

A GIS-Based Sensitivity Analysis of Multi-Criteria Weights

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Abstract: Sensitivity analysis (SA) is a prerequisite for model building since it determines the reliability of the model through assessment of uncertainties in the simulation results. With growing interest in extending GIS to support multi-criteria decision-making (MCDM) methods, enhancing GIS-based MCDM with sensitivity analysis procedures is crucial. SA should be involved in GIS-MCDM model evaluation that tests the robustness of a model and the extent of output variation when parameters are systematically varied over a range of interest. The most common approach is based on varying criteria or their weights which represents input parameters in order to understand the model behavior and its limitations.

This paper presents a novel approach of examining multi-criteria weight sensitivity of a GIS-based MCDM model. The objectives of this study are to explore the dependency of model output on input parameters, identifying criteria that are especially sensitive to weight changes and to show the impacts of changing criteria weights on the model outcomes in spatial dimension. A methodology was developed to perform simulations where the decision weights associated with all criteria used for suitability modelling were varied to investigate their relative impacts on the final results of the evaluation. A tool which incorporates SA with Analytical Hierarchy Process (AHP) within the ArcGIS environment was implemented. It permits a range of user defined simulations to be performed to quantitatively evaluate model dynamic changes, measures the stability of results with respect to the variation of different parameter weights, and displays spatial change dynamics. A comprehensive case study of irrigated cropland suitability assessment addressing the application of the new GIS-based AHP-SA tool is described. After an initial evaluation which is assumed to be the base run according to best available knowledge, the original weights for the five different criteria from the base run were varied within a range of 20% provided that a 1% step was used for simulations. Summary tables for 40 simulation runs of each criterion and the resultant evaluation maps were generated and displayed. The tables demonstrate the change in the output suitability classification relative to changes in input criteria weights, identify criteria that are especially sensitive to weight variations, and visualise the spatial dimension of change dynamics. The results indicate that the evaluation map derived from base run could be used for analysing potential expansion of irrigated cropland because, when water is available, the highest possibility of such expansion will occur on highly suitable and moderately suitable lands which are relatively stable from the SA investigation in this study.

The integration of SA with AHP using GIS has enhanced the conventional AHP module, improved the reliability of MCDM output, and extended existing GIS functionalities. This GIS-based AHP-SA tool supplies more immediate feedback to evaluators/modellers. It is easier for non-experts to understand, and provides a mechanism to explore the decision problem while learning how changes in criteria weights affect evaluation outcomes spatially and quantitatively. It enables decision makers to follow/conduct a comprehensive yet easy-to-use procedure to examine weight sensitivity in both criteria and geographic space. It can give better insights for improving the capabilities of current GIS-based AHP-MCDM models to create more realistic output scenarios. Continued advances in this research area will allow GIS and MCDM to be applied to practical land-management issues with greater success.

Keywords: Sensitivity, Multi-criteria decision-making, AHP, ArcGIS

1. INTRODUCTION

There is growing interest in incorporating GIS capability with multi-criteria decision-making (MCDM) processes. As GIS-based MCDM becomes one of the most useful methods for spatial planning and management (Joerin *et al.*, 2001; Karnatak, *et al.*, 2007; Chen *et al.*, 2007; Chen *et al.*, 2009), the request for tools supporting collaborative decisions has increased over the last decade. Combining GIS and MCDM is a powerful approach to land suitability assessments. It involves a set of geographically defined basic units (e.g. polygons in vectors, or cells in rasters), and a set of evaluation criteria represented as map layers. The problem is to combine the criterion maps according to the attribute values and decision maker's preferences using a set of decision rules, or weights, in order to classify each unit into a suitability level. Therefore, the efficient use of the MCDM approach in decision making problems depends on the choice of the order weights. Using Analytical Hierarchy Process (AHP, Saaty, 1977, 1980; Saaty and Vargas, 1991) is one of the most popular methods to obtain them.

The AHP has been employed into the GIS-based landuse suitability procedures (Marinoni, 2004). It calculates the needed importance weighting factors associated with criterion map layers by the help of a preference matrix where all identified relevant criteria are compared against each other with reproducible preference factors. Then the weights can be aggregated with the criterion maps in a way similar to weighted combination methods. The GIS-based AHP gained high popularity because of its capacity to integrate a large amount of heterogeneous data and the ease in obtaining the weights of enormous alternatives (criteria), and therefore, it is applied in a wide variety of decision making problems.

It should be recognised that MCDM-derived rankings are often conditional (i.e. dependent on the nature of the alternatives under consideration, the criteria used to compare alternatives, and the weights derived for criteria, etc.). Criteria weights are often the greatest source of controversy and uncertainty. This could be because decision makers are not absolutely aware of their preferences regarding the criteria, and may be because nature and scale of the criteria is not known. Or, especially when multiple decision makers are involved, it is often not possible to derive only one set of weights, but ranges of weights, and thus a variety of results.

It is well-known that sensitivity analysis (SA) is crucial to the validation and calibration of numerical models. It can be used (as a tool) to check the robustness of the final outcome against slight changes in the input data. The SA procedures can help reduce uncertainty in how a MCDM method operates and the stability of its outputs by illustrating the impact of introducing small changes to specific input parameters on evaluation outcomes (Crosetto *et al.*, 2000). Besides (other than) checking for changes regarding the criteria values, it is perhaps relatively/more common to use SA for the analysis of changes in the weights given to the criteria. Delgado and Sendra (2004) conducted a review on how sensitivity analysis has been applied to GIS-based MCDM models. It indicated little attention had been paid to the evaluation of the final results. SA is not a common practice in the field of spatial MCDM. It is still largely absent or rudimentary for MCDM studies. In addition, the SA method most frequently used is based on the variation of the weights of the factors implied in the process to test whether it significantly modifies the results obtained. Perhaps the most critical shortcoming of SA procedures found in limited GIS-MCDM applications is the lack of insight they provide into the spatial aspects of weight sensitivity. It is recommended that SA procedures should permit weight sensitivity to be visualized geographically and to facilitate the spatial analysis of sensitivity, where appropriate (Robert and Hall, 2004).

This paper addresses the above issues by presenting a new approach for investigating the spatial dimension of multi-criteria weight sensitivity. It implements a generic SA methodology in a GIS-based AHP-MCDM model, which serves as an AHP-SA tool to be used for examining the sensitivity of MCDM evaluations to criteria weight changes and subsequently visualizing the spatial change dynamics relative to the decision problem. The approach is demonstrated using GIS-based multi-criteria land suitability assessment for potential irrigated agriculture in the Macintyre Brook catchment of Queensland, Australia.

2. METHODOLOGY

2.1. AHP Procedure

Saaty's (1977 and 1980) Analytical Hierarchy Process is a popular means to determine the weights which is one of the classical problems in multi-criteria decision analysis. The AHP is a mathematical method of analysing complex decisions problem with multiple criteria. It is based on three principles: decomposition, comparative judgment and synthesis of priorities. The decomposition principle of AHP requires the decision problem to be decomposed into a hierarchy that captures the essential element of the decision problem. The

comparative judgment principle of AHP requires pair-wise comparison of the decomposed elements within a given level of hierarchal structure with respect to the next higher level. An importance scale is proposed for these comparisons based on a large number of experiments (Table 1). The synthesis principle of AHP takes each of the derived ratio scale local priorities in the various levels of the hierarchy and constructs a composite set of priorities for the elements at the lowest level of the hierarchy. The standard method used to calculate the values for the weights from an AHP matrix is to take the eigenvector corresponding to the largest eigenvalues of the matrix, and then to normalize the sum of the components to one. The detailed description and implementation of AHP for spatial decision making is explained in the coming sections.

2.2. SA Procedure

Formal approaches of SA are described in the literature, ranging from physics to economics. Several techniques are available, ranging from differential to Monte Carlo analysis, from measures of importance to sensitivity indices, from regression or correlation methods to variance-based techniques (Archer *et al.*, 1997; Crosetto *et al.*, 2000). A thorough review of many techniques can be found in Saltelli *et al.* (2000). The simplest approach is when the input factors are varied ‘‘One At a Time’’, better known as the OAT method. The OAT method is easy to implement, computationally cheap, and has been frequently applied in various fields where models are employed. This is also the theoretical basis for this methodology.

Table 1. Scale for pair-wise comparisons (Saaty and Vargas, 1991)

Intensity of Importance	Description
1	Equal importance
3	Moderate importance
5	Strong or essential importance
7	Very strong or demonstrated importance
9	Extreme importance
2, 4, 6, 8	Intermediate values
Reciprocals	Values for inverse comparison

An ideal SA tool in support of an MCDM should be capable of taking several levels of uncertainty into account globally (i.e. over the entire problem space). However, there are three aspects of criteria weight sensitivity that are of interest in this study: (1) investing the stability of an evaluation by introducing a known amount of change to one weight and observing changes in the rankings of alternatives, (2) identifying criteria that are especially sensitive to weight changes, and (3) visualizing the spatial change dynamics. Attention is focused on the stability of evaluation rankings relative to standardized changes in criterion evaluation weights.

A generic method to examine these aspects of criteria sensitivity is proposed. A feasible range of weight deviations is required to be specified. The range can be defined in terms of a bounded set of discrete percent changes from an original criterion weight value used for a base run. Either a single range (e.g. plus or minus 20%) can be applied to all criteria or different ranges can be used for each criterion as required.

A series of evaluation runs are conducted where each criterion weight can be altered in a percent (e.g. plus or minus 1%) increments throughout the corresponding feasible range. All other criteria weights are then adjusted proportionally to satisfy the additivity constraint which requires all criteria weights to sum to 1.0. The total number of simulation runs required for a given decision participant is given as:

$$\text{Runs} = \sum_i^m r_i$$

where m = the set of criteria, and r_i = the number increments within the feasible weight range for criterion i .

The ranks of cells of the output grids generated from the SA evaluation runs are stored in multiple relational tables within a Microsoft Access database. Given the volume of the data generated and the need for advanced cartographic capabilities in spatial visualization, ArcGIS (Engine) 9.2 platform is used to visualise the SA results. A sequence of evaluation maps are simultaneously displayed for each simulation run. Consolidating the output into a format that is easy to interpret is a central challenge inherent to SA in general (Malczewski, 1999a and 1999b). A summary database table is created for each criterion. These tables summarise, when the weight of a particular criterion is altered by a specific amount (percent of increments) within the feasible range, values of weights for all criteria, number of cells in each rank, and sum of cells changing from original ranks. Notwithstanding the voluminous nature of these data, they provide a reasonably easy-to-interpret structure for examining the SA run results.

2.3. Tool Implementation

A tool called AHP-SA was developed to implement the SA procedure proposed in Section 2.2 (Figure 1a). It was developed with ArcGIS Engine 9.2. ArcGIS Engine is a core set of cross platform ArcObjects components compatible with multiple APIs (Application Programming Interface). It can be used to read raster layers, generate new grid files and present the analysis results. C#.Net computer language was used to build the framework of the software. C# language is a powerful language that is easy to use as a development environment for applications. It is easy to maintain and has advanced features for memory management. The .Net Framework is required to work with the analysis functions that were developed with C#. MATLAB software embedded components are used for implementing AHP and calculating criteria weights. The MATLAB COM Builder toolbox provides a special feature that the user can use to create Component Object Model (COM) objects from MATLAB M-files. The generated COM objects can then be use in the other programming languages that support COM applications including C#. (MATLAB C# Book, LePhan Publishing, 2004). The COM-Compliant component which implements AHP function is created as a Dynamic Link Library file, which could be referred in Visual Studio 2005. The implementation of AHP Sensitivity Analysis proves that it's an efficient way to augmenting GIS capabilities with MATLAB in the C# environment.

Some of the screen shots of the tool are shown in Figure 1. The two major components in the AHP-SA tool interface are the Map Control and the AHP Sensitivity. The Map Control allows the user to read and display criterion maps and evaluation maps of multi-criteria MCDM in the map frame in the right-hand side of the interface. The AHP Sensitivity carries out AHP and SA procedures (Figure 1b) which consists of two modules. The first one is the AHP Calculation module which provides a facility to select factors and criteria with initial weights, and the second is the Sensitivity Analysis module which performs SA evaluation based user's definition.

The tool starts with loading all standardised criteria layers into the map frame for the decision problem (Figure 1a). This enables the user to choose the relevant map criteria layers. Then the user can select from the Process menu to bring up the AHP Calculation window (Figure 1c) where selected criterion will be used as objectives to define the hierarchical structure of the decision problem. Given the hierarchical structure of the problem and the pairwise comparisons of objectives, the relative weights for objectives and criteria can be generated. The user can input the preference values using the scale in Table 1. Since the pairwise comparison matrix is reciprocal, the transpose cell is filled with the reciprocal value whenever a preference enters into a cell. The weights will be generated by clicking the Calculate icon/button as shown at the bottom of Figure 1d, and an evaluation map will be automatically displayed in the map frame. Results from the above two steps are regarded as the base run.

Step three of the procedure involves the parameterization of SA method described in Section 2.1. The user needs to input four parameters which include selecting a criterion for weight change, defining a range of weight change percentage, assigning the steps (increments) of changes within the range, and specifying the output grid (Figure 1e).

Finally, in the last step of the module, 40 result map layers of evaluation ranking decision will be created and added to the map frame (Figure 1f), and a table which summarises the 40 simulation runs for each criterion (in terms of weights values, cell numbers at different ranking levels, changes of cells between different ranking levels) will be automatically generated in a table every time after clicking the Calculate icon.

By repeating Step three to change or refine SA parameters associated with the criteria, a wide range of decision scenarios can be generated, the resultant summary tables are saved and the corresponding maps are displayed.

3. EXAMPLE APPLICATION

The application of the AHP-SA tool is illustrated/demonstrated using spatial data from a study in which multi-criteria land suitability assessment at a catchment scale was performed/conducted to identify the potential of expanding irrigated cropping landuse in Macintyre Brook Catchment of Queensland in Australia.

3.1. Base Run

In the present case, the suitability classes consisting of four levels used in this study were adapted from the FAO system. They are stated as: highly suitable (S1), moderately suitable (S2), marginally suitable (S3) and unsuitable (N). Selection of evaluation criteria in this study were based on project objective, spatial scale, and in particular, data availability. Five criteria were chosen, including slope, soil texture, depth to water-table

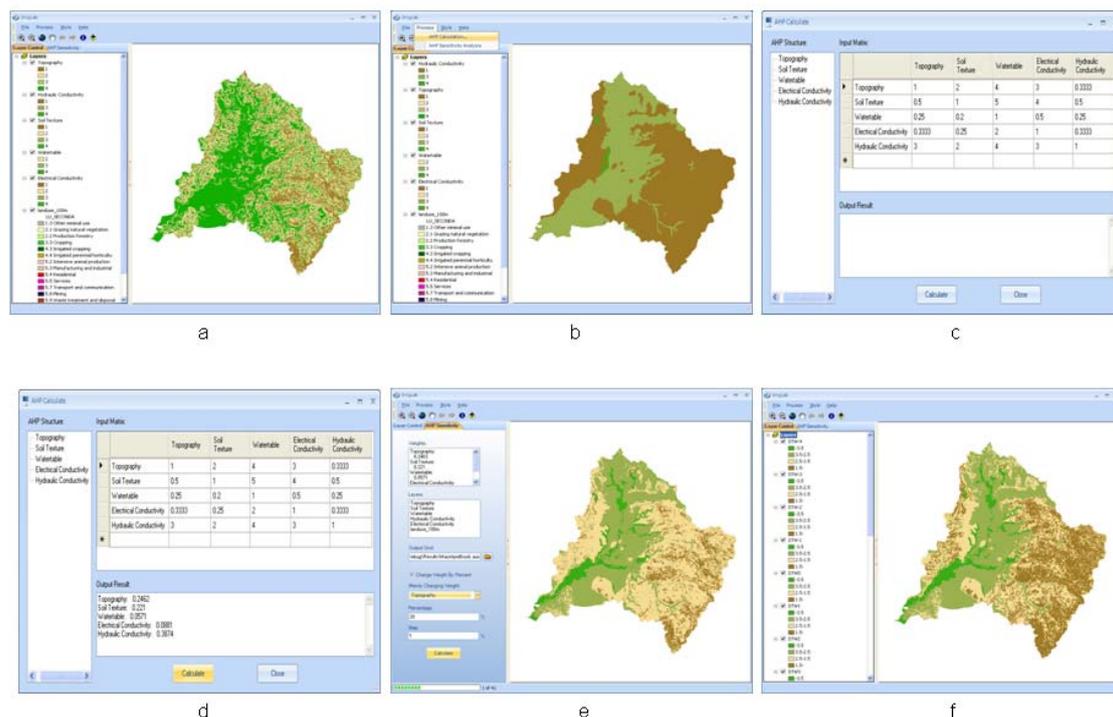


Figure 1. AHP-SA tool interface. (a) Two components in the main interface: Map Control and AHP Sensitivity ; (b) Two modules in the AHP Sensitivity component: AHP Calculation and Sensitivity Analysis; (c) AHP Calculation window: pairwise comparison matrix; (d) AHP Calculation window: Criteria weights calculation; (e) Sensitivity Analysis window: parameterization; and (f) Display simulation runs.

(DTW), electrical conductivity of groundwater (ECw), and hydraulic conductivity of soil (Ks). The threshold values of evaluation criteria for each of the four suitability classes were determined based on literature survey and expert opinion (Chen *et al.*, 2009).

Spatial data were converted into raster layers and projected to UTM Zone56 in ArcGIS 9.2. Slope was generated from a 25m resolution DEM. The other four datasets were also resampled to 25m cell size using a cubic convolution algorithm. They were then classified into four classes as integer rasters representing different suitability levels based on assigned threshold values, and loaded into the map frame of the tool. The maps displayed in Figure 1a and 1b represent Slope and Ks criteria, respectively.

The relative importance of each criterion was determined before weighting each of the relevant criteria. All criteria were compared against each other in a pairwise comparison matrix which is a measure to express the relative preference among the factors. The values of the comparison were determined according to the scale in Table 1 (Figure 1c).

Next, the assigned preference values in the AHP-SA interface were synthesised to determine a ranking of the relevant factors in terms of a numerical value which is equivalent to the weights of the factors (Figure 1c). Once the constructed matrix was entered into the AHP-SA module, the weighting coefficients of criteria were automatically derived (Figure 1d). These criteria weights will be served as the initial weights from base run to be used in the SA process.

Finally, the weighted criterion maps were aggregated to produce a final suitability map (Figure 1e). The resultant map from this base run shows the extent distribution of the land suitability classes. The most suitable locations are in dark green, and the unsuitable lands are in dark brown.

3.2. SA Simulation Framework

A single feasible range of $\pm 20\%$ was applied to a complete set of five criteria. For each criterion, the weight was altered in 1% increments. Within a range of -20% (the 1st run) to +20% (the 41st run) of its initial value from base run (the 21st run), the simulation consists of 200 evaluation runs where each run generates a single new suitability classification (e.g. the map in Figure 1f), and five tables where each table summarises the results of 40 runs for each criterion (Figure 2).

With the aid of results from 200 simulation runs as shown in Figure 2, it can be seen that

- There are no pixels/cells that either increased or decreased more than one suitability level/class from its original rank of the base run.
- Ks factor has the highest sensitivity and ECw and DTW have the lowest among all criteria. The other two criteria have similar degree of sensitivity with the order of slope factor greater than soil texture factor.
- Ks factor is the most sensitive criterion which causes significant suitability class modification from S1 to S2 when its weight change is greater than 8%;
- S1 and S2 are relatively stable despite a certain degree of variations in the weights of slope, soil texture, ECw and DTW. The ranks of most cells in these two suitable levels remained the same, or slightly changed. The fact that the perturbation of the decision weights, in particular DTW and ECw, has a small impact on the ranking of the most cells in S1 and S2 reveals that the degree of domination of these cells is almost independent of changes in the decision weights associated with these selected criteria.
- The biggest difference/alteration of classification happened in S3 and S4. There is a dramatic decrease of the pixels in S3 and a remarkable increase of the pixels in S4. Most of shifts from S3 to S4 occurred within the $\pm 5\%$ of changes, except for ECw where the changes take place at about $\pm 12\%$.
- S3 and S4 appear most sensitive to criteria weight changes. A considerable cell exchange between S2 and S3 can be noted.

While the chart presentations of SA results in Figure 2 are useful, they cannot provide insights into the spatial pattern of weight sensitivity in an evaluation or how similar the spatial patterns of sensitivity are across the simulation runs. To demonstrate the added value of map-based visualization to GIS-MCDM problem solving in general, six examples of simulated evaluation maps where significant suitability classification changes occur corresponding to some weight variations given to certain criteria are shown as below (Figure 3).

4. CONCLUSIONS

This paper has presented a GIS-based AHP-SA approach for generating and visualizing criteria weight sensitivity. The fusion of SA with AHP within ArcGIS environment enhances the conventional AHP module, improves the reliability of MCDM output, and extends existing GIS functionalities. The implementation of the tool enables decision makers to follow a comprehensive yet easy-to-use procedure to examine weight sensitivity in both criteria and geographic space. The application of the methodology was demonstrated using data from an irrigated cropland suitability evaluation study in Macintyre Brook catchment of Australia. The results indicated that the evaluation map derived from base run could be used for analysing potential expansion of irrigated cropland because, when water is available, the highest possibility of such expansion will occur on highly suitable and moderately suitable lands which are relatively stable from the SA investigation in this study. They also showed that SA tool can provide better insights for improving the capabilities of current GIS-based AHP-MCDM models to create more realistic output scenarios.

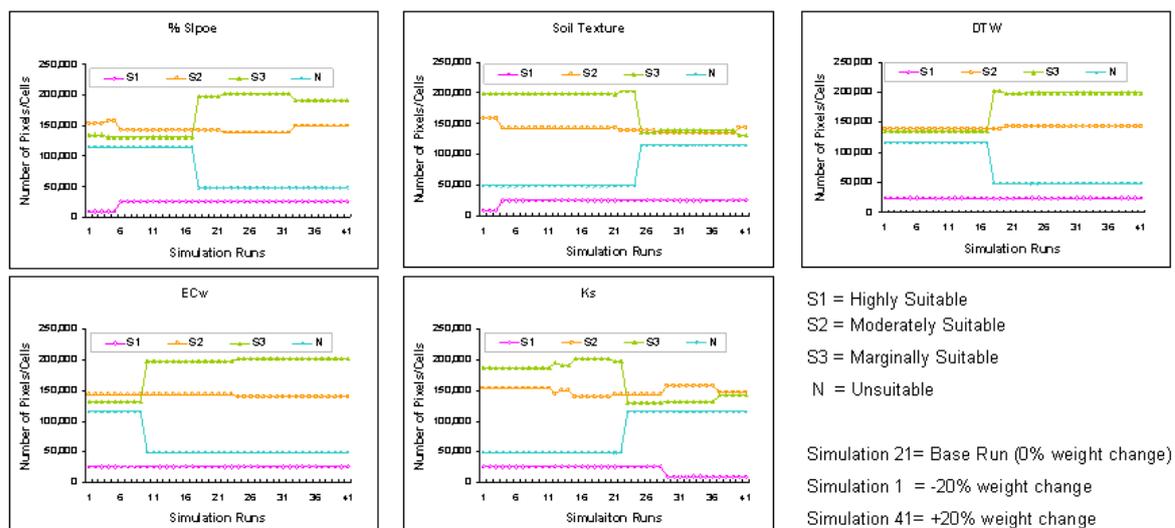


Figure 2. Summary results from 200 simulations (40 runs for each criterion).

In conclusion, SA should be conceived as a stage in the evaluation of MCDM that examines the extent of output variation of a model when parameters including criteria or associated weights are systematically varied over a range of interest. This GIS-based AHP-SA approach supplies more immediate feedback to evaluators/modellers, is easier for non-experts to understand, and provides a mechanism to explore the decision problem while learning how changes in criteria weights affect evaluation outcomes spatially and quantitatively. Continued advances in this research area will permit GIS and MCDM to be applied to practical land-management issues with greater success.

ACKNOWLEDGMENTS

We would like to thank Department of Natural Resources and Water of Queensland Government for providing data of the case study which was supported by the System Harmonisation program of the Cooperative Research Centre for Irrigation Futures (CRC IF), Australia.

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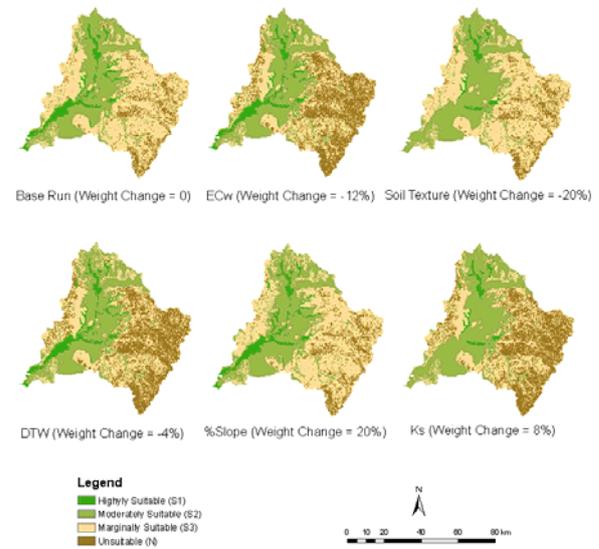


Figure 3. Example evaluation maps presenting irrigated cropland suitability classification as a result of weight changes.