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Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation

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ABSTRACT

With growing interest in extending GIS to support multi-criteria decision-making (MCDM) methods, enhancing GIS-based MCDM with sensitivity analysis (SA) procedures is crucial 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. It explores the dependency of model output on the weights of 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 weights associated with all criteria used for suitability modelling were varied one-at-a-time (OAT) to investigate their relative impacts on the final evaluation results. A tool which incorporates the OAT method with the 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 case study of irrigated cropland suitability assessment addressing the application of the new GIS-based AHP-SA tool is described. It demonstrates that the tool is spatial, simple and flexible.

1. Introduction

Multi-criteria decision making (MCDM) is primarily concerned with how to combine the information from several criteria to form a single index of evaluation. GIS are best suited for handling a wide range of criteria data at multi-spatial, multi-temporal and multi-scale from different sources for a time-efficient and cost-effective analysis. Therefore, there is growing interest in incorporating GIS capability with MCDM processes. Spatial MCDM has also become one of the most useful methods for landuse and environmental planning, as well as water and agricultural management (Davidson et al., 1994; Ahamed et al., 2000; Joerin et al., 2001; Ceballos-Silva and López-Blanco, 2003; Sicat et al., 2005; Chen et al., 2007). As a result, the request for GIS models and tools supporting collaborative decisions has increased over the last decade (Kollias and Kalivas, 1998; Karnatak et al., 2007; Reshmidevi et al., 2009; Chen et al., 2009). GIS-based MCDM 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 or attributes. Based on a particular ranking schema, it ultimately informs a spatially complex decision process by deriving a utility of these spatial entities through overlaying the criterion maps according to the attribute values and decision maker's preferences using a set of weights. Therefore, besides criteria selection, criteria weights severely impact the results of the MCDM.

Using Analytical Hierarchy Process (AHP) is one of the most popular methods to obtain criteria weights in MCDM (Saaty, 1977, 1980; Saaty and Vargas, 1991; Wu, 1998; Ohta et al., 2007). The AHP has been employed in the GIS-based MCDM (Carver, 1991; Malczewski, 1999a, 1999b, 2004; Makropoulos et al., 2003; Marinoni, 2004; Marinoni et al., 2009). It calculates the needed weights associated with criterion map layers by the help of a preference matrix where all identified relevant criteria are compared

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against each other with preference factors. Then the weights can be aggregated with the criterion maps in a way similar to weighted combination methods. GIS-based AHP is popular because of its capacity to integrate a large amount of heterogeneous data and the ease in obtaining the weights of a large number of criteria, and therefore, it has been applied in tackling a wide variety of decision making problems (Tiwari et al., 1999; Nekhay et al., 2008; Hossain and Das, 2009).

It should be recognised that MCDM-derived rankings are often conditional. The uncertainty can come from many different sources, such as original data, data processing, criteria selection and their thresholds. Criteria weights are often the greatest contributor to 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 more than one set of results.

Sensitivity analysis (SA) explores the relationships between the output and the inputs of a modelling application. It is “the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation, and how the model depends upon the information fed into it” (Saltelli et al., 2000). SA is crucial to the validation and calibration of numerical models. It can be used to check the robustness of the final outcome against slight changes in the input data (Ticehurst et al., 2003; Newham et al., 2003; Merritt et al., 2005; Zoras et al., 2007). There are some well established techniques for SA, ranging from differential to well-known Monte Carlo analysis, from measures of importance to sensitivity indices, and from regression or correlation methods to variance-based techniques (Bootlink et al., 1998; Hyde et al., 2004; Manache and Melching, 2008). A thorough review of many SA methods can be found in Saltelli et al. (2000) and Campolongo et al. (2000).

The SA procedures can help reduce uncertainty in MCDM and the stability of its outputs by illustrating the impact of introducing small changes to specific input parameters on evaluation outcomes (Archer et al., 1997; Crosetto et al., 2000; Crosetto and Tarantola, 2001; Ravalico et al., 2010). A variety of different procedures, most taking non-spatial forms, exist for dealing with the SA issues in MCDM. Several examples are described in the literature. Hill et al. (2005) analysed the ASSESS AHP and the role of quantitative methods in spatial decision support. Hyde and Maier (2006) developed a spreadsheet program that examines the robustness of a model run results obtained using MCDM. It is perhaps more common to use SA for the analysis of changes in the weights given to the criteria rather than checking for changes regarding the criteria values. For example, Janssen (1996) investigated sensitivity to changes in the importance of criteria within the decision rule. Hyde et al. (2005) proposed a sensitivity analysis to analyse the effects of uncertainties associated with the criteria weights in multi-criteria decision analysis for water resource decision making. However, SA is not a common practice in the field of spatial MCDM. It is still largely absent or rudimentary for MCDM studies. Delgado and Sendra (2004) conducted a review on how SA has been applied to GIS-based MCDM models. It indicated little attention had been paid to the evaluation of the final results from these model simulations. In addition, the SA method most frequently used is based on the variation of the weights of criteria 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 (Feick and Hall, 2004).

This paper addresses these documented shortcomings 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 decision making problems. The approach is demonstrated using GIS-based multi-criteria land suitability assessment for potential irrigated agriculture in the Macintyre Brook catchment of Queensland, Australia.

Table 1
Scale for pairwise 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

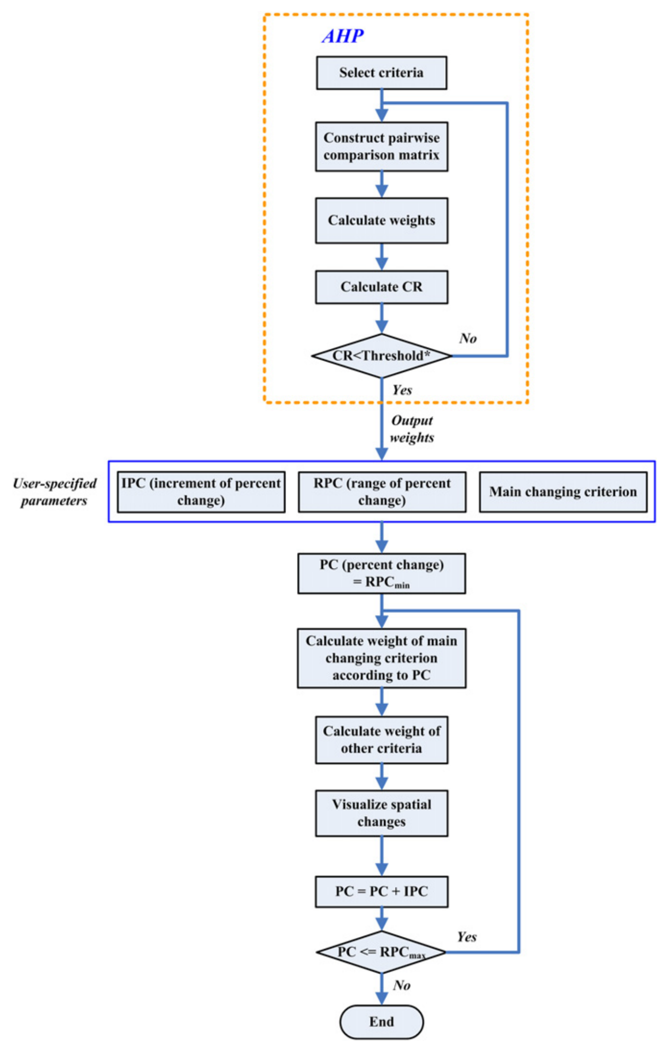

Fig. 1. Flowchart of AHP and SA methodology (*user-defined value; default is 0.10).

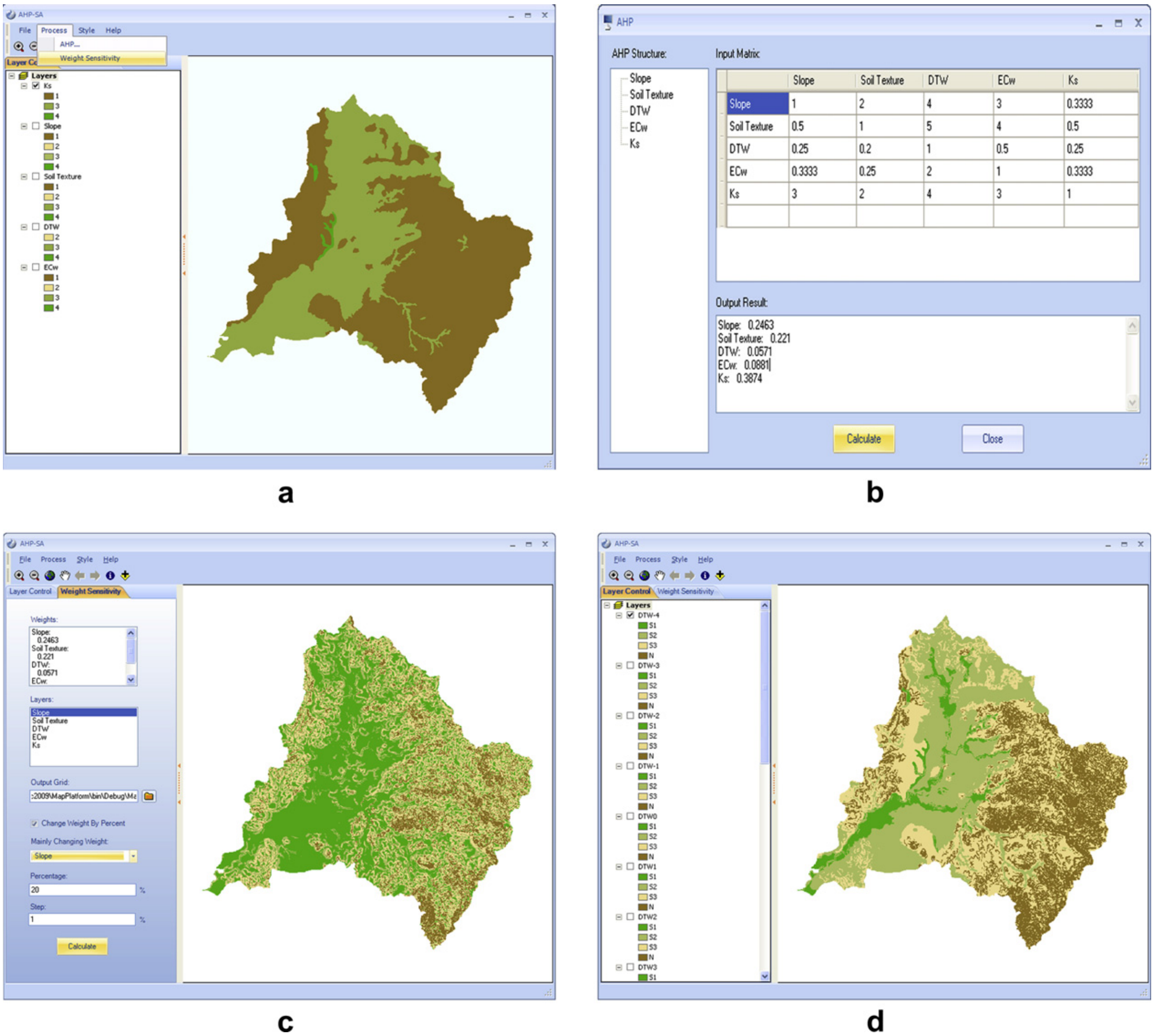

Fig. 2. AHP-SA tool interface. Map layers are from a case study in Macintyre Brook catchment. (a) Three components in the main interface: Map Control, AHP and Weight Sensitivity; (b) AHP window: pairwise comparison matrix; (c) Weight Sensitivity window: SA parameterisation; and (d) Map Control, display simulation runs.

2. Approach

2.1. AHP pairwise comparison

Determination of criterion weights is crucial in MCDM. The AHP is a popular mathematical method for this purpose when analysing complex decision problems (Saaty, 1977, 1980). It derives the weights through pairwise comparisons of the relative importance between each two criteria. Through a pairwise comparison matrix, the AHP calculates the weight value for each criterion (w_i) by taking the eigenvector corresponding to the largest eigenvalue of the matrix, and then normalising the sum of the components to a unity as:

$$\sum_{i=1}^{n} w_i = 1 \tag{1}$$

An importance scale is proposed for these comparisons (Table 1). The basic input is the pairwise comparison matrix A of n criteria constructed based on Saaty's scaling ratios, which is of the order $(n \times n)$ as defined in equation (2):

$$A = [a_{ij}], \ i, j = 1, 2, 3, \dots, n \tag{2}$$

where A is a matrix with elements a_{ij}. It generally has the property of reciprocity, i.e. mathematically:

$$a_{ij} = 1/a_{ji} \tag{3}$$

and after it has been generated, it is normalised as a matrix B:

$$B = [b_{ij}], \ i, j = 1, 2, 3, \dots, n \tag{4}$$

where B is the normalised matrix of A with elements b_{ij}:

$$b_{ij} = a_{ij} / \sum_{i=1}^{n} a_{ij}, \quad i, j = 1, 2, 3, \dots, n \tag{5}$$

Each weight value w_i is computed as:

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij}}, \quad i, j = 1, 2, 3, \dots, n \tag{6}$$

Equations (7)–(9) represent the relationships between the largest eigenvalue (λ_{max}) and corresponding eigenvector (W) of the matrix B (Xu, 2002):

$$BW = \lambda_{max} W \tag{7}$$

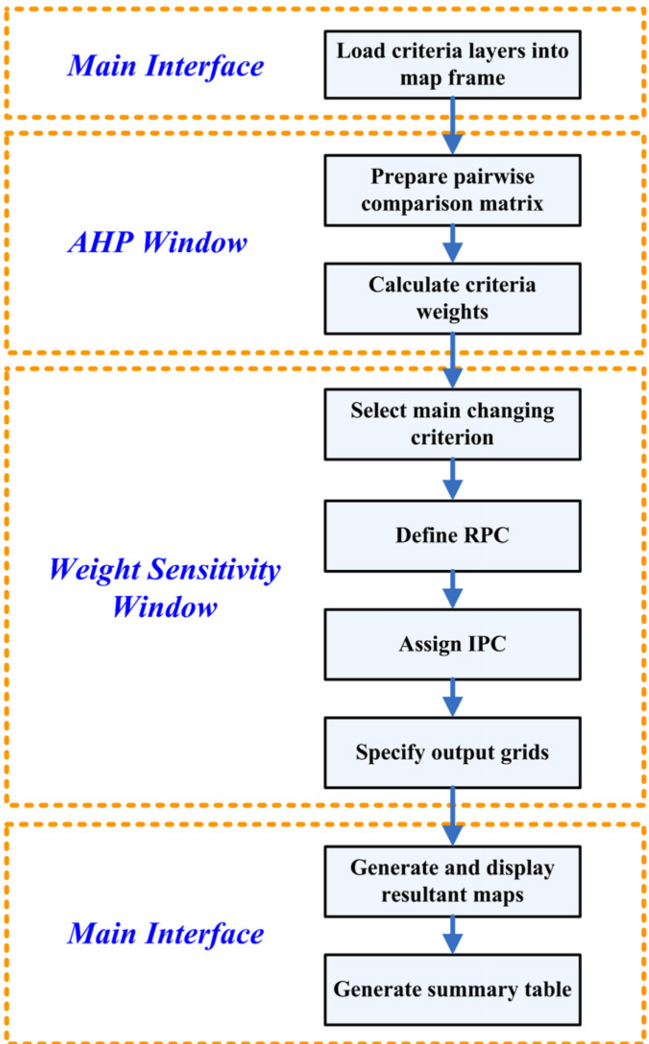

Fig. 3. Steps of using AHP-SA tool.

$$W = (w_1, w_2 \ldots w_n)^T \tag{8}$$

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(BW)_i}{nw_i}, \quad i = 1, 2, 3, \ldots, n \tag{9}$$

where $(BW)_i$ is the i-th value of the vector BW.

It is necessary to verify the consistency of the matrix B after obtaining the weight values. The consistency is judged on the basis of a consistency ratio CR:

$$\mathrm{CR} = \frac{\lambda_{\max} - n}{(n-1)\mathrm{RI}} \tag{10}$$

where RI is a constant which corresponds to the mean random consistency index value according to n.

The determination of CR value is critical. In our case study, we adopted a standard CR threshold value of 0.10 which has been widely used as a measure of the consistency in a set of judgments of AHP applications in literature. If CR $<$0.10, it deems that the pairwise comparison matrix has acceptable consistency and the weight values calculated in equation (6) are valid and can be utilised. Else if CR $\geq$0.10, it means that the pairwise comparisons are lack of consistency, in other words, the matrix is better to be adjusted and the element values should be modified. However, although one might think that being consistent is of utmost importance, allowing for some inconsistency is reasonable. One of the strengths of AHP is that it does allow for inconsistent relationships, while, at the same time, providing CR as an indicator of the degree of consistency or inconsistency (Forman and Selly, 2001). Therefore, the AHP implementation in this study has incorporated an option to let the user define an acceptable CR threshold value. SA should proceed if the user-defined CR requirement is met. But when CR is greater than 0.10, the user has to be careful to accept the resultant weights without changing input to the pairwise comparison matrix, as well as feel confident that the matrix really reflects the user's beliefs rather than contain an error (Bodin and Gass, 2003).

2.2. SA framework

In sensitivity analysis a common approach is to change input factors One-At-a-Time, better known as the OAT method (Daniel, 1958, 1973), to see what effect this produces on the output. This appears a logical approach as any change observed in the output will unambiguously be due to the single factor changed. By changing one factor at a time, all other factors can be fixed, at least to a great extent, to their central or baseline value. This increases the comparability of the results. Furthermore, the OAT is easy to implement and computationally cheap.

There are three most commonly used ways to analyse criteria sensitivity: changing criteria values, changing relative importance of criteria and changing criteria weights. This study is interested in varying criteria weights only, with four specific aspects of interests: (1) investing the stability of an evaluation by introducing a known amount of change to criteria weights; (2) identifying criteria that are especially sensitive to weight changes; (3) quantifying changes in the rankings of criteria and evaluation; and (4) visualising the spatial change of evaluation results. Attention is particularly focused on the stability of evaluation rankings relative to changes in criteria weights in the spatial domain.

A generic method to examine these aspects of criteria sensitivity is proposed by adapting the OAT in this study (Fig. 1). A feasible range of weight deviations is required to be specified. The range can be defined as a bounded set of discrete percent changes, range of percent change (RPC), 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 can be conducted where each criterion weight is altered in percent (e.g. plus or minus 1%) increments, in terms of increment of percent change (IPC), throughout its corresponding feasible range (equation (11)), and the weights of the other criteria are adjusted proportionally to satisfy the additivity constraint in equation (1) which requires all criteria weights to sum to one (equation (12)). The total number of simulation runs required for a given decision problem is given as:

$$\text{Runs} = \sum_{i=1}^{n} r_i \tag{11}$$

where n is the total number of criteria, and r_i is the number of IPC within a RPC (default to $\pm$20%) for criterion i.

The sum of all criteria weights at any percent change (PC) level $W(pc)$ should always equal to 1:

$$W(pc) = \sum_{i=1}^{n} W(c_i, pc) = 1, \quad \mathrm{RPC}_{\min} \leq pc \leq \mathrm{RPC}_{\max} \tag{12}$$

where $W(c_i,\text{pc})$ is the weight of the i-th criterion c_i at a certain PC level; n is the total number of criteria, and $\mathrm{RPC}_{\min}$ and $\mathrm{RPC}_{\max}$ are the minimum and maximum values of RPC, respectively.

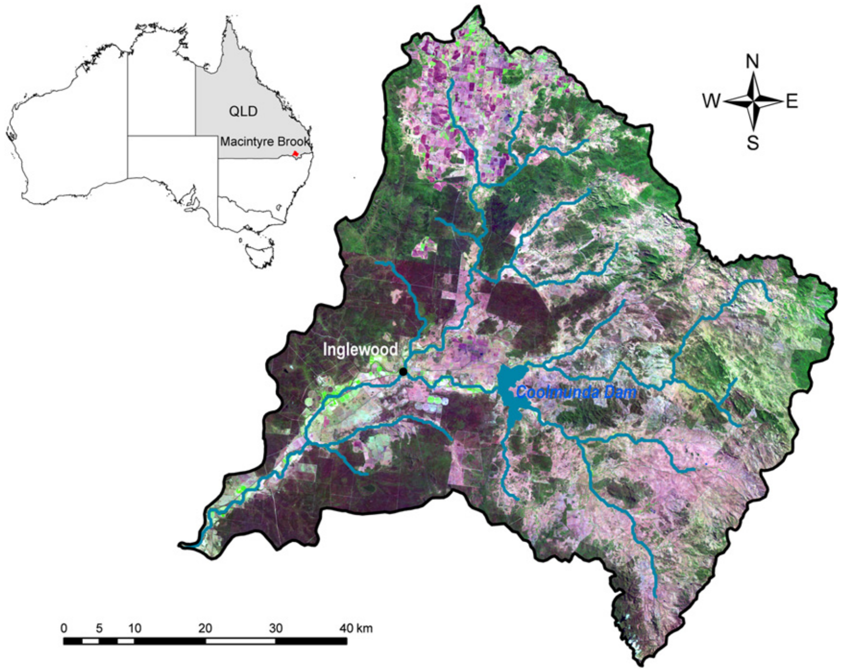

Fig. 4. Location of the study area.

When varying the weight of a criterion which is the main changing criterion c_m under consideration, its weight $W(c_m,pc)$ at a certain PC level can be calculated as:

$$W(c_m, pc) = W(c_m, 0) + W(c_m, 0) \times pc, \quad 1 \le m \le n \tag{13}$$

where $W(c_m,0)$ is the weight of the main changing criterion c_m, at the base run.

In order to meet the condition given in equation (12), the weights of the other criteria $W(c_i,pc)$ are adjusted proportionally in accordance with $W(c_m,p)$ derived in equation (13):

$$W(c_i, pc) = (1 - W(c_m, pc)) \times W(c_i, 0)/(1 - W(c_m, 0)), \quad i \ne m, \quad 1 \le i \le n \tag{14}$$

where $W(c_i,0)$ is weight of the i-th criterion c_i at the base run.

When the weight of a main changing criterion is altered by an IPC within an RPC, a sequence of evaluation maps are generated for each simulation run and a summary table is created for each criterion to quantify the changes in both input (criteria) and output (evaluation results).

2.3. Tool implementation

A raster-based tool called AHP-SA was developed to implement the SA procedure proposed in Section 2.2 (Fig. 2a). Given the volume of the data generated and the need for advanced cartographic capabilities in spatial visualization, ArcGIS (Engine) 9.2 (ESRI, 2008) platform was used to visualise the SA results. C#.Net computer language was used to build the framework of the software. A MATLAB COM-Compliant component which is created as a DLL (Dynamic Link Library) (Phan, 2004) was used to implement AHP and to calculate criteria weights. The summary tables from the SA evaluation runs were stored in multiple relational tables within a Microsoft Access database. The combination of these different programming environments proved an efficient method to augment GIS capabilities.

Some screen shots of the tool are shown in Fig. 2. The three major components in the AHP-SA tool interface are Spatial Mapping, AHP and Weight Sensitivity. The Spatial Mapping window (Fig. 2a) allows users to read and display criterion maps and evaluation maps of MCDM in the map frame in the right-hand side of the main interface. The AHP window (Fig. 2b) provides a facility to select criteria, construct pairwise matrix, and generate criteria initial weights. The Weight Sensitivity window (Fig. 2c) carries out SA procedure which is based on both user-defined SA parameters and initial weights calculated from AHP window.

A flowchart showing a series of basic steps of how to use the tool is given in Fig. 3. The tool starts with loading all criteria data layers into the map frame (Fig. 2a). This enables users to choose relevant criteria map layers for the decision problem. The criteria maps have to be pre-processed as ESRI integer grids with the same extent and coordinate system. Then users select AHP from the Process menu (Fig. 2a) where selected criteria are used to define the hierarchical structure and to construct the pairwise comparison matrix (Fig. 2b). Users can input importance values (1–9) using the scale in Table 1. Since the pairwise comparison matrix is reciprocal, the transpose cell is automatically filled with the reciprocal value whenever an importance value is entered into a cell. The criteria weights are generated by clicking the Calculate button at the bottom of the window (Fig. 2b), and an evaluation map is then automatically displayed in the map frame (Fig. 2d). Results from the above two steps are regarded as the base run if the CR check is passed. Given the calculated criteria weights of the decision problem, the next step of the procedure involves the parameterisation of SA method described in Section 2.2. Users need to input four parameters: 1) selecting main changing criterion (e.g. Slope), 2) defining RPC (e.g. ±20%), 3) assigning IPC (e.g. ±1%) within the RPC, and 4) specifying the name of output grid (Fig. 2c). Finally, as last step of the module, 40 resultant map layers of evaluation ranking decision will be created and added to the map frame (Fig. 2d) together with the results from the base run, and a table which summarises these simulation runs for the selected main changing criterion (in terms of weights values, cell numbers at different ranking levels, changes of cells between different ranking levels) will be automatically generated after clicking the Calculate icon. By resetting SA parameters associated with Weight Sensitivity window, a wide range of

Table 2
Criteria for suitability assessment of irrigated croplands.

	Highly suitable	Moderately suitable	Marginally suitable	Unsuitable
Ks (m/d)	0.3–1	0.05–0.3 or 1–2	2–2.5	<0.05 or >2.5
S (%)	0–2	2–4	4–8	>8
ST	Fine to medium	Heavy clay	Coarse or poorly drained	Very coarse or shallow depth
DTW (m)	>4	3–4	2–3	<2
ECw (dS/m)	0–0.5	0.5–2	2–5	>5 (if depth <4m)

decision scenarios can be generated, the resultant summary tables are saved and the corresponding maps are displayed.

3. Case study

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

3.1. Study area

The Macintyre Brook catchment (Fig. 4) is situated in southern Queensland near the state border with New South Wales. The catchment covers an area of 4200 km^2. It is relatively flat in the western area, with undulations becoming steeper towards east and northeast. The Macintyre Brook flows from east to west, and its tributaries are the main source of surface water for the region. The region is not well endowed with groundwater. Coolmunda Dam supplies irrigation water to Macintyre Brook along which the main irrigation areas of the catchment are located. Daily temperatures range from 18 to 32 °C in summer and 4 to 18 °C in winter, when frosts are common. The monthly average evaporation varies from 50 mm to 200 mm, while the average annual rainfall is 640 mm. Most of the rainfall falls between October and March, but around 100 mm falls in winter. The catchment is characterised by extremely diverse soil types and topography, making it suitable for a wide variety of land uses and rural production. Currently about 1.5% of the catchment area is devoted to irrigated cropping and perennial horticulture, as well as sown pastures. The remainder is dominated by dryland cropping (3%), native pasture grazing country (80%) and State Forest Reserves (15%). Historically, grazing was predominant but dryland and irrigated cropping have become increasingly significant over time. The main crops include fodder (lucerne), maize, sorghum, peas, and orchard such as peach, plum and apricot (Chen et al., 2009).

3.2. Base run

In the present case, the suitability classes consisting of four levels used in this study were adapted from the FAO system (FAO, 1976). They are stated as: highly suitable (S1), moderately suitable (S2), marginally suitable (S3) and unsuitable (N). Five criteria were chosen based on study objective, spatial scale, and in particular, data availability. They are hydraulic conductivity of soil (Ks), percent slope (S), soil texture (ST), depth to water-table (DTW), and

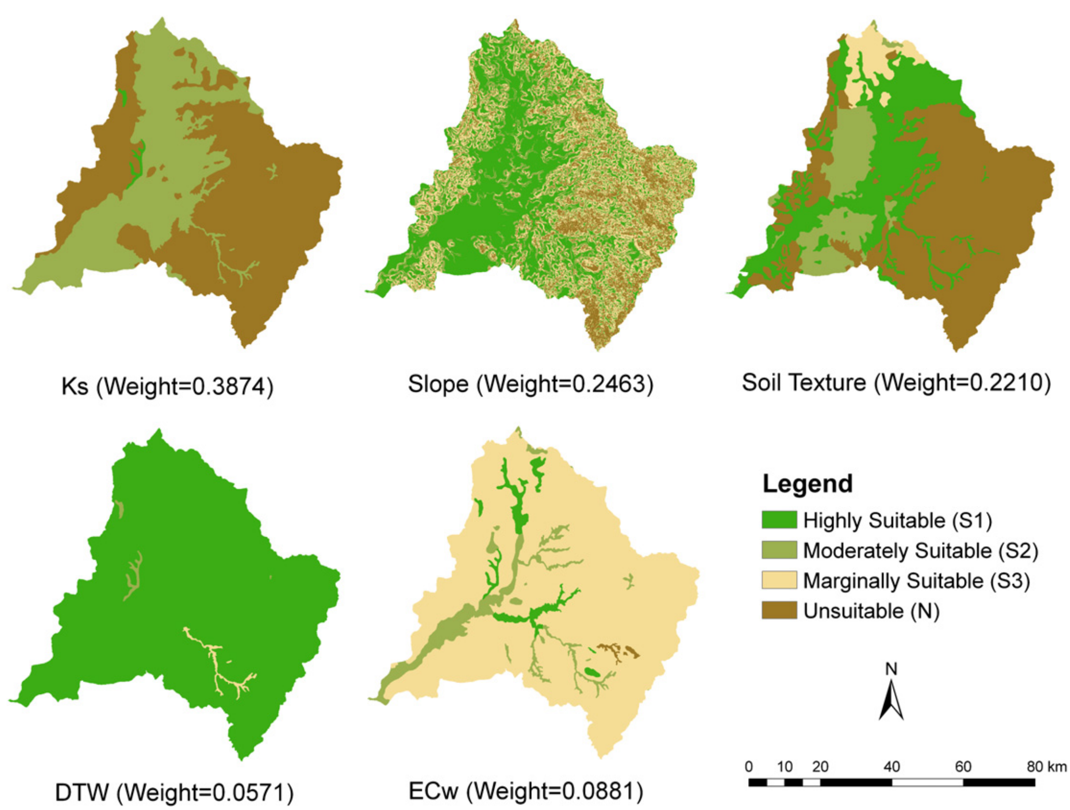

Fig. 5. Criterion maps used for the evaluation of irrigated croplands. The suitability levels are classified based on the threshold values in Table 2.

electrical conductivity of groundwater (ECw). Table 2 gives the threshold values of evaluation criteria for each of the four suitability classes which were determined based on literature survey and expert opinion (Chen et al., 2009).

Spatial data were converted into raster layers and processed in ArcGIS. Slope was generated from a 25 m resolution DEM, which was resampled to match the other four datasets at 100 m 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 in Table 2, and loaded into the map frame of the tool. The maps displayed in Fig. 2a and c represent criteria layers of slope and Ks, respectively. All criteria were compared against each other in a pairwise comparison matrix which is a measure to express the relative importance among the criteria. The values of the comparison were determined according to the scale in Table 1 (Fig. 2b). Once the constructed matrix was entered into the AHP-SA module, the weighting coefficients of criteria were automatically derived (Fig. 2b). These criteria weights will be served as the initial weights for the base run in the following SA process after passing the consistency check. The weighted criterion maps (Fig. 5) were then aggregated to produce a final suitability map (Fig. 2d). The resultant map from this base run shows spatial pattern and distribution of the land suitability classes. The most suitable locations are in dark green, and the unsuitable lands are in dark brown.

3.3. SA simulation results and discussion

An RPC of ±20% and an IPC of ±1% were applied to a complete set of five criteria in this study. Within the range of −20% (the 1st simulation run) to +20% (the 40th simulation run) of its initial value from the base run (the 21st run), the SA simulation consists of 200 evaluation runs where each run generates a single new suitability classification map (e.g. the map in Fig. 2d), and five tables where each table summarises the results of 40 runs for each criterion. These tables summarise criteria weights, cells in each rank, and sum of cells changing from their original ranks in the base run. Table 3 is an example for criterion Ks, which gives ranks of the cells of the output grids, i.e. weights values, number of cells in each ranking class (S1 to N), and changes in number of cells between different ranking classes.

With the aid of results from 200 simulation runs as shown in Fig. 6, it can be seen that

- There are no cells that either increased or decreased more than one suitability level/class from its original rank of the base run.
- Ks 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. This follows the order of criteria weights showed in Fig. 5.

Table 3
Example of the summary table generated from the 41 SA simulation runs for criterion Ks showing the 40 SA simulation runs plus the base run (bold).

Change %	Weight values					Cells in evaluation map				Changes in evaluation map				
	Ks	S	ST	DTW	ECw	S1	S2	S3	N	S1 to S2	S2 to S1	S2 to S3	S3 to S2	S3 to N
−20	0.3099	0.2775	0.2490	0.0643	0.0993	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−19	0.3138	0.2759	0.2476	0.0640	0.0988	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−18	0.3177	0.2743	0.2462	0.0636	0.0982	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−17	0.3215	0.2728	0.2448	0.0632	0.0977	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−16	0.3254	0.2712	0.2434	0.0629	0.0971	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−15	0.3293	0.2697	0.2420	0.0625	0.0966	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−14	0.3332	0.2681	0.2406	0.0622	0.0960	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−13	0.3370	0.2666	0.2392	0.0618	0.0954	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−12	0.3409	0.2650	0.2378	0.0614	0.0949	24,765	153,909	187,347	48,711	0	0	8344	18,684	0
−11	0.3448	0.2634	0.2364	0.0611	0.0943	24,763	153,904	187,354	48,711	0	0	8344	18,677	0
−10	0.3487	0.2619	0.2350	0.0607	0.0938	24,763	153,904	187,354	48,711	0	0	8344	18,677	0
−9	0.3525	0.2603	0.2336	0.0604	0.0932	24,763	145,552	195,706	48,711	0	0	8344	10,325	0
−8	0.3564	0.2588	0.2322	0.0600	0.0927	24,763	149,611	191,647	48,711	0	0	4285	10,325	0
−7	0.3603	0.2572	0.2308	0.0596	0.0921	24,763	149,611	191,647	48,711	0	0	4285	10,325	0
−6	0.3642	0.2556	0.2294	0.0593	0.0915	24,763	139,286	201,967	48,716	0	0	4285	0	0
−5	0.3680	0.2541	0.2280	0.0589	0.0910	24,763	139,286	201,967	48,716	0	0	4285	0	0
−4	0.3719	0.2525	0.2266	0.0585	0.0904	24,763	139,291	201,962	48,716	0	0	4280	0	0
−3	0.3758	0.2510	0.2252	0.0582	0.0899	24,763	139,291	201,962	48,716	0	0	4280	0	0
−2	0.3797	0.2494	0.2238	0.0578	0.0893	24,763	139,291	201,962	48,716	0	0	4280	0	0
−1	0.3835	0.2479	0.2224	0.0575	0.0888	24,763	139,291	201,962	48,716	0	0	4280	0	0
0	**0.3874**	**0.2463**	**0.2210**	**0.0571**	**0.0881**	**24,763**	**143,571**	**197,682**	**48,716**	**0**	**0**	**0**	**0**	**0**
1	0.3913	0.2447	0.2196	0.0567	0.0876	24,763	143,434	197,819	48,716	0	0	137	0	0
2	0.3951	0.2432	0.2182	0.0564	0.0871	24,763	143,434	130,959	115,576	0	0	137	0	66,860
3	0.3990	0.2416	0.2168	0.0560	0.0865	24,763	143,428	130,965	115,576	0	0	143	0	66,860
4	0.4029	0.2401	0.2154	0.0557	0.0860	24,763	143,428	130,965	115,576	0	0	143	0	66,860
5	0.4068	0.2385	0.2140	0.0553	0.0854	24,763	143,428	130,965	115,576	0	0	143	0	66,860
6	0.4106	0.2370	0.2126	0.0549	0.0849	24,763	143,428	130,965	115,576	0	0	143	0	66,860
7	0.4145	0.2354	0.2112	0.0546	0.0843	24,763	143,428	130,965	115,576	0	0	143	0	66,860
8	0.4184	0.2338	0.2098	0.0542	0.0837	9568	158,466	131,122	115,576	15,463	268	379	79	66,860
9	0.4223	0.2323	0.2084	0.0538	0.0832	9568	158,466	131,122	115,576	15,463	268	379	79	66,860
10	0.4261	0.2307	0.2070	0.0535	0.0826	9568	158,466	131,122	115,576	15,463	268	379	79	66,860
11	0.4300	0.2292	0.2056	0.0531	0.0821	9568	158,466	131,122	115,576	15,463	268	379	79	66,860
12	0.4339	0.2276	0.2042	0.0528	0.0815	9568	158,466	131,122	115,576	15,463	268	379	79	66,860
13	0.4378	0.2260	0.2028	0.0524	0.0810	9568	158,512	131,076	115,576	15,463	268	379	125	66,860
14	0.4416	0.2245	0.2014	0.0520	0.0804	9568	158,512	131,076	115,576	15,463	268	379	125	66,860
15	0.4455	0.2229	0.2000	0.0517	0.0798	9664	158,416	131,076	115,576	15,463	364	379	125	66,860
16	0.4494	0.2214	0.1986	0.0513	0.0793	9664	147,674	141,818	115,576	15,463	364	11,121	125	66,860
17	0.4533	0.2198	0.1972	0.0510	0.0787	9664	147,674	141,818	115,576	15,463	364	11,121	125	66,860
18	0.4571	0.2183	0.1958	0.0506	0.0782	9664	147,674	141,818	115,576	15,463	364	11,121	125	66,860
19	0.4610	0.2167	0.1944	0.0502	0.0776	9664	147,674	141,818	115,576	15,463	364	11,121	125	66,860
20	0.4649	0.2151	0.1930	0.0499	0.0771	9664	147,675	141,817	115,576	15,463	364	11,121	126	66,860

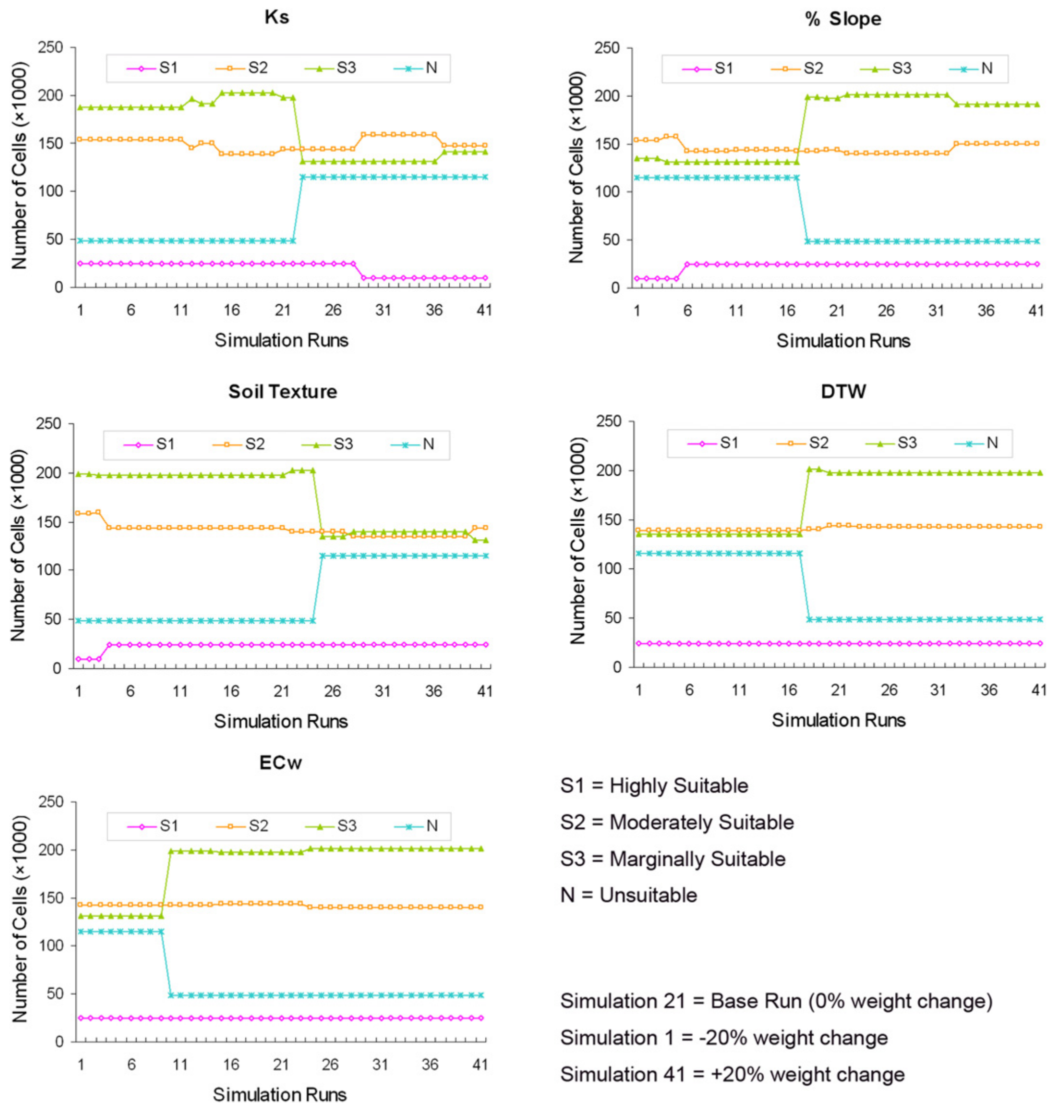

Fig. 6. Summary results from 200 simulations (40 runs for each criterion).

- Ks 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 variation of evaluation classification happened in S3 and N. There is a dramatic decrease in the number of cells in S3 and a remarkable increase in the number of cells in N. Most shifts from S3 to N occurred within the ±5% of changes, except for ECw where the changes take place at about ±12%.
- S3 and N appear most sensitive to criteria weight changes. A considerable cell exchange between S2 and S3 is noted.

Ks gains the highest weight among the others. It means that Ks has a high influence on the evaluation results. Ks is driven by slope and soil texture. Soil texture controls soil infiltration rate. Slope determines the thickness of soil layer, and the accumulation and movement of soil water. They both have relatively significant impacts on the resultant map according to their weights. Therefore, Ks is the most sensitive criterion as we expected. Compared with the significantly high spatial variability of the above three criteria, EC and DTW are relatively homogeneous. The DTW was assigned a smallest weight because it is almost uniform in the study area. ECw is a measure of groundwater salinity, and is closely related to the water depth in terms of the groundwater flow system. Its value across the whole catchment is at least marginally suitable for irrigation. This indicates that salinity is not a significant problem in this region. Thus the ECw obtained a corresponding lower weight value. As a result, both DTW and ECw suppose to have least impacts on the evaluation results.

While the chart presentations of SA results in Fig. 6 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, examples of simulated evaluation maps where the most significant suitability classification changes take place

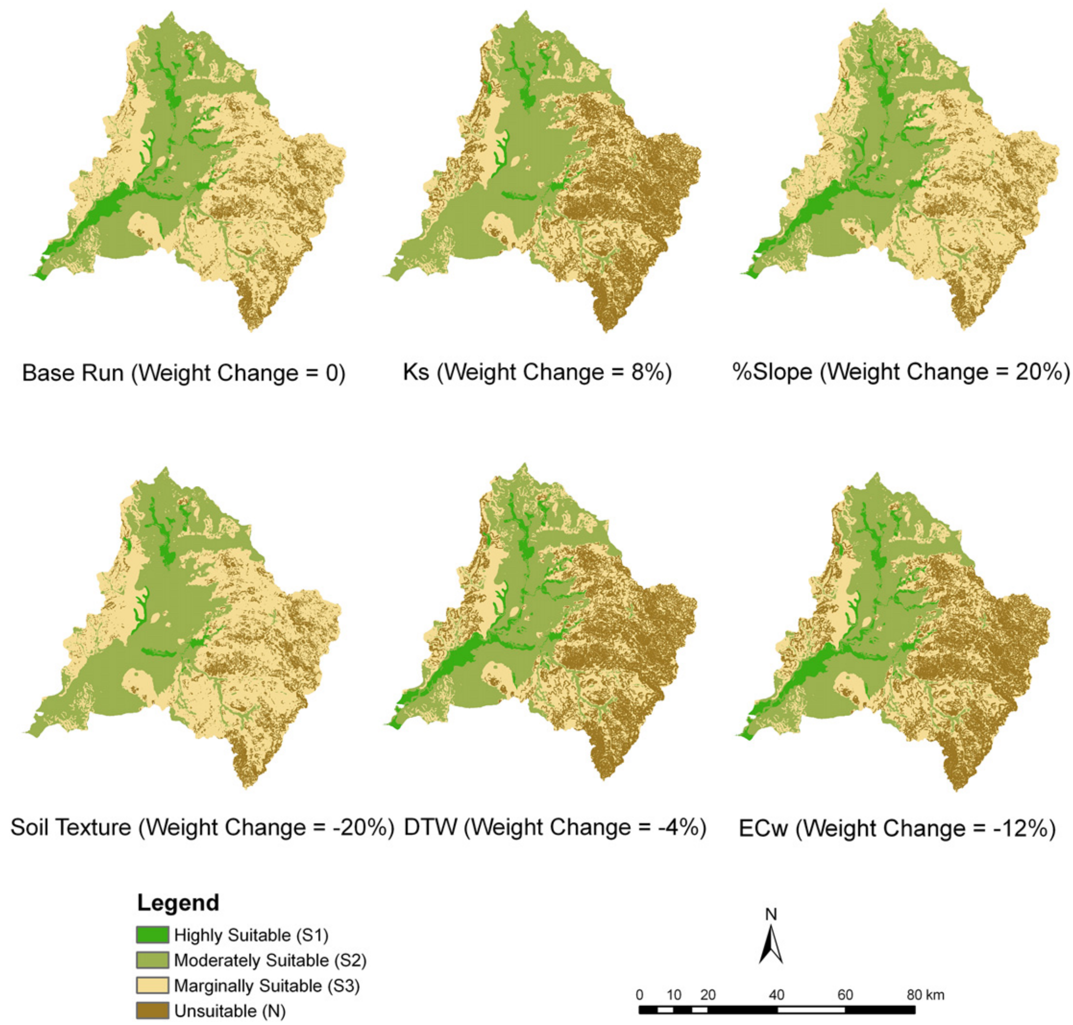

Fig. 7. Example maps presenting irrigated cropland suitability classification as a result of criteria weight changes. Each map shows the maximum changes in evaluation results caused by a selected main changing criterion.

corresponding to some weight variations given to each criterion are shown in Fig. 7. These maps have also confirmed that among all criteria, Ks, ECw and DTW are the most sensitive to changes between S3 and N classes in the east part of the catchment because these two classes are largely constrained by the narrow ranges of relevant properties as compared to S1 and S2 lands which have a wide range and thus yield a relatively stable spatial pattern; Ks and soil texture are most responsive to changes between S1 and S2 classes along the river; and slope is almost not sensitive to any changes. In spite of the fact that some criteria are sensitive to weight changes, the evaluation results derived from the base run could be used to analyse potential expansion of irrigated cropland because, when water is available, the highest possibility of such expansion will only occur on S1 (highly suitable) and S2 (moderately suitable) lands which are relatively stable from the SA investigation in this study. This case study have also proved that SA tool can provide a better approach for improving the capabilities of current GIS-based AHP-MCDM models to create more realistic output scenarios.

According to the simulation results from base run, there is about 7% of total catchment area being classified as highly suitable (S1), unsuitable land (N) covers about 32%, and moderately and marginally suitable classes (S2 and S3) represent 25% and 36% of land area, respectively. The S1 is found mainly on the flood plain of the Macintyre Brook and other big creeks, as well as alluvial fans and flats of smaller streams, where varying areas of land with better drained soils are suitable for cultivation. These potentially irrigable lands are made up of four soil types distinguished by texture which include alluvial sandy loam, alluvial silty loam, clay loam and sandy loam. Generally, most unsuitable areas are located in the east–southeast part of the catchment where the surface is undulating, soil texture is poor and soil hydraulic conductivity is very low. A large proportion of this land is under grazing pasture landuse, only a small portion of it is used for production forestry.

4. Concluding remarks

This paper presents a GIS-based AHP-SA methodology for analysing criteria weight sensitivity in MCDM. The fusion of SA with AHP within ArcGIS environment has enhanced the conventional AHP module, improved the reliability of MCDM output, and extended 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. It has a capability to consolidate output from each simulation run into an easy-to-interpret format, that is map visualisation and table summary, for examining and quantifying the SA results. This has met the current central challenge inherent to SA.

We suggest SA should be conceived as a stage in the evaluation of MCDM that looks into the extent of output variation of a model when parameters including criteria or associated weights are systematically varied over a range of interests. The GIS-based AHP-SA tool developed in this study is simple, spatial, and flexible. It supplies more immediate feedback to evaluators or 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, such as SA on changing criteria threshold values, altering relative importance of criteria and hence preference matrix, will permit GIS and MCDM to be applied to practical land-management issues with greater success.

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