Irrigation Intensification or Extensification Assessment: A GIS-Based Spatial Fuzzy Multi-Criteria Evaluation

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Abstract. This paper presents some preliminary results from a research on spatial multi-criteria evaluation of land suitability for intensification or extensification in irrigated cropland at a catchment scale in Australia. The project was conducted using the fuzzy linguistic ordered weighted averaging (FLOWA) approach which integrates AHP and fuzzy linguistic OWA operators in ArcGIS 9.2 environment. Several scenarios were derived to show how the uncertainties involved in the suitability decision-making process will influence the outcomes. The study has indicated that there is no need for irrigation extensification in the catchment; there is a good potential of intensifying irrigation in some areas if water is available.

Keywords: irrigated cropping, land suitability, fuzzy linguistic ordered weighted averaging

1. Introduction

Land suitability assessment is a multicriteria evaluation process of estimating the potential of land for alternative land uses, among which agricultural land use may be the most important area where it is applied, especially in irrigation regions where intensification (enhanced productivity through greater application of water and other inputs per unit area), or extensification (retirement of area under irrigation) of irrigated area, is needed to meet the production demands.

A number of multicriteria evaluation methods have been implemented in the GIS environment over the last decade (Carver, 1991; Banai, 1993; Pereira and Duckstein, 1993; Jankowski and Richard, 1994; Jankowski, 1995; Tkach and Simonovic, 1997; Malczewski, 1999, 2004, 2006a, 2006b; Bojorquez-Tapia et al., 2001; Dai et al., 2001; Joerin et al., 2001; Makropoulos and Butler, 2005; Malczewski and Rinner, 2005; Borourshaki and Malczewski, 2008). In general, the GIS-based multicriteria evaluation 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 in order to classify each unit into a suitability level (Malczewski, 2006a).

The Analytical Hierarchy Procedure (AHP) method (Saaty, 1977, 1980; Saaty and Vargas, 1991) is a well-known means of multicriteria technique which has been incorporated into the GIS-based suitability procedures (Marinoni, 2004; Jankowski and Richard, 1994). It calculates the needed weighting factors by the help of a preference matrix where all identified relevant criteria are compared against each other with reproducible preference factors, and then aggregates the weights of criterion map layers in a way similar to WCL methods. The AHP gained high popularity because of the ease in obtaining the criterion weights and capacity to integrate heterogeneous data, and therefore, it is applied in a wide variety of decision making problems. It is especially useful in situations when it is impractical or even impossible to specify the exact relationships between a large number of evaluation criteria. However, one of the major drawbacks of AHP is its inability to address the uncertainty and imprecision of the decision maker’s perceptions (Deng, 1999).
The Ordered weighted averaging (OWA) is a framework of multicriteria aggregation procedures (Yager, 1988, 1996). The nature of OWA depends on its capability to implement different combination operators by specifying an appropriate set of order weights. There have been several applications of the conventional OWA which uses quantitative approach in the GIS environment in the past (Jiang and Eastman, 2000; Araújo and Macedo, 2002; Rinner and Malczewski, 2002; Makropoulos et al., 2003; Malczewski et al., 2003; Rashed and Weeks, 2003; Calijuri et al., 2004; Makropoulos and Butler, 2005). Yager (1996) suggested that the conventional OWA operators are of limited applicability in accommodating situations involving a large set of evaluation criteria. Under a complex spatial decision situation, the decision maker might find it difficult or impossible to provide the precise numerical information on the OWA parameters (Malczewski, 2006a). This calls for an extension of the conventional OWA which should be developed in the context of fuzzy logic theory. Malczewski (2006a) incorporated the concept of fuzzy (linguistic) quantifier into the GIS-based land suitability analysis via the OWA. By applying or changing the parameter, quantifier-guided OWA can generate a wide range of decision strategies or scenarios. The two most widely used conventional decision rules in GIS, the weighted linear combination (WLC) methods and the Boolean overlay operations such as intersection (AND) and union (OR), can be considered as specific cases of an OWA family.

Both AHP and OWA procedures have been employed individually in GIS environments (Boroushaki and Malczewski, 2008). Eastman (1997) and Jiang and Eastman (2000) implemented OWA operators in GIS-IDRISI. Malczewski et al. (2003) implemented parameterized OWA procedures in ArcView3.2 environment as a GIS-OWA module. Also, the AHP has been part of the IDRISI functionality for years. It also has been implemented in the ArcGIS environment as a VBA macro (Marinoni, 2004). The fusion of AHP and OWA can provide a more powerful multicriteria decision making tool for structuring and solving spatial decision problems. Yager and Kelman (1999) introduced an extension of the AHP using OWA operators (AHP_OWA), suggesting that the capabilities of AHP as a comprehensive tool for decision making can be improved by integration of the fuzzy linguistic OWA operators. These have paved the way to the development of the AHP_OWA operators using fuzzy linguistic quantifiers within ArcGIS environment, that is, the fuzzy linguistic ordered weighted averaging (FLOWA) module (Boroushaki and Malczewski, 2008). The FLOWA includes two sets of weights: the weights of criterion importance and order weights. The former can be derived using the built-in AHP procedure; and the latter can be generated by means of fuzzy approach employed in the tool.

This paper presents some preliminary results from a study of irrigated cropland suitability assessment at a catchment scale using an application of a spatial multi-criteria evaluation procedure for the assessment of irrigated cropland suitability in the Macintyre Brook Catchment, Queensland, Australia. The goal of this research is to identify the levels and geographical patterns of biophysical constraints and hence, irrigated cropland suitability for maintaining and developing irrigated cropping landuse of the region. There are two objectives: (1) to apply the FLOWA approach to achieve a rapid assessment of determining areas of irrigation intensification or extensification in the catchment; and (2) to obtain several scenarios addressing the uncertainty associated with this research to explore how the uncertainties involved in land suitability multi-criteria decision-making will influence the outcomes of the process.

2. Study Area

The Macintyre Brook Catchment is situated in southern QLD near the state border with NSW, and lies between 27°57’01’’S and 28°47’48’’S latitude, and 150°45’05’’E and 151°42’ 24’’E longitude (Fig. 1). The catchment is relatively flat in the western area, with undulations becoming steeper towards east and northeast. The Elevation at the major town, Inglewood, is 284 m. Macintyre Brook, which flows from east to west, and its tributaries are the main source of surface water. 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. Average annual rainfall is 640 mm. Most of it falls between October and March, but around 100 mm falls in winter (Malcolmson and Lloyd, 1977).

The catchment covers an area of 4,200 km². It is characterised by extremely diverse soil types and topography (Harris, 1986), making it suitable for a wide variety of landuse 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.

Fig. 1. Location of the Macintyre Brook catchment. The image is a colour composite of Landsat 7 bands 7, 4, 2 as red, green, and blue at 25m resolution.

3. Methodology

3.1. Derivation of criterion maps

(1) Suitability classification
Irrigated cropland suitability analysis at a catchment scale is an interdisciplinary approach by including the information from different sources such as climate, topography, soils, groundwater and irrigation. Each of these components consists of many factors which affect evaluation results, e.g. physical and chemical properties of soil, as well as quantity and quality of groundwater. As early as 30 years ago, the Food and Agricultural Organisation (FAO, 1976) proposed an approach for land suitability evaluation in terms of suitability ratings from highly suitable to not suitable based on land characteristics to different crops. 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).

(2) Selection of criteria
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 (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 opinions (Table 1). It should be noted that some of these criteria might be interdependent when used for determining the suitability classes (e.g. depth and salinity of the groundwater, or soil texture and hydraulic conductivity). The threshold values are therefore subjective and they are only applicable to broad scale analysis of irrigated cropping in the catchment. Table 1 provides the fundamental basis to construct the criteria maps.

(3) Definition of hierarchical structure
Malczewiski (1999) stated that relationship between the objectives and attributes has a hierarchical structure. At the highest level the goal can be distinguished as the objectives and at lower levels, the attributes can be decomposed. The overall goal here is evaluating irrigated cropland suitability for an irrigation intensification or extensification assessment on the basis of topography, soils and groundwater objectives. The objectives are measured in terms of five criteria including slope, soil texture, soil hydraulic conductivity, electronic conductivity of groundwater and depth to watertable. Each criterion will be represented by a spatial dataset.
Table 1. Criteria for suitability assessment of irrigated croplands

<table>
<thead>
<tr>
<th>CRITERION</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope (%)</td>
<td>0-2</td>
<td>2-4</td>
<td>4-8</td>
<td>&gt;8</td>
</tr>
<tr>
<td>Soil Texture</td>
<td>fine to medium</td>
<td>heavy clay</td>
<td>coarse or poorly drained</td>
<td>very coarse or shallow depth</td>
</tr>
<tr>
<td>DWT (m)</td>
<td>&gt;4</td>
<td>3-4</td>
<td>2-3</td>
<td>&lt;2</td>
</tr>
<tr>
<td>ECw (dS/m)</td>
<td>0-0.5</td>
<td>0.5-2</td>
<td>2-5</td>
<td>&gt;5 (if depth &lt; 4m)</td>
</tr>
<tr>
<td>Ks (m/d)</td>
<td>0.3-1</td>
<td>0.05-0.3 or 1-2</td>
<td>2-2.5</td>
<td>&lt;0.05 or &gt;2.5</td>
</tr>
</tbody>
</table>

(4) Generation of criterion maps
Spatial data were converted into raster layers and projected into UTM Zone56 in ArcGIS 9.2. Slope was generated from a 25m resolution DEM. All datasets were resampled to 100m cell size using a bilinear algorithm, and classified into four classes as integer rasters representing different suitability levels (Fig. 2) based on the threshold values assigned to them in Table 1. They were then linear-transformed to a 0 to 1 scale before input into the GIS-based FLOWA module. Given these standardised criterion maps, the problem is to combine the maps so that the suitable level for each cell can be classified. One of the key of these combination procedures is identifying the weight of criterion importance, in other words, the weight of each criterion map. This was done by using the AHP tool within the FLOWA.

3.2. Determination of criterion weights
According to the hierarchical structure of the study, a pair-wise comparison matrix at each level of the hierarchy was developed, beginning at the top and working down. The pair-wise comparison method employs an underlying semantical scale with values from 1 to 9 to rate the relative preferences/importance for two elements of the hierarchy (Table 2). The procedure greatly reduces the conceptual complexity of a problem since only two components are considered at any given time. This approach required the experts to provide their best judgment to the relative intensity of importance of one evaluation factor (objective and criterion) against another. The pair-wise comparison matrix for objective level of this study is presented in Table 3 which assigns a numerical value showing relative importance of each objective. In this case, topography objective has been regarded slightly more important than objective soil, hence a value of 2 has been assigned to the corresponding matrix position. The transpose position automatically gets a value of the reciprocal value, in this case 1/2. At the attribute level, a pair-wise comparison matrix was also constructed for each of the objectives by comparing associated attributes (Table 4, 5). Based on these matrixes, the relative weights for objectives and criteria were derived by FLOWA (Table 3, 4, 5).

Fig. 2. Criterion maps used for the evaluation of irrigated croplands. The suitability levels are classified based on the threshold values in Table 1.
3.3. Specification of order weights

After the weights associated with criterion maps were input into the FLOWA, the module requires specifying a linguistic quantifier to the levels of goal and objectives so as to generate a set of ordered weights, and therefore, computing the overall evaluation by means of the OWA combination function.

The FLOWA module employed the relative quantifiers which can be represented as fuzzy subsets over the unit interval, with proportional fuzzy statements such as all, most, many, half, some, few, at least one, etc. According to Malczewiski (2006a) and Boroushaki and Malczewski (2008), FLOWA only considers a class of the relative quantifiers known as the regular increasing monotone (RIM) quantifiers. Thus if $Q$ is a linguistic quantifier, then it can be represented as a fuzzy subset over the unit interval $[0, 1]$, where for each $p$ in the unit interval, the membership grade $Q(p)$ indicates the degree of compatibility of $p$ with the concept denoted by $Q$. To identify the quantifier, one of the most often used methods for defining a parameterized subset on the unit interval (Yager, 1996) has been adopted:

$$Q(p) = p^\alpha, \alpha > 0.$$  

It can be applied for generating a series of the RIM quantifiers. FLOWA module associates the quantifier with a value of a single parameter, $\alpha$, and by changing the value of $\alpha$, user can generate different types of linguistic quantifiers between two extreme cases of the “At least one” and “All” quantifiers (Table 6). In this study, linguistic quantifiers “All” are assigned to the topography objective and “Many” are assigned to both soil and groundwater objectives. This means that “All” of the important criteria (according to their relative weights) associated with topography objective (slope) must be satisfied by an acceptable solution. In terms of soil and groundwater objectives, an acceptable alternative should satisfy “Many” of the important criteria associated with them. Given the weights for objectives and corresponding criteria, and linguistic quantifiers for topography, soil and groundwater objectives, we applied selected values of fuzzy linguistic quantifiers in Table 6 for the goal of the decision making. Five resultant maps representing different scenarios were obtained (Fig. 3).

<table>
<thead>
<tr>
<th>INTENSITY OF IMPORTANCE</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance of one factor over another</td>
</tr>
<tr>
<td>5</td>
<td>Strong or essential importance</td>
</tr>
<tr>
<td>7</td>
<td>Very strong or demonstrated importance</td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>Intermediate values</td>
</tr>
<tr>
<td>Reciprocals</td>
<td>Values for inverse comparison</td>
</tr>
</tbody>
</table>

Table 2. Scale for pair-wise comparisons (Saaty and Vargas, 1991)

<table>
<thead>
<tr>
<th>Objective</th>
<th>Topography</th>
<th>Soils</th>
<th>Groundwater</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography</td>
<td>1</td>
<td>1/2</td>
<td>3</td>
<td>0.301</td>
</tr>
<tr>
<td>Soils</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>0.571</td>
</tr>
<tr>
<td>Groundwater</td>
<td>1/3</td>
<td>1/4</td>
<td>1</td>
<td>0.128</td>
</tr>
</tbody>
</table>

Table 3. Pair-wise comparison matrix of objectives and calculated weights

<table>
<thead>
<tr>
<th>Objective</th>
<th>Attribute</th>
<th>Soil Texture</th>
<th>Ks</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soils</td>
<td>Soil Texture</td>
<td>1</td>
<td>1/2</td>
<td>0.333</td>
</tr>
<tr>
<td></td>
<td>Ks</td>
<td>2</td>
<td>1</td>
<td>0.667</td>
</tr>
</tbody>
</table>

Table 4. Pair-wise comparison matrix of soil attributes and calculated weights

<table>
<thead>
<tr>
<th>Objective</th>
<th>Attribute</th>
<th>ECw</th>
<th>DTW</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Groundwater</td>
<td>ECw</td>
<td>1</td>
<td>2</td>
<td>0.667</td>
</tr>
<tr>
<td></td>
<td>DTW</td>
<td>1/2</td>
<td>1</td>
<td>0.333</td>
</tr>
</tbody>
</table>

Table 5. Pair-wise comparison matrix of groundwater attributes and calculated weights

<table>
<thead>
<tr>
<th>(Q) $\alpha$</th>
<th>At least one</th>
<th>Some</th>
<th>Half</th>
<th>Many</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001</td>
<td>0.5</td>
<td>1</td>
<td>2</td>
<td>1000</td>
<td></td>
</tr>
</tbody>
</table>
4. Results and Discussion

Fig. 3 shows the five alternative land suitability maps derived from five scenarios by changing the linguistic quantifier and the corresponding $\alpha$ parameter for the goal of the decision problem. These alternative scenarios have been developed under the assumption that only the linguistic quantifier associated with the goal of the decision problem changes. Ultimately, for the decision problem here, 73 alternative scenarios can be developed.

The scenario associated with fuzzy quantifier “At least one” is referred to as an extremely optimistic scenario. This scenario selects the highest possible value is at each location (100x100m pixel). In other words, the decision maker is characterised by optimistic attitudes represented by the best possible outcomes. Under this scenario, Most of the area should be at least marginally suitable for irrigation. However, an implementation of the extremely optimistic scenario would be beyond the limited resources available for landuse planning.

The end of the continuum, the scenario associated with fuzzy quantifier “All”, represents another extreme scenario, that is, the worst-case scenario. Under this scenario, the land suitability pattern is composed of the worst possible outcomes. Over two thirds of the area has been classified as unsuitable land.

The scenario associated with the “Half” ($\alpha = 1.0$) represents the scenario corresponding to the conventional weighted linear combination on the level of objectives. The decision maker is characterised by neutral attitudes. It implies a situation in which an equal probability is associated with all possible outcomes at that location.

Comparison of corresponding maps in Fig. 3 indicates that along with increasing the value of $\alpha$ corresponds to the decreasing the degree of optimism. This implies that gradually lower and lower probabilities (ordered weights) are assigned to the higher-ranking criterion values at a given location (100x100m pixel). As a result, the size of the areas suitable for irrigated cropping gets gradually smaller and smaller.

The percentage areas of suitability classes derived from the five resultant scenario maps are compared against each other in Fig. 4.

With $\alpha = 0.0001$, 40% of catchment is dominated by areas highly suitable for irrigated cropping (S1). 27% and 33% of the region are moderately suitable and marginally suitable (S2 and S3), respectively. There is no unsuitable land (N) at all. The whole catchment can be used for irrigated croplands at different suitability levels.

With $\alpha = 0.5$, class S1 covers 21% of the area and S2 has slightly increased to 29% of the area. S3 is restricted only to 18% of the area. Here, it is noticeable that area under the unsuitable (N) class has largely increased to 32% of the area.
With $\alpha = 1$, area with high suitability is down to 7%. The S2 class has been relatively stable in compare to the S3 class. S3 is up to 36% of the area which has doubled the area of same class under $\alpha = 0.5$. It has exactly the same percentage of the total area as under $\alpha = 0.5$.

With $\alpha = 2$, highly suitable class are squeezed down to 0. Moderately suitable class has a little increase. Both marginally suitable and unsuitable classes have dramatically decreased and increased, respectively. In particular, the S3 class are only one fourth of the percent area under $\alpha = 1$.

![Fig. 4. Percentage areas of suitability classes derived from the five resultant scenario maps.](image)

With $\alpha = 1000$, there are no highly suitable irrigated croplands. It is visually interpretable that there has been a big shift from areas under moderately suitable class S2 (at $\alpha = 2$) towards areas under marginally suitable class S3 (at $\alpha = 1000$). The unsuitable class N has no change and still is the dominant one in the region. The two lower suitability classes (S3 and N) together score more than 91% of the total catchment area.

Therefore, by specifying suitable order weights, in terms of $\alpha$ value, it is possible to change the form of aggregation from the minimum-type combination through all intermediate types including the conventional weighted linear combination, to the maximum-type combination. This means that the $\alpha$ can be used to address the uncertainty involved in the evaluation process. An $\alpha$ value of 0.0001 indicates that the assessment procedure involves no uncertainty, and $\alpha$ equals 1000 indicates that decision environment is highly uncertain. Intermediate values indicate uncertainty between these two extreme ranges.

The resultant scenario map associated with the fuzzy quantifier “Half” (Fig. 5), which is a moderately optimistic scenario and the equivalent to the conventional WLC, was selected for more detailed analysis in this study. It 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. It can be clearly seen that the greenish areas coincide well with the areas where $K_s$ ranges from 0.5 m/d to 2 m/d since this criterion received highest weight (about 39%) among the others. Therefore, we expect a high influence of classified $K_s$ values in the result map. The DWT is almost uniform with values greater than 4 m in most of the catchment (only a few local areas along Bracker Creek and Pariagara Creek are between 2-4 m). So this criterion has been assigned a smallest weight. ECw is a measure of groundwater salinity. It is either greater than 0.05 dS/m, or less than 2.5 dS/m in the catchment, which means the whole area is at least marginally suitable for irrigation. It also indicates that salinity is not a significant problem at present. Thus this criterion obtained a corresponding lower weight value. As a result, both DTW and ECw had no great impacts on the evaluation result.

The effects of soil texture on soil infiltration rate, and consequently the suitability level for irrigation, is critical. Unfortunately, we had no detailed quantitative data on this factor. So a relatively lower value was gained by this criterion. Slope is not only an essential factor, but also a reliable criterion derived from the high resolution DEM. It can generate fine discrimination of land units to delineate areas of different suitability levels for a detailed assessment. It accordingly received a high weighting factor. Both slope and soil texture produced relatively significant impacts on the resultant map.

The statistics based on Fig. 5 shows there is about 7% of total catchment area being classified as highly suitable (S1), unsuitable land covers about 32%, and moderately and marginally suitable classes represent 25% and 36% of land area respectively.

The S1 is found mainly on the flood plain of Canning Creek and the Macintyre Brook, and 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 were 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.

The suitability map derived from WLC approach was overlaid with present landuse map to identify differences and similarities between the present landuse and the potential landuse (Fig. 5). The overlay revealed that, in the study area, a substantial portion (70%) of present irrigated cropland falls in the highly suitable class, while approximately 25% is in moderately suitable areas. There is only 5% under marginally suitable areas and none is under unsuitable regions. Highly suitable land (S1) should be retained for irrigation agriculture since limitations to irrigated cropping in S1 land can be overcome by standard management practices. Policies should be considered which protect this land from unnecessary and subdivision for urban or rural residential use or from alienation caused by other landuse such as roads. Limitations to irrigated cropping on moderately suitable land (S2) need to be recognised because a decline in productivity may occur and a range of landuse problems may develop if this land is used and managed inappropriately.

Currently, only 14% of the total highly suitable lands have been used for irrigation which mainly distributed in the southwest part of the catchment. A large proportion (70%) of highly suitable land for irrigated cropping located in the north part of the catchment has been dominated by grazing pasture. Therefore, there is a great potential in cultivating more irrigated cropping if water is available, in other words irrigation intensification, in these highly suitable areas. On the other hand, there is no need for irrigation extensification in the unsuitable areas since there is no irrigation practice occurring on these lands.

Fig. 5. An evaluation map of irrigated cropland suitability derived from WLC approach and overlaid with present landuse map in Macintyre Brook Catchment.

5. Conclusions
A GIS-based spatial fuzzy multicriteria evaluation approach, in terms of FLOWA module, has been applied to a catchment scale irrigation intensification or extensification assessment. The tool brings the capabilities of fuzzy quantifiers within the ArcGIS environment, enhances the existing AHP module and improves ArcGIS functionalities by integrating a multicriteria decision analysis module. It incorporates uncertainty of expert opinions on the criteria and their weights, and provides a mechanism for guiding the decision maker through the multicriteria combination procedures. Several scenarios of suitability for irrigated croplands obtained in this study showed how the uncertainties involved in land suitability decision-making process will influence the outcomes. It has also been found that this module is a valuable and user-friendly tool. In comparison to the conventional GIS-based multicriteria evaluation methods, it gives more flexibility and high efficiency for evaluating land suitability. The capability of it to generate and visualise a range resultant scenarios is particularly useful. Consequently, it facilitates a better understanding of the alternative landuse
suitability patterns for future development.

The overlay results obtained from comparison of resultant map derived from WLC approach against present landuse map have revealed that most (95%) of existing irrigated cropping is located in highly suitable and moderately suitable lands in the southwest part of the catchment; a significant proportion (70%) of highly suitable areas lie in the north part of the catchment where irrigation can be intensified; and there is no extensification from unsuitable areas needed in the catchment.

6. Acknowledgments

This study was supported by the System Harmonisation program of the Cooperative Research Centre for Irrigation Futures (CRCIF). We would like to thank Department of Natural Resources and Water of Queensland Government for providing DEM, groundwater and soils data of the study area.

7. References


