain independent on each other.

\*\*\* Figure 1

An example of a goal approximation MCDM technique is the Feasible Goals Method [15][16], or FGM. It uses a mathematical model to compute from a given set of options with their characteristics so-called non-dominated frontiers, or efficiency frontiers, of the space of feasible solutions. A reasonable strategy is to select one of the alternatives positioned on these frontiers or close to them, since the options lying inside are dominated and, hence, not optimal. If the number of decision criteria is relatively small, the frontiers can be visually represented on graphs called “decision maps” (these should not be mixed with conventional geographical maps). A decision map for three criteria is shown in Figure 2.

\*\*\* Figure 2

In this display, the X-axis corresponds to the attribute “Fertility rate” and the Y-axis to “Low-weight birth rate”. The coloured regions represent the spaces of feasible alternatives depending on the values of the third attribute, “Poverty rate”. The largest, outer region corresponds to the lowest values of the poverty rate, specifically, below 13.7 (the minimum value in the dataset is 7.09). The second largest region nested inside the first one shows the feasible decision space when the poverty rate values are from 13.7 up to 15.3. The next region corresponds to the poverty rate from 15.3 up to 16.9, and so on. One may observe that, with increasing the values of the criterion “Poverty rate”, the space of feasible alternatives shrinks. Respectively, with increasing the poverty rate values, the values of the other two criteria that can be potentially attained decrease.

The boundaries of the coloured regions, in turn, represent the relationships between the criteria “Fertility rate” and “Low-weight birth rate” (for each particular value range of the third criterion). It may be seen that attaining higher values of one of the criteria can only be achieved by sacrificing the other criterion. Hence, the decision map represents the possible trade-offs among the criteria.

The “decision map” visualisation technique may be extended to represent four or five criteria. In the first case, several decision maps corresponding to representative values of the fourth criterion are shown in a row. In the second case, a matrix of decision maps is displayed.

Having explored the feasible decision space and the possible trade-offs, the user may identify a goal within this space she/he wishes to attain, that is, a particular combination of values of the attributes. For this purpose, the user needs to click on the corresponding position on the decision map. In the example presented in Figure 2, the user decided that sufficient conditions for giving funding are the poverty rate being around 18.56, the low-weight birth rate being about 7.2, and the fertility rate being about 81.2. The cross marks the corresponding position on the decision map. The choice of this particular position was affected by the shapes of the efficiency frontiers, that is, the boundaries of the coloured regions on the graph. It may be seen from the picture that, for the selected poverty rate value, moving the cross farther up (i.e. increasing the value of the low-weight birth rate) would lead to a dramatic decrease for the criterion “Fertility rate”, since it is only possible to move along the boundary. At the same time, increasing the poverty rate value is only possible at the cost of moving to one of the inner frontiers, where no appropriate combination of fertility and low-weight birth rates can be attained.

After the desired goal has been indicated, the FGM tool finds among the available options the options close to this goal. To visualise the result, it creates a barchart map that represents the values of the criteria involved in the computations by bar heights. The map is set to the mode of showing only selected objects. Then the FGM tool creates two events: an object selection event sent to the core, which distributes it among the listening components, and a value selection event sent directly to the map. The object selection event contains the set of objects close to the goal. The value selection event contains the user-specified combination of desired criteria values. After the barchart map receives the object selection event from the core, it marks the selected counties by thick black boundaries and hides the charts corresponding to the counties that are not currently selected. After the map receives the value selection event from the FGM tool, it changes the bar charts of the selected counties so as to show the differences between the characteristics of these counties and the desired values (Figure 3). A bar chart contains a bar for each criterion with the height being proportional to the difference of the value of this criterion and the desired value. Upward-oriented bars represent values higher than the desired values of the respective criteria, and downward-oriented bars represent values lower than the desired values. When a value is equal or very close to the desired value, the corresponding bar has zero height and, hence, does not appear. More information about this method of representing and comparing decision options can be found in [3].

\*\*\* Figure 3

It should be noted that the options close to the goal are not only shown on the map but also highlighted in all displays currently present on the screen (see Figure 1). This provides an opportunity to analyse various characteristics of these options and compare them with other options.

When the user redefines the goal, i.e. alters the desired values of the attributes, the FGM tool performs a new search for the closest options and sends the new set of options to the core and the new set of the desired values to the geographic map display. The map is automatically updated to represent the new result. For example, the map in Figure 4 represents the result of increasing the desired value of the criterion “Low-weight birth rate” to 7.95 at the cost of decreasing the values of the fertility and poverty rates to 72.9 and 17.03, respectively. Three of the earlier selected options have remained in the set of the options approximating the goal while one option has been replaced. Note that the bar charts now represent the result of comparison with the new set of the desired values.

\*\*\* Figure 4

This example shows that the link between the FGM tool and the visualisation components can be effectively used for testing the robustness of the outcomes of the FGM, which is usually hard to do in a GIS-MCDM combination. Like in a typical GIS-MCDM combination, a geographical map in CommonGIS shows positions of the recommended solutions in the geographical space. At the same time, the decision map display used by the FGM tool allows the user to see the space of feasible alternatives and the positions of the solutions in this space. The link between all displays in the system through highlighting provides good opportunities for comparing characteristics of the recommended options with those of the others. Hence, MCDM results can be comprehensively and conveniently analysed in both geographical and attribute spaces.

Although the mathematical model underlying the feasible goal method can take into account any number of decision criteria, the decision map visualisation technique is limited to up to five criteria. This limitation can be compensated by applying the FGM tool to different combinations of criteria and comparing the results.

### 3.4. Integration of option ranking methods

Option ranking methods aggregate values of multiple attributes characterising each decision option into a single evaluation score reflecting the degree of appropriateness of this option. Then the options are ranked according to the scores received. Option ranking methods typically pose no limitations on the number of the criteria involved. CommonGIS includes several option ranking MCDM methods, which are realised as interactive computation tools producing dynamic attributes. These attributes may be visualised on maps and other displays.

Figure 5 shows schematically how an option ranking method is linked and coordinated with visualisation components. The method computes the evaluation scores and ranks of the options and stores them as new attributes in the internal data table containing the source data for the computations. Any of these two attributes may be visualised, alone or in combination with other attributes, on maps and other displays. When the user changes the input parameters, the MCDM tool immediately re-computes the results and changes the values of the produced attributes in the table. After that, it generates an attribute change event referring to the modified attributes and requests the internal table to distribute this event among its registered listeners. Since all displays visualising data from this table are listening to events coming from it, they will receive the attribute change event. If the event is relevant for a display, i.e. the display visualises any of the attributes that have changed, the display updates itself using the new data from the internal table.

\*\*\* Figure 5

Let us now use our example decision problem to demonstrate the work of this type of component coordination.

\*\*\* Figure 6

All the option ranking methods available in CommonGIS explicitly involve criteria weighting. Figure 6 shows the user interface for specifying types (cost or benefit) and weights of decision criteria in CommonGIS. Below each criterion name there is a slider allowing the user to select/adjust the criterion weight within the value range (0, 1). The adjustment of one weight causes all other weights to automatically change values proportionally to their values before the adjustment in order to keep the sum of weights equal to 1. Through the weights the user expresses the relative importance of criteria. The North-East pointing arrow, on the left of each weight slider, indicates a benefit criterion, the South-East pointing arrow corresponds to a cost criterion. The user can easily change the directionality of criteria with a mouse click.

As we already mentioned, values of multiple attributes are aggregated into evaluation scores, which are then used for ranking the options. The results of the computations are automatically represented, together with the initial characteristics of the options, on a parallel coordinate plot [11], as is demonstrated in Figure 7.

\*\*\* Figure 7

In our implementation, we customise the general technique of parallel coordinates to the use for decision support. Thus, the axes for benefit and cost criteria have different orientation (indicated by arrows): left to right vs. right to left. With such a solution, the most appropriate values of each attribute are always on the right, and the worst are on the left. This makes it easy to estimate visually how good any specific option is: the closer to the right edge of the plot is a line, the better is the option.

Differences in relative weights of criteria can be (optionally) reflected by variation of lengths of the axes: the more important is a criterion, the longer is the corresponding axis. Due to this transformation, lines of options surpassing others in more important criteria shift visually more to the right (“good”) pole of the plot.

The two axes at the bottom of the plot represent the results of the computation by the selected MCDM support method. The axis second from the bottom represents the aggregated scores, and the next axis shows how the options are ordered (ranked) according to these scores. Note that the axis for the ranks has the inverse (right to left) orientation: better options have smaller rank values.

Any line on the plot can be selected using the mouse. As a result, the corresponding object will be highlighted in all displays. This also helps to see the position of any option among the other options with respect to the initial characteristics and the scores and ranks computed. Thus, in Figure 7 the line of the top-scoring (i.e. the first in rank) option is highlighted. It may be seen that this option has the best values of the attributes “Burden on on-call providers” and “Availability of obstetrical care” and rather good values of other attributes except for the last three ones.

Both the computation module and the parallel coordinate plot are sensitive to any changes in the criteria weights. The scores and ranks are immediately recomputed, and the plot immediately redraws itself when a change occurs. This allows the user to investigate how sensitive the result of the multi-criteria evaluation is to minor changes in the criteria weights.

In decision-making, it is often necessary to select a subset of appropriate options rather than a single option. For this purpose, it may be convenient to classify options according to the ranks received. For example, in the Idaho problem it might happen that the whole amount of funding available needs to be distributed among three counties which are the most in need. Using the interactive classification tool of CommonGIS, the decision-maker can define the classes so as to separate three options with the topmost ranks from the rest. The decision-maker may wish to introduce more classes. Thus, a class of “conditionally fundable” options may be defined for the case when additional funding becomes available.

The map in Figure 8 represents a classification of the Idaho counties according to the ranks produced by the “Ideal Point” MCDM support method [10] for the ten criteria described in §2.2 with the weights as is shown in Figure 7. The class boundaries are chosen so that the first class includes 3 best options (i.e. with the ranks from 1 to 3), the second class contains 3 next options (with the ranks from 4 to 6), and the third class is formed by the remaining options. The top-scoring option is highlighted (marked with a thick boundary). The same option is highlighted on the parallel coordinate plot in Figure 7.

\*\*\* Figure 8

\*\*\* Figure 9

Let us now alter some of the criteria weights, for example, increase the weight of the criterion “Population in more than 35 miles from hospitals” to 0.20. The map immediately changes as is shown in Figure 9. The definition of the classes (i.e. the class boundaries) has not changed, but some options have moved from one class to another.

Perhaps, it is even more convenient than with the map to observe changes of ranks using the dynamic table view. The table view (Figure 10) is dynamic in the sense that it can show dynamic attributes and update itself when the values of these attributes change. The user may choose an attribute to be used for ordering rows in the table view. If this is a dynamic attribute, the order of the rows will change each time when the values of the attribute change. Hence, if the user selects the dynamic attribute “Ranking” resulting from a MCDM support tool to be used for ordering, the best options will always appear at the top of the table.

\*\*\* Figure 10

The user can not only see which options are the best for the current set of weights, but also view their characteristics and compare them with those for the other options. Especially convenient for this purpose is the “Table Lens” technique [23], which draws a bar in each cell with the length proportional to the value of the attribute in this cell.

Furthermore, the table view may show not only option ranking (along with the other characteristics), but also the classification of the options according to the ranking. In general, any object classification can be propagated from the map display in which the classes are defined to all displays currently present on the screen (through object classification events, as is explained in §2). In a table view, this results in colouring the table rows according to the classes the corresponding objects fit in and in grouping the rows by the classes. Any changes of the classes are immediately reflected in the table view. The classes may change as a result of changing the values of the dynamic attribute(s) used for the classification, but the user can also interactively redefine them, for example, by moving the class boundaries.

### 3.5. Automatic sensitivity analysis

The capability of the MCDM support tools to immediately react to changes of the input parameters by re-computing the results, and the capability of the displays representing the results to immediately update when the results change, can be used for testing the robustness of the solutions provided by the MCDM methods. However, with a large number of decision criteria, the process of the interactive alteration of the input parameters (in particular, criteria weights) may become time-consuming. Therefore we have implemented in CommonGIS a procedure of automatic variation of the weights, which is called “sensitivity analysis”. For each criterion, the user may specify the variation range and the number of intermediate steps between the minimum and the maximum. In response, the system will assign different weights from the specified interval to the criterion, proportionally adjust the weights of the other criteria, and compute the aggregated scores and the ranks for the resulting set of weights. The same procedure is repeated for each criterion. The computation results are summarised into four new attributes specifying for each option the minimum rank received in the course of weight variation, the maximum rank, the mean rank, and the variance. These attributes can be visualised, for example, as is shown in Figure 11. Certainly, a decision-maker is interested most of all in the options with the smallest values of all the attributes.

On the map in Figure 11, one of the counties (marked by the thick border) has all bars of zero length. This means that it is extremely robust with respect to the weight variation and, hence, this is the most appropriate candidate for receiving funding. If the funding were to be distributed among several counties, the second candidate would be the southern neighbour of the top candidate: it has the heights of all the bars close to zero. The exact values of the minimum, mean, and maximum ranks and the variance can be accessed by pointing on the counties on the map with the mouse, as is shown in Figure 11.

\*\*\* Figure 11

## 4. Conclusion

Most decisions in people’s everyday life are made ad hoc, without any sophisticated analysis. However, when the cost of making a poor decision may become quite high, such an analysis becomes necessary. Therefore, organisations and companies, where the decision equity is usually high, often use software for decision support. Such software usually realises one or more computational MCDM methods [10] [28].

Malczewski [20] acknowledges that techniques of EDA, which involve various methods of data visualisation and user interaction, are useful in the initial phase of the process of decision-making, the so-called intelligence phase [25]. We believe, however, that visualisation and interaction should be also applied during the choice phase as a complement to the computational methods. Whatever mathematical model is used in a MCDM support tool, any solution of a decision problem it suggests inevitably involves trade-offs between conflicting goals, since a perfect solution never exists in real-world situation. A person who makes the decision and, hence, bears the responsibility for it must understand why the tool recommends this or that solution and what trade-offs are involved. Visualisation allows the decision-maker to see the position of the suggested solution in the attribute (as well as geographical) space with respect to other feasible alternatives. It discloses which of the characteristics of the solution are not optimal and how this is compensated by better values of other attributes. Multiple coordinated displays allow comprehensive, multi-sided investigation of the outcomes of MCDM methods.

Another reason for using visualisation tools in combination with MCDM methods is that the latter often base their computations on subjective information such as the desired goal or the relative importance of the criteria. Such information is difficult to quantify, and the decision-maker can usually provide only approximate judgements. It is

important to find a solution that is insensitive to minor fluctuations of these judgements. Hence, the decision-maker must be given the opportunity to test whether the solutions suggested by a MCDM tool are sufficiently robust. A possible way to achieve this is to allow the decision-maker to alter the input information of the MCDM tool so that the tool immediately re-computes the results and the visual displays immediately update to reflect the changes. Hence, visualisation and its dynamic integration with computational methods can greatly contribute to making informed, well-substantiated decisions.

The dynamic integration of computational and visual tools is realised in our system CommonGIS by means of a generic mechanism of event propagation. This makes the system easily extendable to new visualisation techniques and computational methods.

The decision support tools of CommonGIS have been tested in several experiments on cooperative decision-making, in which the participants were engaged in role games on collective selection of suitable places. The experiments and their results are described in [3]. Here we can briefly state that we observed a very active utilisation of the dynamic link between the computational MCDM tools and the visualisation components, in particular, the map display, which is not surprising for a geographically related decision problem. In general, the users were quite able to understand the purpose and the functionality of the tools and to use them for finding appropriate options. Moreover, the users liked the tools and found them certainly helpful. Thus, in one of the experiments, the average subjective estimation of the ease of use was 5.8 and the effectiveness of the tools was estimated as 6.0 on a 7-point scale. It should be borne in mind that the subjects had not got previous training in the use of the system.

One of the most important observations concerns the existence of different styles of decision-making. The necessity to meet the needs of different users justifies the existence of a variety of decision support methods. We consider the availability of several alternative MCDM tools as a significant advantage of CommonGIS. In the paper we have demonstrated how different types of MCDM tools can be integrated with visualisation software using different coordination mechanisms. It should be noted that these mechanisms could be used for integrating not only MCDM methods but also various other computational tools. However, this requires the computations to be sufficiently fast to provide quick response to data and parameter variation.

## 5. Implementation notes

CommonGIS is implemented in Java language and can run either as a local application or as an applet in the Web. The major part of the system is available for downloading at the URL <http://www.CommonGIS.de/>. However, this does not include the Feasible Goal method and the Decision Map visualisation component, according to an agreement with the copyright owners, the Department of Mathematical Methods for Economic Decision Analysis of the Computing Centre of the Russian Academy of Sciences (<http://www.ccas.ru/mmes/mmeda/>). The downloadable package contains extensive software documentation, including a programmer's manual for those who would like to configure or extend the system, or combine it with other software.

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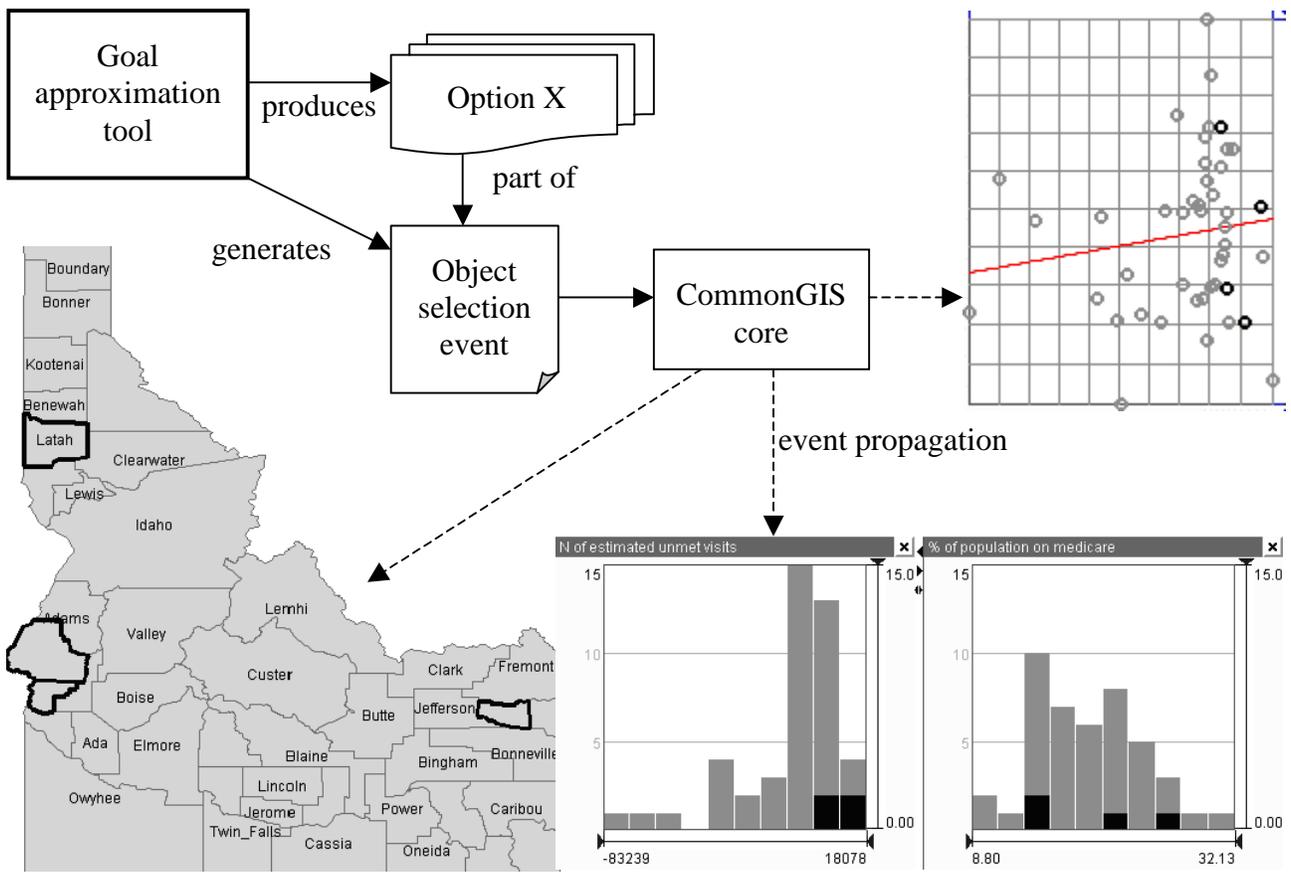
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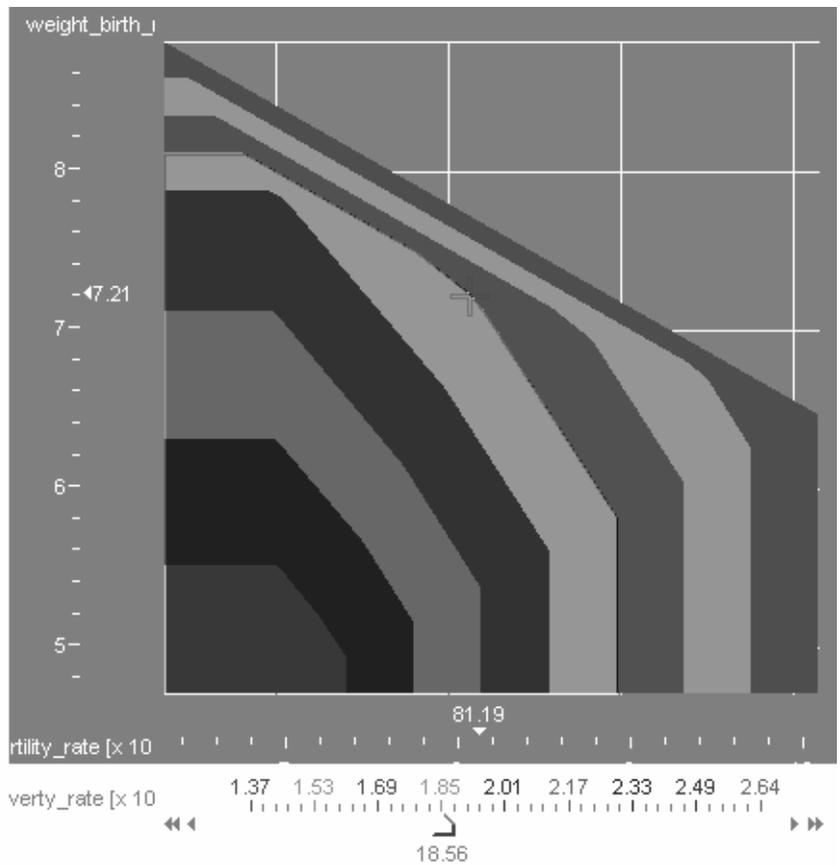
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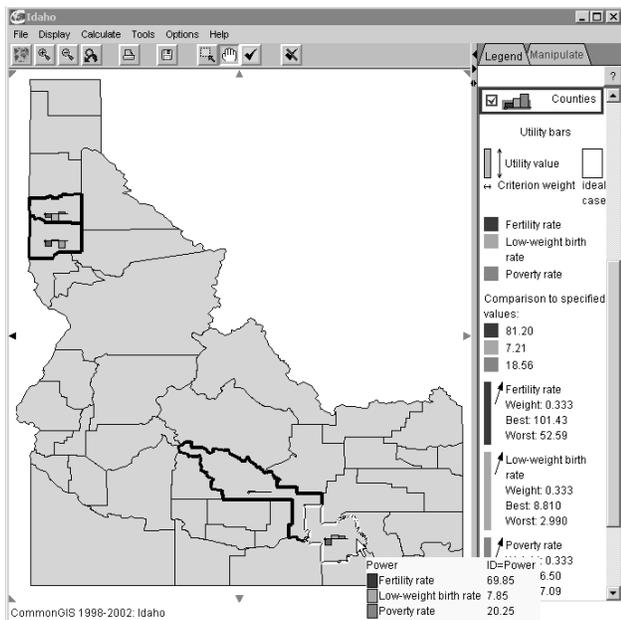
**Figure 1.** Integration of a goal approximation MCDM tool with visualisation components of CommonGIS.

**RGDB, Version 1.1.1**  
 (c) 2000 Lotov, Efremov, Kistanov, Zaitsev  
<http://www.ccas.ru/mmes/mmeda/>

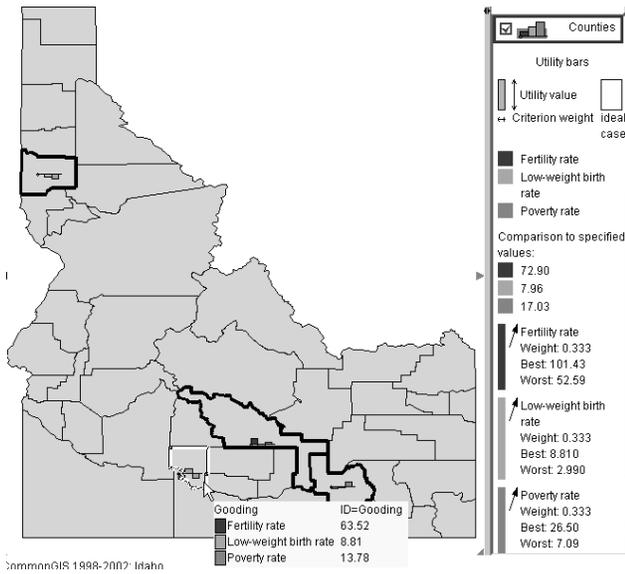
Criteria	Values
<b>X: Fertility_rate</b>	81.19
<b>Y: Low-weight_birtl</b>	7.21
<b>Z: Poverty_rate</b>	18.56



**Figure 2.** A decision map for three criteria.



**Figure 3.** The map shows the options (Idaho counties) close by their characteristics to the goal defined by the user on the decision map from Figure 2. These three counties are suitable candidates for receiving funding, with respect to the criteria “Fertility rate”, “Low-weight birth rate”, and “Poverty rate”.



**Figure 4.** In order to probe the robustness of the solution presented in Figure 3, the user has slightly altered the goal. Three of the four initially selected options have remained in the new set of the recommended options.

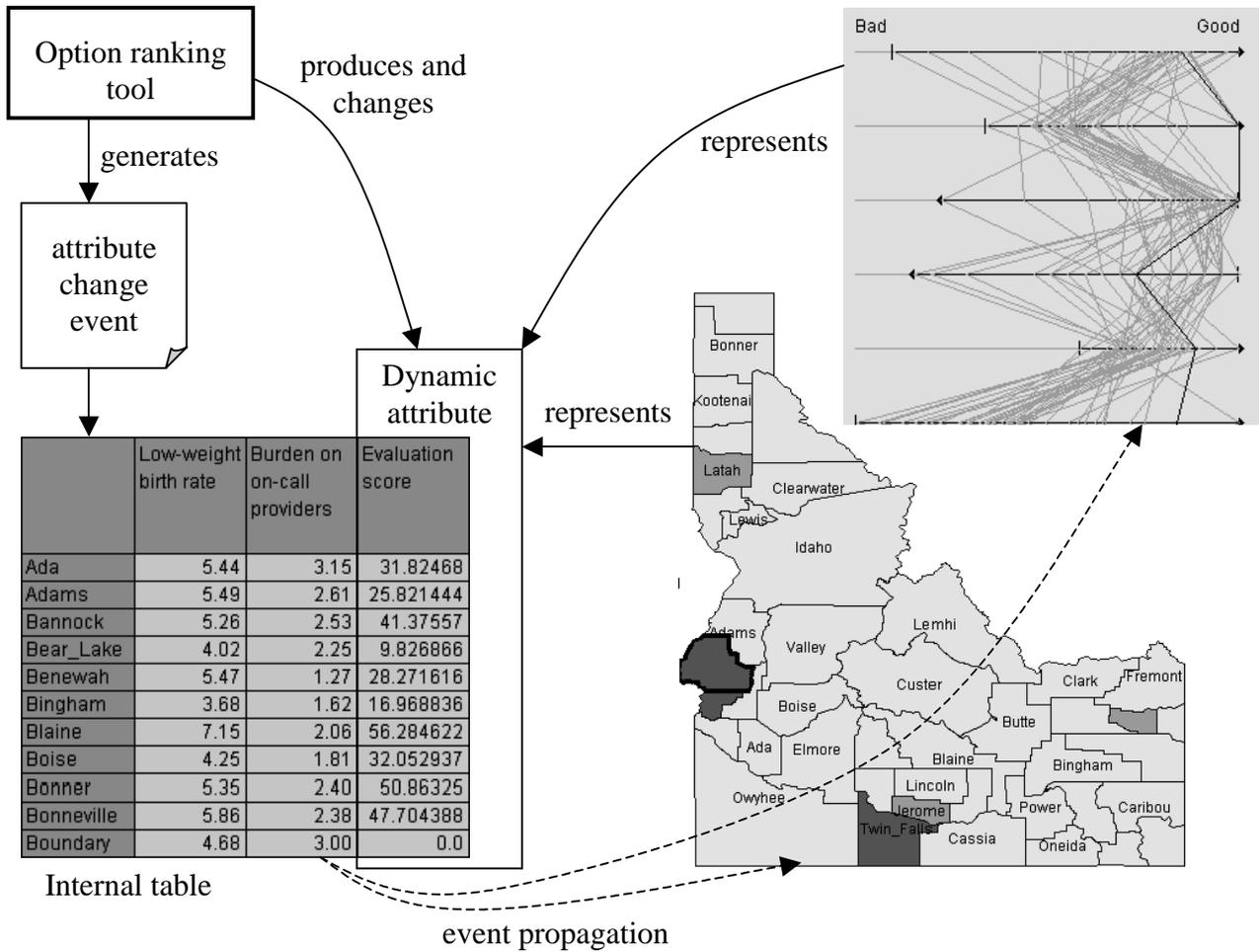


Figure 5. Integration of an option ranking MCDM tool with visualisation components of CommonGIS.

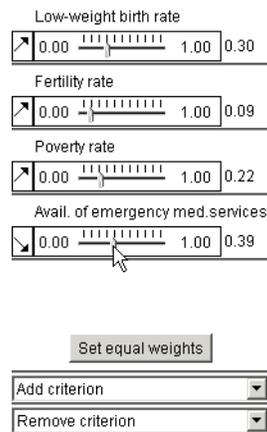
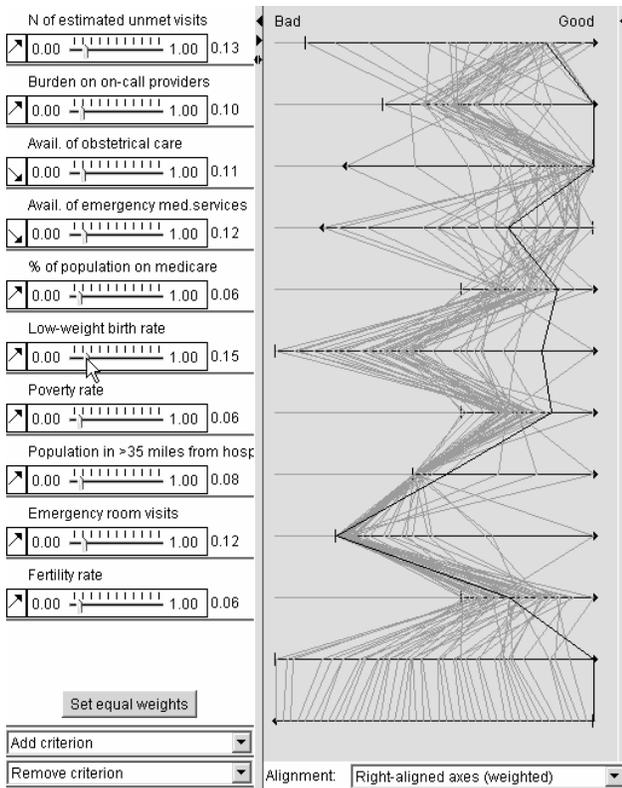
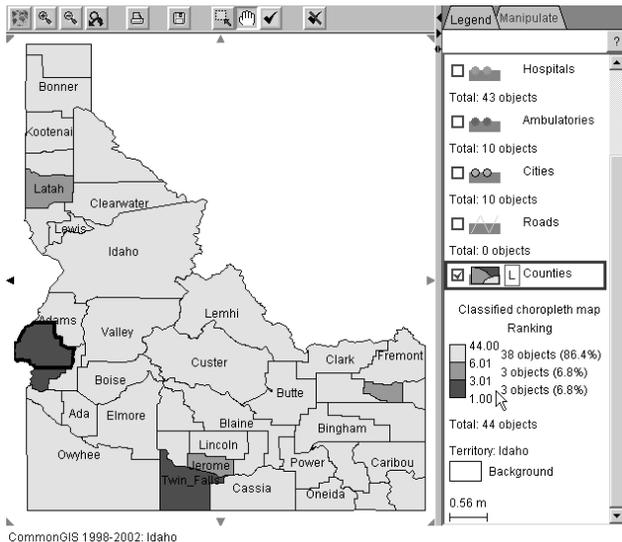


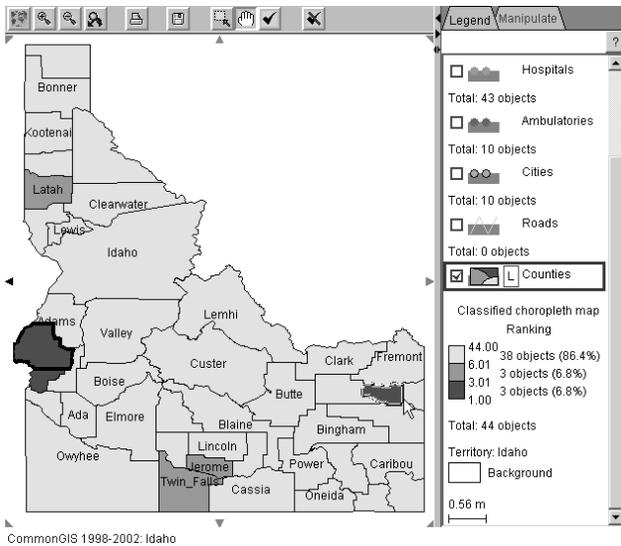
Figure 6. The user interface for specifying types and weights of decision criteria in CommonGIS.



**Figure 7.** Characteristics of options in terms of multiple criteria are aggregated into evaluation scores. The initial characteristics and the resulting scores are represented on the parallel coordinates. The parallel coordinate plot is transformed so that the axes reflect the weights and types of the criteria.



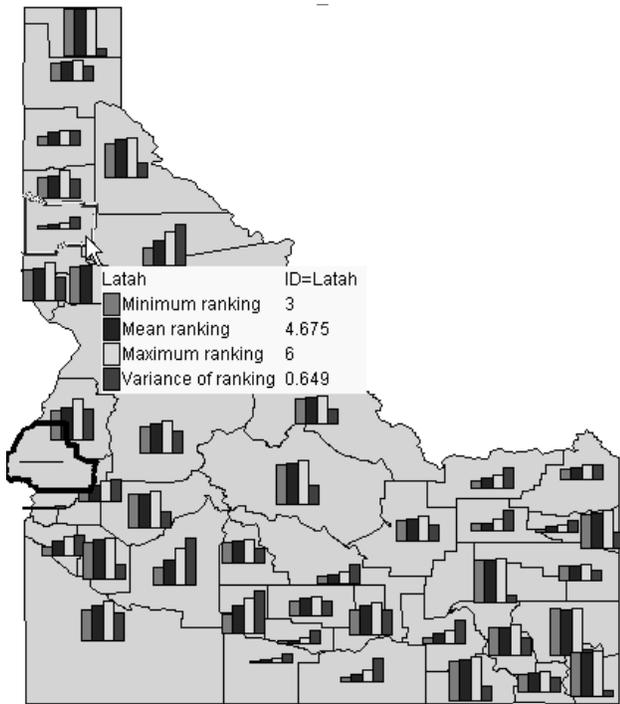
**Figure 8.** The map represents option ranking computed by the Ideal Point method with the weights of the criteria as is shown in Figure 7. Marked with the thick border is the same option that is highlighted on the parallel coordinate plot in Figure 7.



**Figure 9.** After increasing the weight of the criterion “Population in more than 35 miles from hospitals” to 0.20, the county Twin Falls has moved from the first to the second class, while the county Madison (in the east, pointed with the mouse cursor) has changed from the second to the first class. The classification of the remaining options stays the same.

County	Ranking	N of estimated sunset visits	Burden on on-call providers	Avail. of obstetrical care	Avail. of emergency med services	% of population on medicare	Low-weight birth rate	Poverty rate
Madison	1	8806	3.89	0.0004	0.0005	13.14	9.21	19.26
Washington	2	990	7.80	0.0000	0.0007	25.61	7.85	20.25
Payette	3	2994	7.80	0.0000	0.0003	14.79	6.74	16.90
Jerome	4	3607	7.00	0.0000	0.0005	13.78	6.46	13.93
Twin_Falls	4	14733	2.99	0.0009	0.0003	17.80	6.63	13.83
Latah	6	14168	2.55	0.0011	0.0002	20.72	7.36	13.75
Clearwater	7	653	5.00	0.0002	0.0019	17.45	2.99	14.84
Jefferson	8	18078	4.03	0.0004	0.0002	10.23	4.71	26.50
Cassia	9	8282	1.29	0.0008	0.0001	21.15	4.85	15.48
Clark	10	2614	7.00	0.0000	0.0003	20.44	4.94	15.64
Blaine	11	2546	2.86	0.0000	0.0008	24.26	7.15	16.40
Power	12	3256	1.86	0.0009	0.0007	25.81	7.85	20.25
Fremont	13	4614	3.10	0.0004	0.0002	24.32	5.29	16.89
Kootenai	14	-11709	1.91	0.0005	0.0002	16.00	6.35	15.62
Bonneville	15	-25764	2.38	0.0005	0.0002	14.20	5.86	10.35
Canyon	16	-30283	2.47	0.0010	0.0002	16.65	5.51	13.77
Germ	17	-33984	7.00	0.0000	0.0010	13.86	6.77	12.16
Lincoln	18	-2461	3.07	0.0006	0.0007	28.75	6.23	16.23
Valley	19	-4127	2.80	0.0023	0.0008	22.96	4.57	15.76
Bonner	20	-3967	2.40	0.0000	0.0004	12.67	5.95	12.74
Franklin	21	-4677	1.67	0.0016	0.0002	23.42	5.43	17.83
Camas	22	2002	2.28	0.0000	0.0005	19.58	5.04	13.96
Butte	23	-12231	3.63	0.0011	0.0003	20.42	4.94	15.63
Beneviah	24	-3634	1.27	0.0022	0.0006	32.13	5.47	19.56
Elmore	25	-63239	1.84	0.0007	0.0002	14.40	5.43	6.23
Gosling	26	-40800	5.29	0.0000	0.0020	15.16	6.91	13.78
Lemhi	27	833	3.88	0.0013	0.0008	23.17	4.88	12.96
Minidoka	28	-5039	5.60	0.0021	0.0006	15.15	3.33	18.09
Bannock	29	-7137	2.53	0.0007	0.0007	15.05	5.26	14.18
Owyhee	30	-2359	7.00	0.0000	0.0017	15.91	3.39	13.56
Boise	31	-18929	1.81	0.0006	0.0003	13.78	4.25	18.29
Adams	32	-60930	2.61	0.0012	0.0003	18.93	5.40	12.86
Nez_Perce	33	-39579	1.41	0.0016	0.0004	20.22	5.81	16.14
Teton	34	-6288	0.00	0.0014	0.0005	20.89	5.07	14.09
Lewis	35	-2127	1.37	0.0012	0.0007	21.52	4.53	12.21
Shoshone	36	1837	2.46	0.0010	0.0011	18.50	4.12	13.97
Ada	37	-1018	3.15	0.0013	0.0013	16.00	5.44	7.09
Custer	38	-73023	2.20	0.0005	0.0003	22.41	3.88	12.03
Oneida	39	-4533	0.92	0.0044	0.0007	24.94	5.32	16.29
Bingham	40	1822	1.82	0.0007	0.0012	17.87	3.88	13.50
Bear_Lake	41	-13818	2.25	0.0017	0.0012	26.96	4.02	14.46
Idaho	42	32640	2.33	0.0026	0.0005	8.80	5.21	7.68
Caribou	43	-17605	1.42	0.0031	0.0009	20.56	4.68	12.73
Boundary	44	-6058	3.00	0.0061	0.0009	20.56	4.68	12.73

**Figure 10.** The table view dynamically updates when the current option ranks (shown in the second column) change. Since the user has specified that the rows must be ordered according to the ranks, the best options always move to the top of the table.



**Figure 11.** Results of the sensitivity analysis (minimum, mean, maximum ranking, and variance of ranking) are represented by bar charts.