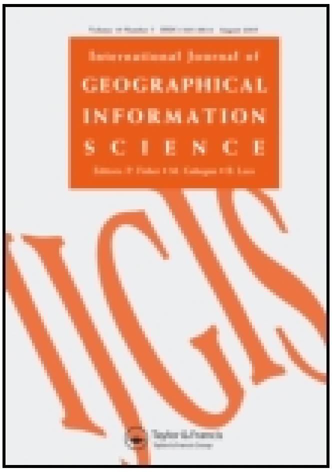

International Journal of Geographical Information Science
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tgis20

Cellular automata-based spatial multi-criteria land suitability simulation for irrigated agriculture

Jia Yu [a b] , Yun Chen [c d] , Jianping Wu [a] & Shahbaz Khan [e]
[a] Key Laboratory of Geographic Information Science, East China Normal University, Ministry of Education , Shanghai , P.R. , China
[b] Department of Geography, Shanghai Normal University, Shanghai , P.R. China
[c] CSIRO Land and Water , Canberra , Australia
[d] Cooperative Research Centre for Irrigation Futures , Darling Heights , Australia
[e] UNESCO Division of Water Resources,Paris, France
Published online: 18 Feb 2011.

International Journal of Geographical Information Science
Vol. 25, No. 1, January 2011, 131–148

Taylor & Francis
Taylor & Francis Group

Cellular automata-based spatial multi-criteria land suitability simulation for irrigated agriculture

Jia Yu[a,b]*, Yun Chen[c,d], Jianping Wu[a] and Shahbaz Khan[e]

[a]*Key Laboratory of Geographic Information Science, East China Normal University, Ministry of Education, Shanghai, P.R. China;* [b]*Department of Geography, Shanghai Normal University, Shanghai, P.R. China;* [c]*CSIRO Land and Water Canberra, Australia;* [d]*Cooperative Research Centre for Irrigation Futures, Darling Heights, Australia;* [e]*UNESCO Division of Water Resources, Paris, France*

(*Received 8 November 2009; final version received 4 March 2010*)

Cellular automata (CA) models are increasingly used to simulate various dynamic courses, e.g. urban spatial growth, forest fire spread and soil desertification. CA can express space structures and patterns of complex systems, which are difficult to perform only with mathematical equations. In this study, a new CA-based spatial multi-criteria evaluation (MCE) methodology was developed to conduct land suitability simulation (LSS). The approach incorporated MATLAB to build the analytical hierarchy procedure (AHP) for criteria weighting. The method is implemented as a tool, called AHP–CA–GIS, using C# .NET computer language in ArcGIS environment. It has adjustable parameter values which allow users to rectify model inputs for deriving different scenarios. It is spatial-based, flexible, low-cost and robust, as well as suitable for long-term evaluation. It has increased the scope of GIS application in MCE and makes the application practical for decision-making. The AHP–CA–GIS model has been applied to simulate an evaluation of irrigated cropland suitability in the Macintyre Brook catchment of southern Queensland, Australia. Five suitability scenarios were generated. The resultant land suitability map was compared with present land use. The analysis has clearly revealed the potential for irrigation expansion in the catchment. It has also represented the possible suitability of spatial distribution in the long run. This, in turn, can help the decision-makers optimise land allocation and make better land-use planning decisions.

Keywords: cellular automata; suitability simulation; multi-criteria evaluation; GIS; analytical hierarchy procedure

1. Introduction

Land suitability is used to assess the potential of land for a specific land use (Littleboy *et al.* 1996). Land suitability evaluation (LSE) for irrigated agriculture involves the interpretation of data relating to soils, topography, vegetation, etc., during an effort to match the land characteristics with crop requirements (Wang *et al.* 1990). Due to a number of factors involved in decision-making, LSE can be identified as a multi-criteria evaluation (MCE) approach (Reshmidevi *et al.* 2009). MCE is primarily concerned with how to combine the information from several criteria to form a single index of evaluation. A number of MCE methods have been proposed in the field of LSE over the last decade or so, such as weighted linear combination

*Corresponding author. Email: yujiaecnu@yahoo.com.cn

ISSN 1365-8816 print/ISSN 1362-3087 online

DOI: 10.1080/13658811003785571
http://www.informaworld.com

(WLC) (Carver 1991, Eastman 1997, Giordano and Riedel 2008), analytical hierarchy process (AHP) (Saaty 1980, Store and Kangas 2001, Hübner and Günther 2007), ordered weighted averaging (OWA) (Yager 1988, Malczewski *et al.* 2003, Malczewski and Rinner 2005, Boroushaki and Malczewski 2008) and concordance analysis (Carver 1991, Joerin *et al.* 2001).

The AHP (Saaty and Vargas 1991) is a well-known method of multi-criteria technique which has been widely utilised. This approach of decision-making involves structuring multiple-choice criteria into a hierarchy, assessing the relative importance of these criteria and determining criteria weights. It is especially useful in situations where it is impractical to specify the exact relationships between large numbers of evaluation criteria (Chen *et al.* 2010). A geographic information system (GIS) is a computing application capable of creating, storing, manipulating, visualising and analysing geographic information (Goodchild 2000). Because one of the most useful GIS applications for planning and management is the land suitability mapping and analysis (McHarg 1969, Hopkins 1977), GIS has been integrated with the AHP method to solve LSE problems (Cram *et al.* 2006, Hossain *et al.* 2007, Anagnostopoulos *et al.* 2010). However, land is a complex system which is composed of a physical environment as well as the results of past and present human activity (FAO 1976). Using the MCE method only to cope with the LSE problem may neglect some potential phenomena and rules implicated. Therefore, a simulation model which can deal with such a complex system is necessary to be exposed.

Cellular automata (CA) models have been applied as tools to support land-use planning and policy analysis (Geertman and Stillwell 2004) and to explore scenarios for future development (Barredo *et al.* 2003, Nijs *et al.* 2004). CA can describe a complex system through modelling the system starting from the elementary dynamics of its interrelation and allowing the system complexity to emerge by interaction of simple individuals following simple rules (Malczewski 2004). Therefore, CA is a good tool for land suitability analysis, which is an important measure for land-use planning. Here we refer to simulation model–based potential LSE as land suitability simulation (LSS). CA-based LSS can reveal implicated and potential phenomena and rules of land use, which is the main difference compared with traditional LSE. Traditional LSE may only integrate experts' knowledge or use GIS to plot the suitability of land use for irrigation, but perhaps it neglects the potential rules in land suitability and only pays attention to current circumstances. On the other hand, CA can dynamically reveal the possible land suitability spatial distribution in the long run, if data are available, with its special 'bottom-up' (Liu *et al.* 2008a) characteristic which can reflect complex patterns in macro derived from simple rules in micro. This is difficult to accomplish by traditional methods without CA.

The core of CA is how to define transition rules, which can be expressed in lots of forms (Li *et al*. 2008), such as logistic regression (Wu 2002), dynamic urban evolutionary model (DUEM) (Batty *et al.* 1999), slope, land use, exclusion, urban extent, transportation and hillshade (SLEUTH) model (Clarke and Gaydos 1998), MCE (Wu and Webster 1998), neural networks (Li and Yeh 2002), support vector machines (Yang *et al.* 2008), ant colony optimisation (Liu *et al.* 2007, 2008a) and nonlinear transition rules (Liu *et al.* 2008b). We choose the MCE method to represent transition rules in this study due to its extensive applications in LSE (Tiwari *et al.* 1999). The inspiration source is Wu and Webster's MCE-CA method (Wu and Webster 1998) in urban growth simulation, but the application of hybrid usage of CA and MCE in LSS has significant differences. First, transition rules for urban growth simulation are obtained from building inner relationships of real urban land uses in different times. But the transition rules for LSS problems mainly rely on the suitability classification according to indigenous knowledge (Sicat *et al.* 2005), as well as experts' and local decision-makers' opinions in decision-making. Second, the simulation results of urban growth could be calibrated according to the actual urban land use. As to LSS, the validation and calibration method of the model inherits the method for LSE, which more depends on the indigenous knowledge (Sicat *et al.* 2005), field surveys (Corona *et al.* 2008), opinions of decision-makers (Joerin *et al.* 2001), expert knowledge (Kalogirou 2002) and comparison with existing location of the specific land use (Hossain *et al.* 2007, Hossain and Das 2010). However, issues such as use of expert knowledge, GIS and field survey in model calibration and validation are complex. Each type of these experimental methods has its strengths and weaknesses (Robinson *et al.* 2007), which deserves further investigation in future.

The objective of the study is to propose a new method which applies CA, in combination with AHP in GIS environment, to simulate potential land suitability for irrigated agriculture land use. A tool called AHP–CA–GIS has been developed to implement LSS process. A case study in the Macintyre Brook catchment of southern Queensland of Australia is presented here to illustrate the feasibility of this tool in the evaluation of irrigated cropland suitability.

2. Study area

The Macintyre Brook catchment is located in southern Queensland near the state border with New South Wales, and lies between 27°57′01″S and 28°47′48″S latitude and 150°45′05″E and 151°42′24″E longitude (Figure 1). The catchment is relatively flat in the western area, with undulations becoming steeper towards east and north-east. The elevation at the major town of Inglewood is 284 m. Macintyre Brook River 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. The irrigation water to Macintyre Brook is supplied by Coolmunda Dam, along which the main irrigation areas of the catchment are located (Malcolmson and Lloyd 1977).

The catchment covers an area of 4200 km^2. It is characterised by extremely diverse soil types and topography (Harris 1986), making it suitable for a wide variety of land use (Figure 1) and agricultural 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 dry-land cropping (3%), native pasture grazing country (80%) and state forest reserves (15%). Historically, grazing was predominant, but dry-land and irrigated cropping have become

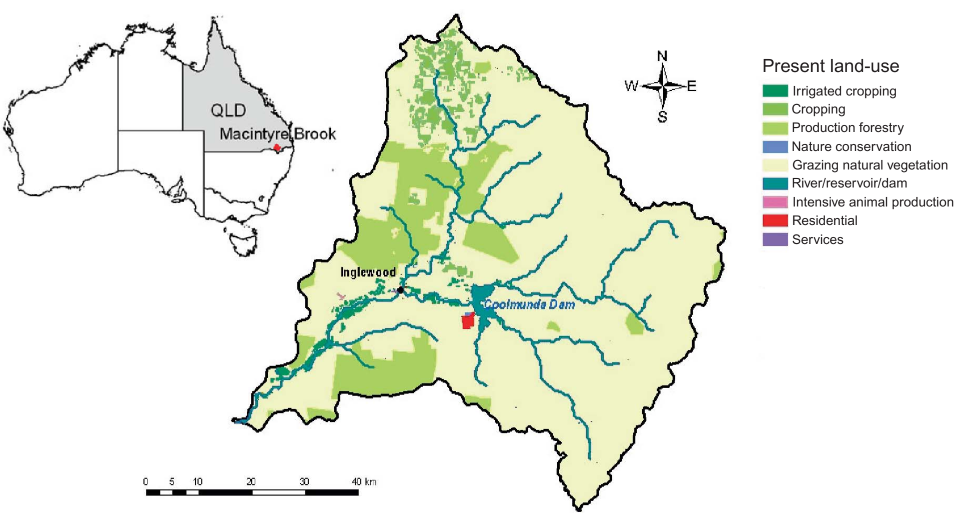

Figure 1. Location and land use (50 m resolution) of Macintyre Brook (Chen *et al.* 2010).

increasingly significant over time. The main crops include fodder (lucerne), maize, sorghum and peas and there are orchards as well of peach, plum and apricot.

The area under irrigation in the catchment has increased steadily following the construction of the Coolmunda Dam in 1968. Irrigation in the region was traditionally geared around tobacco production, but the demise of that industry in the 1960s led many irrigators to fall back on opportunistic irrigation of pastures and crops. More recently, there has been significant development in olive and peanut production (Chen *et al.* 2010).

3. Methodology

CA essentially consists of the following elements: (1) a grid space, (2) a set of grid cell states, (3) a definition of a cell's neighbourhood, (4) a set of transition rules that compute a cell's state transitions with a function of the states of neighbouring cells and (5) discrete time steps in which all cells updated simultaneously (White and Engelen 2000). In the simulation of this study, we attempted to model potential land suitability with CA transition rules and represent suitability distribution in a spatial context. The grid space in this study is two-dimensional, and the cell state represents irrigated land suitability. Moore neighbourhood (Gray 2003) (with eight adjacent cells) was adopted here with the spirit of simplicity. The detailed simulation method is described below.

3.1. Assumptions

Three assumptions are made to ensure the compatibility between the CA model, nature system and practical operations of decision-makers during the simulation courses.

(1) Lands surrounding irrigated area have higher suitability and more possibility to be developed as irrigated lands. In other words, regions close to irrigated areas have more chance to be expanded to irrigated agriculture land use. We define this assumption as an irrigation neighbour effect (INE) here.
(2) Only the highly suitable areas will be selected by decision-makers for the new development of irrigated cropland, considering water-use efficiency and production benefit.
(3) In reality, irrigation will never occur on some lands, such as rivers, residential areas, forestry and mining areas. We set these lands as restrictive areas which constrain the expansion of irrigation areas.

3.2. Derivation of criterion maps

The derivation of criterion maps consists of three steps:

The first step is suitability classification. This study used the suitability classes which were proposed by the Food and Agricultural Organisation (FAO 1976). The classification consists of four levels: highly suitable (S1), moderately suitable (S2), marginally suitable (S3) and unsuitable (N). Detailed descriptions of these four levels are given in Table 1.

The second step is selection of criteria. Seven criteria were chosen to evaluate the suitability. These include percent slope (S), soil texture (ST), depth to water table (DTW), electrical conductivity of groundwater (ECw), hydraulic conductivity of soil (Ks) (Chen *et al.* 2010), distance to stream (DS) and irrigation land use (IL). IL describes irrigation distribution with binary values (0 or 1). It was used to generate the INE layer, described in Assumption 1. The threshold values of other criteria are given in Table 2. They were

Table 1. Land suitability classification (Chen *et al.* 2010).

Class	Definition
S1	Highly suitable: land having no significant limitations for sustained applications to irrigated cropping, or only minor limitations that will not significantly reduce the productivity
S2	Moderately suitable: land having limitations that are moderately severe for sustained application to irrigated cropping, and may reduce the productivity marginally
S3	Marginally suitable: land with limitations that are severe for sustained application to irrigation cropping, and as such reduce productivity significantly but is still marginally economical
N	Unsuitable: land with extreme limitations which appear to preclude sustained application to irrigation cropping

Table 2. Criteria for suitability assessment (Chen *et al.* 2010).

Criterion	S1	S2	S3	N
S (%)	0–2	2–4	4–8	>8
ST	Fine to medium	Heavy clay	Coarse or poorly drained	Very coarse or shallow depth
DWT (m)	>4	3–4	2–3	<2
ECw (dS/m)	0–0.5	0.5–2	2–5	>5 (if depth < 4 m)
Ks (m/d)	0.3–1	0.05–0.3 or 1–2	2–2.5	<0.05 or >2.5
DS (m)	<1000	1000–2000	2000–3000	>3000

determined based on literature survey and expert opinions, and are only applicable to a broad-scale analysis of irrigated cropping in this specific catchment.

The last step is generation of criterion maps. All the criterion maps need to have the same geographic scale, boundary, cell size and spatial reference. In this study, the criterion maps were standardised in raster format with a cell size of 100×100 m. UTM Zone 56S was used as the spatial reference. Based on the thresholds in Table 2, we classified the criterion maps S, ST, DTW, ECw, Ks and DS into four classes. Raster layers have numerical values 4, 3, 2 or 1, which represent S1, S2, S3 and N, respectively. The IL map is the seventh criterion map used to complete the implementation of CA algorithms. Irrigated area was picked from the present land-use map. The present land-use map has a cell size of 50×50 m (Figure 1). To meet the requirement of uniform cell size, we re-sampled the map to 100×100 m using bilinear interpolation and then selected the irrigated area to generate the IL map. Cells in the IL map layer have a value 1 or 0, which represents whether the cell is an irrigated area or not. The IL map in Figure 2 is the initial IL layer used to generate the INE layer. A detailed generating method will be given in Section 3.4.The INE layer carries out Assumption 1 and has values of real numbers ranged between 0 and 1. Its value reflects the possibility of land being developed into irrigated land. Criterion map DS is generated by buffer zone analysis. Taking into account the requirement and availability of surface water for irrigated agriculture, we selected the downstream parts of Macintyre Brook River, which seldom run out of water in dry season, and generated buffer zones for the downstream parts. Buffer zones of different levels were classified by the thresholds of DS in Table 2.

3.3. *Determination of criterion weights using AHP*

AHP was used to determine criterion weights. Saaty's (1977) AHP is a method to determine the weights through pair-wise comparisons of parameters. A pair-wise comparison matrix

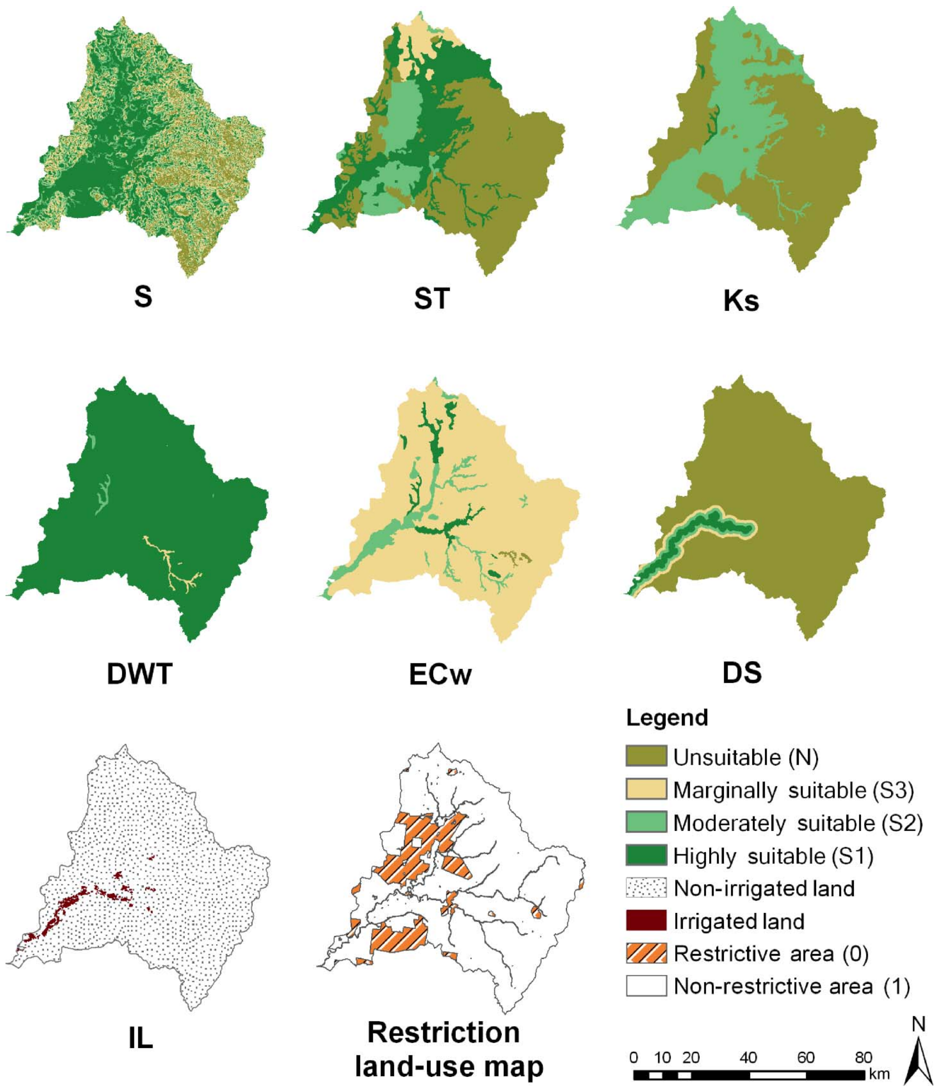

Figure 2. Criterion maps used for the evaluation of irrigated agricultural land and restriction land-use map. The suitability levels are classified based on the threshold values. Criterion maps are S, ST, Ks, DWT, ECw, DS and IL.

was created to express the relative importance between each two criteria. The comparison matrix is basically a list of criteria, which are weighted depending on their respective importance. Table 3 shows the comparison values, which were determined according to judgements of experts including surface-water hydrologists, groundwater hydrologists, soil scientists and irrigation specialists. The matrix values, which could be 1/9, 1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 1/2, 1, 2, 3, 4, 5, 6, 7, 8 or 9, represent the relative degree of importance of one criterion against another. A bigger matrix value means one criterion is more important than the other for a particular pair of criteria, and vice versa. Value 1 means the two compared criteria have equal importance. Value 9 represents absolute importance and 1/9 the absolute triviality (Saaty and Vargas 1991). In Table 3, the comparison value between Ks along the

Table 3. Comparison matrix of objectives.

	S	ST	DTW	ECw	Ks	DS	IL
S	1	2	4	3	1/3	1	2
ST	1/2	1	5	4	1/2	2	2
DTW	1/4	1/5	1	1/2	1/4	1/2	1
ECw	1/3	1/4	2	1	1/3	1	1
Ks	3	2	4	3	1	3	4
DS	1	1/2	2	1	1/3	1	2
IL	1/2	1/2	1	1	1/4	1/2	1

Table 4. The weights calculated from comparison matrix using AHP method.

Criterion	Weight
S	0.1854
ST	0.1873
DTW	0.0518
ECw	0.0787
Ks	0.3141
DS	0.1116
IL	0.0711
Total	1.0

side of the table and S along the top is 3, which illustrates that Ks is moderately more important than S, while the comparison value between ECw and S is 1/3, which shows ECw is moderately of less importance thanS. The weight of each parameter value obtained through importing this comparison matrix into AHP algorithm is shown in Table 4. The sum of all weight values equals to 1.

3.4. Process of CA simulation

After calculating the weight of each parameter, we applied a CA model in which MCE was used to simulate irrigation suitability. The model prescribes that the state of a cell in time $t+1$ is determined by its state and its neighbours in time t as well as corresponding transition rules. It is described as follows:

$$S_{xy}^{t+1} = f\left(S_{xy}^{t},\ \Omega_{xy},\ T\right) \tag{1}$$

where S_{xy}^{t+1} and S_{xy}^{t} are land suitability states in location (x, y) at times $t+1$ and t, Ω_{xy} is the development status of the neighbours of location (x, y) and T is a series of transition rules. In the process of simulation, the development status is obtained through eight-neighbour rule. With a 3×3 window, the central cell picks the values of its eight neighbour cells, and then calculate land suitability state of the next time. With Equation (1), transition rules can be defined flexibly. The state at time $t+1$ can be determined by

$$S_{xy}^{t+1} = f\left(P_{xy}^{t}\right) \tag{2}$$

where S_{xy}^{t+1} is the land suitability state in location (x, y), time $t + 1$; P_{xy}^{t} is the transition probability of suitability of state S in location (x, y) in time t, which is represented as

$$P_{xy}^{t} = \phi\left(r_{xy}^{t}\right) = \phi\left[\omega\left(F_{xyk}^{t},\ W_k\right)\right] \tag{3}$$

where r_{xy}^{t} is the estimated suitability transition intensity of state S in location (x, y); F_{xyk}^{t} is the value of criterion k in location (x, y), which is extracted from each criterion map, including the INE map generated from the IL map in state t; W_k is the weight for each factor; ω is the united function which calculates the combined score with the parameters of F_{xyk}^{t} and W_k; and ϕ is used to translate suitability into a function of probability.

Equation (3) can be expressed as below (Wu and Webster 1998):

$$P_{xy}^{t} = \phi\left(r_{xy}^{t}\right) = \exp\left[\alpha\left(\frac{r_{xy}^{t}}{r_{\max}} - 1\right)\right] \tag{4}$$

Equation (4) is the key equation used in suitability evaluation. In this equation, P_{xy}^{t} is the transition probability of suitability of state S in location (x, y), $0 \leq P_{xy}^{t} \leq 1$. α is the dispersion parameter, which takes a value between 1 and 10. The value of α governs the stringency of suitability estimation, with a higher value reflecting a more stringent evaluation process. Thus, this parameter has an important influence on the whole evaluation pattern. Detailed discussion about it can be found in Section 4.3. $r_{\max}$ is the maximum value of r_{xy}. r_{xy}^{t} is the estimated suitability transition intensity of state S in location (x, y), which is calculated by the following equation:

$$r_{xy}^{t} = \left(\sum_{k=1}^{m} W_k F_{xyk}^{t}\right) \mathrm{Restrict}_{xy} \tag{5}$$

where F_{xyk}^{t} is the value of criterion k in location (x, y) in time t, W_k is the weight for each criterion and $\mathrm{Restrict}_{xy}$ is the value of restriction in location (x, y). $\mathrm{Restrict}_{xy}$ has a binary value, 0 or 1. It carries out Assumption 3 in Section 3.1.We take into account the classes in the land-use layer. If a land-use class has restriction, the corresponding cells of it will be valued 0, else valued 1. For instance, rivers, reservoirs and other protected areas should be treated as restrictive factors. They have absolute restriction to irrigation because the probability of irrigation on these lands is zero. In such cases, $\mathrm{Restrict}_{xy} = 0$. In Equation (5), $1<k \leq m$ represents a criterion in the evaluation process; m is the total number of criteria. In this study, $m = 7$: they are S, ST, DTW, ECw, Ks, DS and INE.

Therefore, in this study, the specification of r_{xy}^{t} becomes

$$r_{xy}^{t} = \left(w_1 S_{xy} + w_2 \mathrm{ST}_{xy} + w_3 \mathrm{DTW}_{xy} + w_4 \mathrm{ECw}_{xy} + w_5 \mathrm{Ks}_{xy} + w_6 \mathrm{DS}_{xy} + w_7 \mathrm{INE}_{xy}\right) \mathrm{Restrict}_{xy} \tag{6}$$

where $w_1, w_2, \ldots, w_7$ are AHP weighting parameters; S_{xy}, ST_{xy}, DTW_{xy}, ECw_{xy}, Ks_{xy} and DS_{xy} are standardised values of each criterion in location (x, y); $\mathrm{Restrict}_{xy}$ is the value of restriction in location (x, y) with a binary value 0 or 1 and INE_{xy} is the value for INE in location (x, y) generated from IL layer with the eight-neighbour rule using Equation (7):

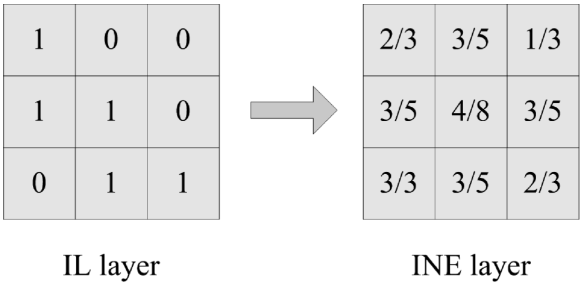

Figure 3. Generation of INE layer from IL layer.

$$\mathrm{INE}_{xy} = \frac{\sum_{i=x-1}^{x+1} \sum_{j=y-1}^{y+1} \mathrm{IL}_{ij} - \mathrm{IL}_{xy}}{\sum_{i=x-1}^{x+1} \sum_{j=y-1}^{y+1} N_{ij} - 1} \tag{7}$$

where N_{ij} is defined to cope with cells on the border of the layers. $N_{ij} = 1$ when the value in location (i, j) is not null (null for cells out of border), otherwise $N_{ij} = 0$; IL_{ij} is the binary value of the cell in location (i, j) of the IL layer. Figure 3 gives an example of illustrating the method with a raster layer of 3×3 cells.

When the transition probability of suitability (P^t_{xy}) of each grid cell has been obtained from Equation (4), the transition probability matrix of the next state is generated, which will be used for the next iterative run to build a probability map for irrigation suitability. The probability values ranged from 0 to 1 can then be transformed into four suitability classes through three classification thresholds in Table 5. In this study, the range of probability value is equally divided into four parts by four classes, so that values of $\mathrm{Threshold}_{\mathrm{S1–S2}}$, $\mathrm{Threshold}_{\mathrm{S2–S3}}$ and $\mathrm{Threshold}_{\mathrm{S3–S4}}$ in Table 5 are 0.75, 0.5 and 0.25, respectively.

After the transition process, each cell was reclassified into four classes and the assumed irrigated land use of the next state was ascertained according to Assumption 2 defined in Section 3.1.It means highly suitable areas are regarded as irrigated agriculture lands for the next state processing.

There are two methods to terminate CA evolution. First, compare two layers at time t and $t + 1$. If there are no differences between them, it means steady state has been reached. Second, experts pick an eligible result with experience or preset limitation (threshold). The first method was used in this study to get a steady resultant suitability evaluation map.

It should be noted that simulation time has no necessary correspondence to real time (Cecchini 1996). In this study, the generated irrigated land-use maps by iteration were not mapping into real time. With sufficient time-series data, each criterion layer of real time could be input corresponding to a specified iteration. This will be studied in future research.

Table 5. The rules for suitability classification from probability value.

Probability value	Suitability class
$P^t_{xy} \geq \mathrm{Threshold}_{\mathrm{S1–S2}}$	Highly suitable (S1)
$\mathrm{Threshold}_{\mathrm{S1–S2}} > P^t_{xy} \geq \mathrm{Threshold}_{\mathrm{S2–S3}}$	Moderately suitable (S2)
$\mathrm{Threshold}_{\mathrm{S2–S3}} > P^t_{xy} \geq \mathrm{Threshold}_{\mathrm{S3–N}}$	Marginally suitable (S3)
$P^t_{xy} < \mathrm{Threshold}_{\mathrm{S3–N}}$	Unsuitable (N)

4. Implementation of the integrated simulation

4.1. Key technology in development

The AHP–CA–GIS tool was developed using C# .NET to construct the framework of the simulation software for suitability evaluation. MATLAB software–embedded components, which provide special features enabling users to create a component object model (COM) (Phan 2004), were incorporated to implement AHP for calculating criteria weights. The Environmental Systems Research Institute (ESRI) ArcGIS Engine, which is a core set of cross-platform ArcObjects components compatible with multiple application programming interfaces (APIs) (ESRI 2008), was employed for spatial data manipulation and result displaying.

4.2. Simulation implementation

The implementation of the AHP–CA–GIS tool (Figure 5a) is expressed through Figure 4. It is a set of processes of spatial iteration in accordance with CA evolution (Figure 5b).

4.2.1. Process 1: AHP calculation

Import AHP comparison matrix into the model with the same format to Table 3, so the tool can read the matrix (Figure 5c) and calculate and return the weight values of all criteria (Figure 5d). Measure the consistency ratio (CR) of the result. If it cannot meet the predefined requirements, the pair-wise values in the matrix should be re-evaluated and return a new matrix to be re-calculated in the AHP module.

4.2.2. Process 2: Data preparation

(1) According to present land uses, select areas where irrigation is impossible to occur, such as mining areas, rivers, residential areas and manufacturing and industrial zones. Make them as restrictive areas with a value of 0; then create a restriction land-use map, which is shown in Figure 2. The figure shows portions hatched and non-hatched for restrictive and non-restrictive areas, respectively.
(2) Input the IL map. Calculate the INE value for each cell which derived from the IL map according to the eight-neighbour CA rule mentioned in Equation (7); then store all cell values into an INE map.

4.2.3. Process 3: Model simulation

(1) Read cell values of the criterion maps, restriction land-use map and the INE map in value matrices; input these matrices and corresponding weights obtained from the AHP calculation into the AHP–CA–GIS model, and output the suitability probability value matrix. The parameter configuration window of the tool is shown in Figure 5e.
(2) Generate the probability layer from the probability value matrix. Based on the suitability classification rule defined in Table 5, standardise the probability layer into a suitability classification layer with four suitability classes (S1, S2, S3 and N).
(3) Compare the suitability classification layer with the simulated classification layer of the previous iteration. If there are differences between these two layers, it means the steady state has not been reached, and the CA process needs to be further evolved. (If it is the first iteration, then it assumes steady state has not been reached and directly

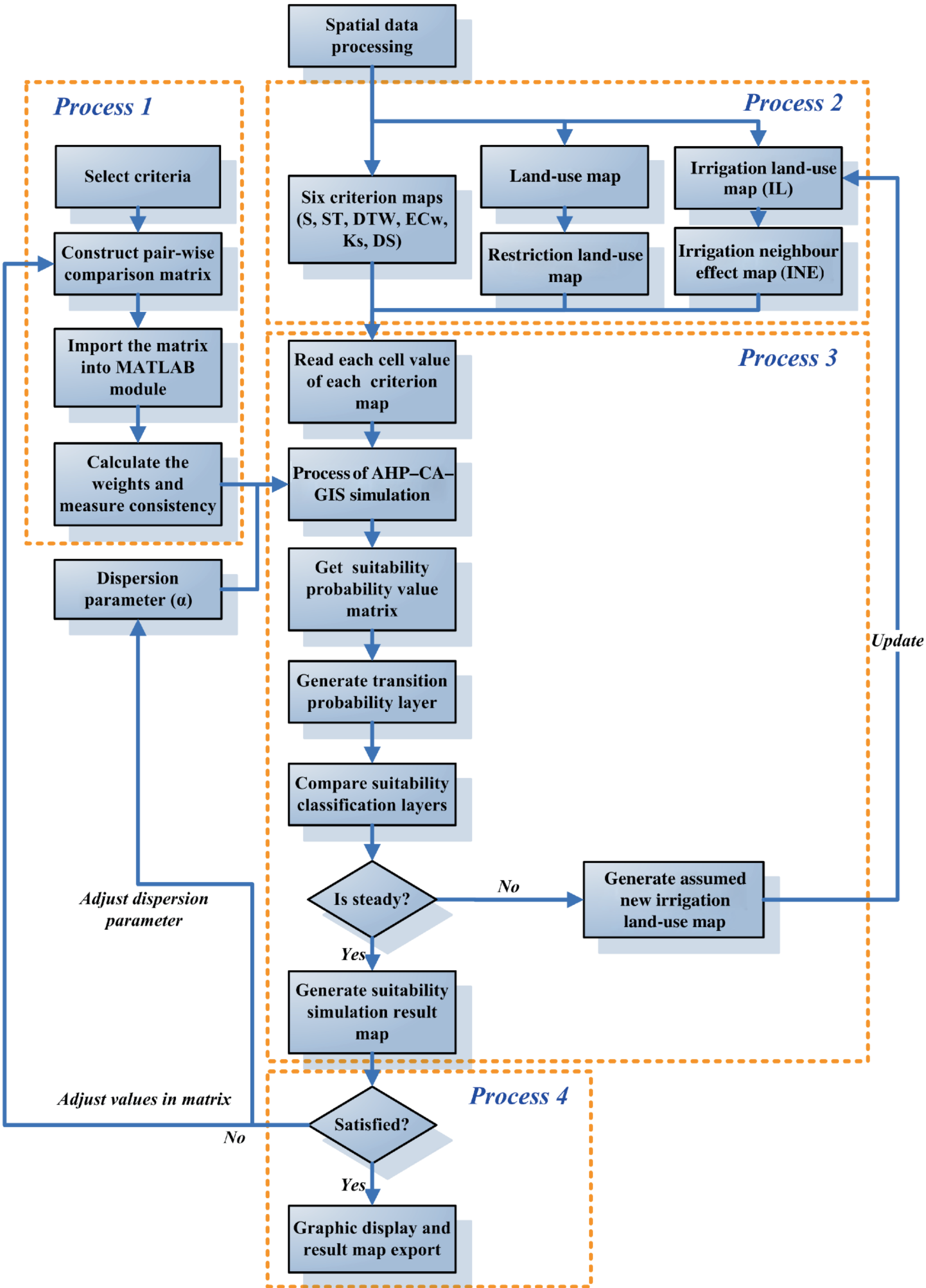

Figure 4. Workflow for implementation of simulation process.

goes to the next iteration.) Based on Assumption 1 in Section 3.1, an assumed IL map is generated. This map is regarded as a new condition layer to replace the previous IL map; then go back to repeat all steps in process 3. A series of iterations will be implemented until the spatial distribution of suitability achieves steady state (Figure 5f).

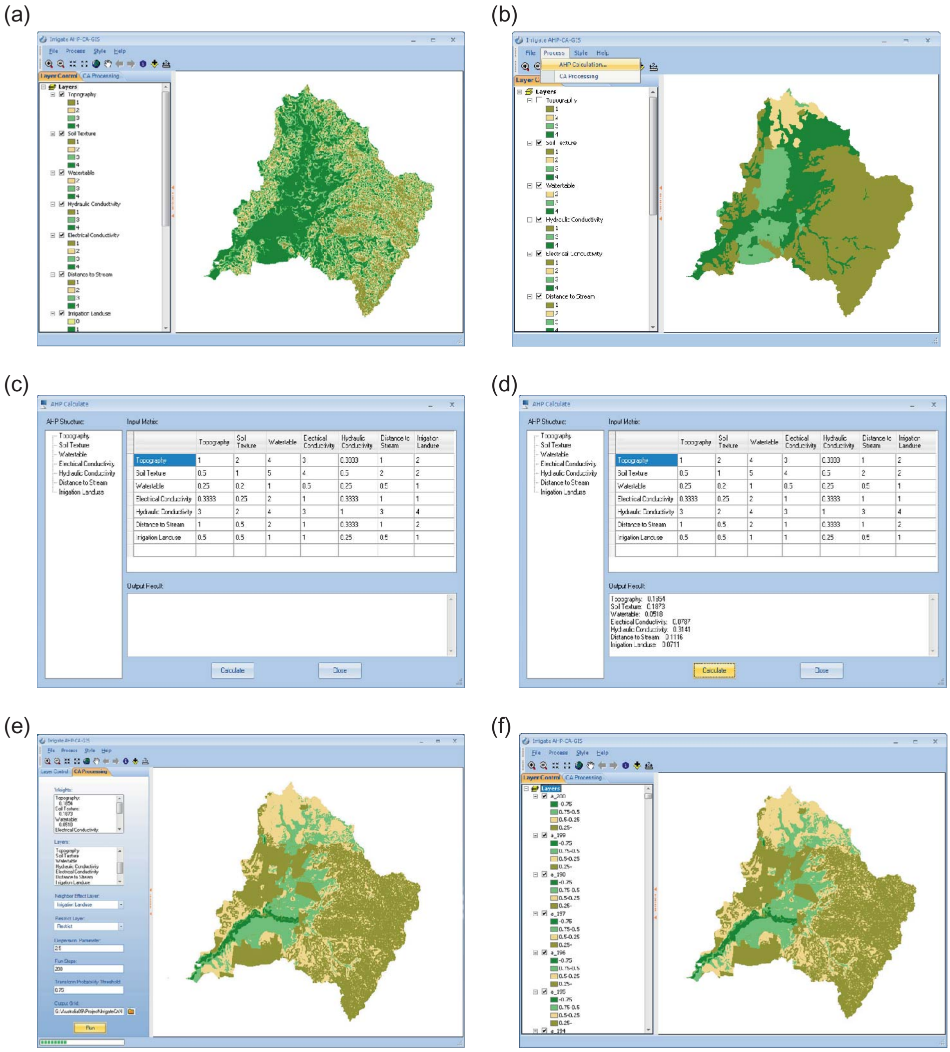

Figure 5. AHP–CA–GIS simulation tool interface. (a) The main interface of AHP–CA–GIS tool with map control and layer control. (b) Two main components: AHP calculation and CA processing. (c) AHP calculation interface. (d) AHP calculation interface with criteria weights calculated. (e) CA processing window for parameter configuration. (f) A simulation result after iterative runs.

4.2.4. Process 4: Result verification

Because there are subjective factors present in the simulation process, such as the comparison matrix whose values are filled by experts, the result has to be verified. Based on a field survey, judge if the suitability map is realistic. If not, the dispersion parameter mentioned in Equation (4) or AHP matrix values may need to be adjusted as new inputs; execute steps in process 3 again to generate a more reasonable scenario.

4.3. LSS results and discussion

With different input parameter values, the AHP–CA–GIS tool can generate various simulation results. The parameter value which is provided to be adjusted by decision-makers to form different scenarios is the value of dispersion parameter α. It can control the dispersion degree of the suitability distribution. A lower α value derives a more optimistic scenario corresponding to the situation that abundant resource available for irrigated cropland. With a higher dispersion value, the possibility for irrigation suitability is depressed, which is corresponding to a less optimistic scenario. Figure 6 shows five suitability maps generated from five scenarios by changing α values to 1, 2.5, 5, 7.5 and 10. Criteria weights were kept the same for all scenarios. For practical demand, more values could be picked by decision-makers to run other scenarios. The percentage areas of suitability classes derived from the five resultant scenario maps are compared against each other in Figure 7.

The scenario with $\alpha = 1$ has the most optimistic situation. About 22% of the catchment area is dominated by highly suitable (S1). Sixty-two percent of the area is moderately suitable (S2) and 16% is marginally suitable (S3). There is no unsuitable land (N) in the catchment at all under this scenario.

The scenario with $\alpha = 2.5$ has a declined optimistic situation compared to the scenario with $\alpha = 1$. About 3% of the area is dominated by S1. S2 has decreased to 16% and S3 has increased to 27%. It is obvious that the N class appears and occupies 54% of the total area.

With $\alpha = 5$, there is only no more than 1% of the area covered by S1. The S2 class decreases to 2% and the S3 class is down to 17%. The N class largely increases to about 80%.

With $\alpha = 7.5$, the area with high suitability is close to 0. The area of S2 class is also no more than 1%. S3 class reduces to 7%. The N class now has the dominating area of more than 92%.

With the greatest value of α ($\alpha = 10$), it derives a worst-case scenario. Highly suitable area and moderately suitable areas are almost 0. Small areas of marginally suitable class (2%) are located along riverside where ground water is available. Unsuitable class covers nearly 98% of the total catchment area.

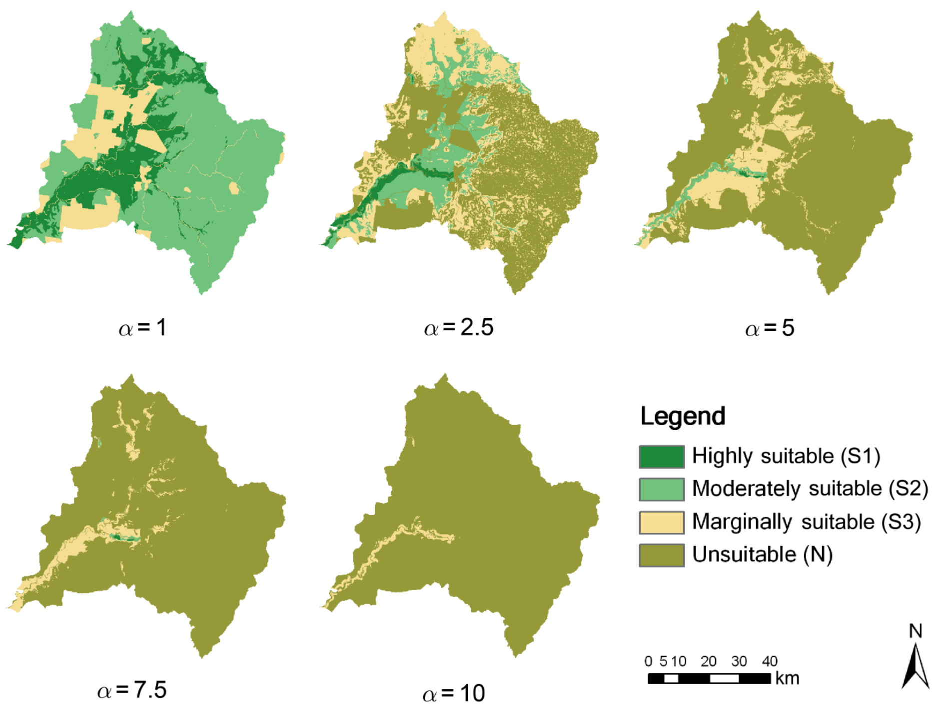

Figure 6. Suitability evaluation maps of irrigated agriculture in the Macintyre Brook catchment.

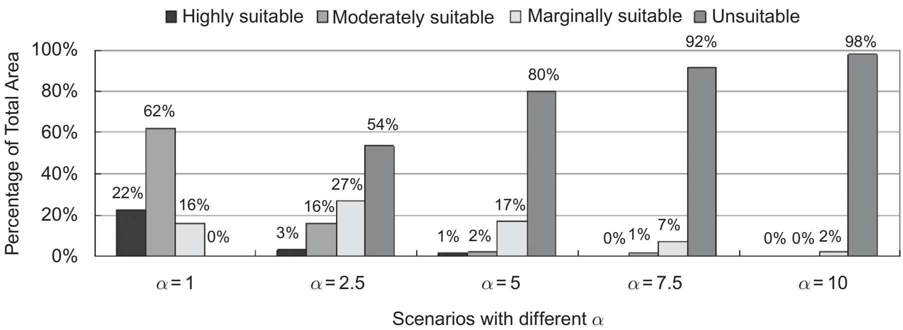

Figure 7. Percentage areas of suitability classes derived from the five resultant scenario maps.

Figure 8 illustrates a method of how to select a reasonable α parameter value which is crucial to model simulation. It shows the probability values P^t_{xy} [defined in Equation (4), $0 \leq P^t_{xy} \leq 1$] for suitability evaluation with different suitability transition intensities r^t_{xy} [defined in Equation (6), $0 \leq r^t_{xy} \leq r_{\max}$] in these five scenarios. It is a nonlinear transition from r^t_{xy} to the probability value. The probability curve of $\alpha = 2.5$ has a more uniform probability distribution than in the case of others. Based on the decision-makers' opinions, the field survey and expert knowledge, the resultant map with $\alpha = 2.5$ was selected in this study for more detailed analysis.

According to the resultant suitability map with $\alpha = 2.5$, the S1 class is mainly distributed on the flood plain of the Macintyre Brook, where the water resources and soil conditions are suited for irrigation. The N regions are mainly located in the south-eastern areas of the catchment, which are characterised with complex topography, relatively steep slopes, poor soil texture, lower hydraulic conductivity and relatively high distance from streams.

Using GIS overlay analysis, the resultant map was validated by the existing location of irrigated croplands in the study area. The present irrigated land was compared with the simulated highly suitable (S1) regions. The result showed that only about 36% of the highly suitable lands have been used for current irrigation practice. It revealed the irrigation land-use development potential of the area. The spatial distribution of suitability has indicated that

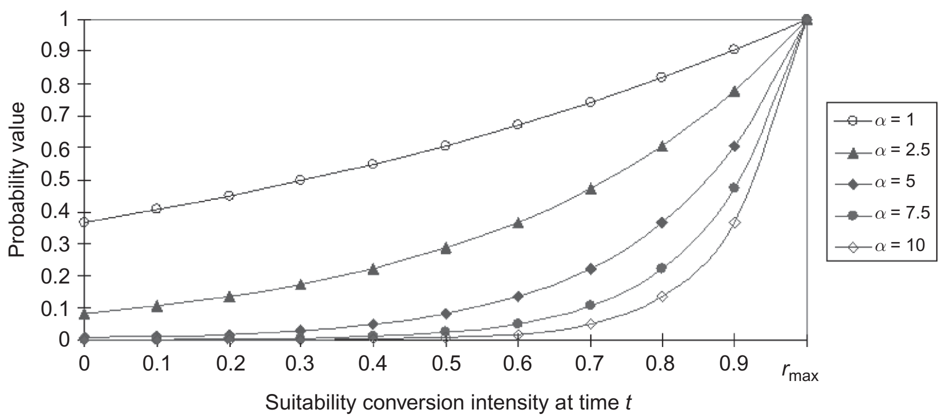

Figure 8. The probability values for suitability evaluation with different transition intensity (r^t_{xy}).

the impact of ECw and DWT to evaluation results is not pronounced. Ks has a great impact on the simulation result. More than 95% of the S1 and S2 classes are located in the areas where Ks is within the range of 0.05–2 m/d. Soil texture also has a significant influence on the evaluation classification. More than 95% of S1 and S2 lands are located in regions with fine to medium soil texture. The results have also illustrated that about 80% of S1 and S2 regions are on surfaces with slopes less than 2%. The S1 areas in the resultant map and the buffer areas in the DS criterion map have a close match (similar spatial distribution pattern), with about 75% of S1 areas falling into the 1000 m buffer zone of the main stream.

It is evident that, with satisfied budget and water supply, the catchment has potential to expand its irrigation areas and provide more food supplies. The results from this study will provide a basis to support decision-making in the future development of irrigated land in the catchment.

5. Conclusion

As a new attempt to expand CA application into the field of agriculture, this article has introduced CA concept into multi-criteria suitability evaluation for irrigated land use. Combined with AHP using MATLAB components, we have integrated CA into MCE in GIS environment. A new model, AHP–CA–GIS, has been developed and implemented to achieve LSS. The AHP–CA–GIS tool has the following advantages:

(1) Spatial-based: All analysis results are displayed with spatial format and spatial processing. They are spatially explicit and easy to understand.
(2) Flexibility: The values of the dispersion parameter and criteria weights are adjustable, which allows the users to rectify the modelling inputs so as to adapt to different scenarios. It increases the scope of application of the GIS simulation and makes it practical for decision-making.
(3) Low cost: The tool can provide an integrated solution of irrigated land suitability evaluation. It simplifies the traditional MCE method and makes cost-effective solutions for expert knowledge integration and spatial data analysis.
(4) Long-term evaluation: The methodology takes into account the irrigation neighbour effect. It incorporates the CA conception that surrounding development will affect suitability assessment and dynamically evolve the simulation. This reveals the possible potential for irrigation expansion in the study area and represents the spatial distribution of irrigated cropland suitability in the long run. The approaches make the result more in line with the actual decision-making requirements.

Five suitability scenario maps have been generated using the AHP–CA–GIS tool in this study. There is a significant correlation between suitability distribution and criteria weights. The results have also been verified in comparison with the present land-use map. It showed that the irrigated land could be expanded in the region and the potential development areas have been represented in a spatial context. This has provided decision-supporting for regional resources management and investment. It put forward a novel methodology to enhance sustainable agricultural land-use planning.

The limitation of this study lies in three aspects. First, there are still some uncertainties associated with the selection of two key parameters: dispersion parameter and classification threshold. In combination with experts' participation and field investigation, special attention needs to be paid to the determination of the parameter values in future work. Second, more criteria may be required in the suitability simulation for irrigated agriculture. There are seven criteria used in the study. But in reality, criteria such as social and economic effects are recommended to be considered. Third, specific iterations could be calibrated using real-time data to make further improvement to the reliability of LSS results if sufficient time-series data are available.

Acknowledgements

The authors sincerely express their appreciation to the Department of Natural Resources and Water of the Queensland Government for providing data for the study, which was supported by the System Harmonisation programme of the Cooperative Research Centre for Irrigation Futures (CRC IF), Australia.

References

Anagnostopoulos, K.P., Vavatsikos, A.P., Spiropoulos, N., and Kraias, I., 2010. Land suitability analysis for natural wastewater treatment systems using a new GIS add-in for supporting criterion weight elicitation methods. *Operational Research*, 10 (1), 91–108.

Barredo, J., et al., 2003. Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. *Landscape and Urban Planning*, 64 (3), 145–160.

Batty, M., Xie, Y., and Sun, Z., 1999. Modelling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems*, 23 (3), 205–233.

Boroushaki, S. and Malczewski, J., 2008. Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in ArcGIS. *Computers and Geosciences*, 34 (4), 399–410.

Carver, S.J., 1991. Integrating multi-criteria evaluation with geographical information systems. *International Journal of Geographical Information Systems*, 5 (3), 321–339.

Cecchini, A., 1996. Urban modeling by means of cellular automata: generalized urban automata with the help on-line (AUGH) model. *Environment and Planning B: Planning and Design*, 23 (6), 721–732.

Chen, Y., Khan, S., and Paydar, Z., 2010. To retire or expand? A fuzzy GIS-based spatial multi-criteria evaluation framework for irrigated agriculture. *Irrigation and Drainage*, 59 (2), 174–188.

Clarke, K.C. and Gaydos, L.J., 1998. Loose-coupling a cellular automata model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science*, 12 (7), 699–714.

Corona, P., et al., 2008. Land suitability for short rotation coppices assessed through fuzzy membership functions. *In*:R. Lafortezza, et al., eds. *Patterns and processes in forest landscapes*. Dordrecht, The Netherlands: Springer, 191–211.

Cram, S., et al., 2006. Suitability of the vegetation types in Mexico's Tamaulipas State for the siting of hazardous waste treatment plants. *Journal of Environmental Management*, 80 (1), 13–24.

Eastman, J.R., 1997. Idrisi for Windows, Version 2.0: tutorial exercises. Worcester, MA: Graduate School of Geography – Clark University.

ESRI, 2008. *Introduction to ArcGIS Desktop and ArcGIS Engine development* [online]. Available from: http://www.esri.com [Accessed 23 October 08].

FAO, 1976. *A frame work for land evaluation* (Soils Bulletin No. 32). Rome: Food and Agriculture Organization of the United Nations.

Geertman, S. and Stillwell, J., 2004. Planning support systems: an inventory of current practice. *Computers, Environment and Urban Systems*, 28 (4), 291–310.

Giordano, L.C. and Riedel, P.S., 2008. Multi-criteria spatial decision analysis for demarcation of greenway: a case study of the city of Rio Claro, São Paulo, Brazil. *Landscape and Urban Planning*, 84 (3–4), 301–311.

Goodchild, M.F., 2000. The current status of GIS and spatial analysis. *Geographical Systems*, 2 (1), 5–10.

Gray, L., 2003. A mathematician looks at Wolfram's new kind of science. *Notices of the American Mathematical Society*, 50 (2), 200–211.

Harris, G.A., 1986. *Soil limitations of irrigated cropping on Macintyre Brook*. Brisbane: Queensland Department of Primary Industries, Project Report Q086017.

Hopkins, L., 1977. Methods for generating land suitability maps: a comparative evaluation. *Journal for American Institute of Planners*, 34 (1), 19–29.

Hossain, M.S., et al., 2007. Multi-criteria evaluation approach to GIS-based land-suitability classification for tilapia farming in Bangladesh. *Aquaculture International*, 15 (6), 425–443.

Hossain, M.S. and Das, N.G., 2010. GIS-based multi-criteria evaluation to land suitability modelling for giant prawn (*Macrobrachium rosenbergii*) farming in Companigonj Upazila of Noakhali, Bangladesh. *Computers and Electronics in Agriculture*, 70 (1), 172–180.

Hübner, R. and Günther, H.O., 2007. Using AHP for strategic production site assessment: a case study from specialty chemicals industry. *In*: H.O. Günther, D.C. Mattfeld and L. Suhl, eds. *Management logistischer netzwerke, entscheidungsunterstützung, informationssysteme und OR-tools*. Heidelberg: Physica-Verlag, 3–22.

Joerin, F., Thériault, M., and Musy, A., 2001. Using GIS and outranking multicriteria analysis for land-use suitability assessment. *International Journal of Geographical Information Science*, 15 (2), 153–174.

Kalogirou, S., 2002. Expert systems and GIS: an application of land suitability evaluation. *Computers, Environment and Urban Systems*, 26 (2–3), 89–112.

Li, X., Yang, Q., and Liu, X., 2008. Discovering and evaluating urban signatures for simulating compact development using cellular automata. *Landscape and Urban Planning*, 86 (2), 177–186.

Li, X. and Yeh, A., 2002. Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science*, 16 (4), 323–343.

Littleboy, M., Smith, D.M., and Bryant, M.J., 1996. Simulation modelling to determine suitability of agricultural land. *Ecological Modelling*, 86 (2–3), 219–225.

Liu, X., Li, X., and Yeh, A., 2007. Discovery of transition rules for geographical cellular automata by using ant colony optimization. *Science in China (Series D)*, 50 (10), 1578–1588.

Liu, X., et al., 2008a. A bottom-up approach to discover transition rules of cellular automata using ant intelligence. *International Journal of Geographical Information Science*, 22 (11), 1147–1169.

Liu, X., et al., 2008b. Simulating complex urban development using kernel-based non-linear cellular automata. *Ecological Modelling*, 211 (1–2), 169–181.

Malcolmson, G.H. and Lloyd, P.L., 1977. Inglewood Shire Handbook: an inventory of the agricultural resources and production of Inglewood Shire, Queensland, Brisbane: Queensland Department of Primary Industries.

Malczewski, J., 2004. GIS-based land-use suitability analysis: a critical overview. *Progress in Planning*, 62 (1), 3–65.

Malczewski, J., et al., 2003. GIS multicriteria evaluation with ordered weighted averaging (OWA): case study of developing watershed management strategies. *Environment and Planning A*, 35 (10), 1769–1784.

Malczewski, J. and Rinner, C., 2005. Exploring multicriteria decision strategies in GIS with linguistic quantifiers: a case study of residential quality evaluation. *Journal of Geographical Systems*, 7 (2), 249–268.

McHarg, I.L., 1969. *Design with nature*. New York: Wiley.

Nijs, T.de, Niet, R.De, and Crommentuijn, L., 2004. Constructing land-use maps of the Netherlands in 2030. *Journal of Environmental Management*, 72 (1–2), 35–42.

Phan, J., 2004. *MATLAB C# Book*. Colorado: LePhan Publishing.

Reshmidevi, T.V., Eldho, T.I., and Jana, R., 2009. A GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds. *Agricultural Systems*, 101 (1–2), 101–109.

Robinson, D.T., et al., 2007. Comparison of empirical methods for building agent-based models in land use science. *Journal of Land Use Science*, 2 (1), 31–55.

Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology*, 15 (3), 234–281.

Saaty, T.L., 1980. The analytic hierarchy process: planning, setting priorities, resource allocation. New York: McGraw Hill International Book Cooperation.

Saaty, T.L. and Vargas, L.G., 1991. *Prediction, projection and forecasting*. Dordrecht, The Netherlands: Kluwer Academic Publisher.

Sicat, R.S., Carranza, E.J.M., and Nidumolu, U.B., 2005. Fuzzy modeling of farmers' knowledge for land suitability classification. *Agricultural Systems*, 83 (1), 49–75.

Store, R. and Kangas, J., 2001. Integrating spatial multi-criteria evaluation and expert knowledge for GIS-based habitat suitability modeling. *Landscape and Urban Planning*, 55 (2), 79–93.

Tiwari, D.N., Loof, R., and Paudyalc, G.N., 1999. Environmental-economic decision-making in lowland irrigated agriculture using multi-criteria analysis techniques. *Agricultural Systems*, 60 (2), 99–112.
Wang, F. and Hall, G.B., and Subaryono, 1990. Fuzzy information representation and processing in conventional GIS software: database design and applications. *International Journal of Geographical Information Systems*, 4 (3), 261–283.
White, R. and Engelen, G., 2000. High resolution integrated modeling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, 24 (5), 383–400.
Wu, F., 2002. Calibration of stochastic cellular automata: the application to rural–urban and conversions. *International Journal of Geographical Information Science*, 16 (8), 795–818.
Wu, F. and Webster, C.J., 1998. Simulation of land development through the integration of cellular automata and multicriteria evaluation. *Environment and Planning B: Planning and Design*, 25 (1), 103–126.
Yager, R.R., 1988. On ordered weighted averaging aggregation operators in multi-criteria decision making. *IEEE Transactions on Systems, Man and Cybernetics*, 18 (1), 183–190.
Yang, Q.S., Li, X., and Shi, X., 2008. Cellular automata for simulating land use changes based on support vector machines. *Computers and Geosciences*, 34 (6), 592–602.