A local spatial decision support system for developing countries based on MCA, fuzzy sets and OWA – case study of a municipality in Cuba

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This paper presents a Spatial Decision Support System for local governments of developing countries. It allows municipality government, enterprises, scientific community and civil society to address decision problems using GIS. The framework is supported by four modules of information technologies: Environmental Decision Support Database, Data Manipulation, Decision Support, and Mapping. A case study is presented covering the implementation of this framework in one municipality of Cuba. An example of land suitability planning for coconut crops is used to evaluate the system performance and usability. Results show local municipalities are able to use this framework to solve local decision problems using state of the art decision making even with low infrastructure development.

Keywords: GIS; Spatial Decision Support System; MCA; OWA; developing countries

1. Introduction

Spatial Decision Support Systems (SDSS) based on Geospatial Information Science (GIS) are relevant tools for sustainable development available to decision makers (1). SDSS provides valuable information to government bodies managing natural resources at a global (2), regional (3, 4) or local scales (5–7). Research on small administrative regions or Local SDSS (LSDSS) has been oriented toward integration of decision models (8), integration of distributed spatial data from heterogeneous sources (9) and collaborative web decision making (10–12).

Despite those developments, LSDSS has not been fully adopted outside big cities in the developing world. For instance, they tend to avoid involvement of local stakeholders (13) or to choose simplistic decision models (7). Reports from several organizations points to organizational downsides and design faults as the more common causes of failure for these type of LSDSS (14, 15). Consequently, local policy makers in the majority of the developing world are deprived from valuable assets for their activities. Moreover, decentralization policies in Latin America and similar underdeveloped areas have become increasingly popular (16, 17). This research aims to create a modern LSDSS focused in local stakeholder’s participation and flexible decision models in these conditions.

Most implementations of LSDSS use Multiple Criteria Analysis (MCA) as primary decision models (18). Recently, MCA models have been complemented with Soft Computing (SC) algorithms (19). SC provides MCA better handling of spatial data and ability to approximate solutions to complex problems (20, 21). One well known application of these novel methods to MCA is the fuzzy set approach to criteria normalization (22) which allows better flexibility describing the relationships between physical variables and expected utility. The recent introduction of Ordered Weighting Average (OWA) operators to MCA (23, 24) provides new capabilities to future LSDSS.

In this paper, the GIS version of the Analytic Hierarchy Process (AHP) is complemented with fuzzy normalization and OWA generated scenarios. This improved Spatial AHP (SAHP) with fuzzy measurements is designed as a wide aspect decision model capable to handle the scope of decision of modern LSDSS.

Section two proposes a general framework for LSDSS, including a decision module based on MCA and fuzzy measures. Section three describes a case study of an implementation of this framework in the municipality of Baracoa, Cuba, oriented to land use suitability modeling. Section four discusses the results and section five lists the conclusions of this work.

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2. The framework for LSDSS

This section describes the principal aspects of the LSDSS framework. An overview of the decision flow is presented as well as the main interactions among policymakers, stakeholders and Information Technologies (IT). Finally it introduces SAHP as recommended decision model.

2.1. Overview of the decision flow

The decision flow was derived from the value focused approach to SDSS based in MCA proposed by([25], [18]). LSDSS reduces the number of steps and diffuses their limits. This approach made it possible to adapt any decision model with ranked outputs to this framework.

1. Problem definition.
2. Data processing
3. Data fusion
4. Post-processing and presentation

First, the decision problem is defined by environmental, economic or social variables with known geographical distribution patterns. This stage focuses on the decision problem goal and the influencing variables. Local policymakers determine the time frames and resource availability for the decision process. The result is a set of options which attributes are assumed to describe the decision problem.

Second, options are adjusted to common GIS data models following the nature of the decision problem. Likely, the LSDSS will use heterogeneous data providers who may require geometric or other transformations to their data. This framework is adequate to manage raster or vector data. However, the implementation presented in this paper is based on raster data.

Third, the option’s attributes are transformed to a ratio scale correlated with the decision problem. This transformation requires known relationships between attributes and the decision goal. These transformed attributes or criterion maps are integrated by the decision model to rank the problem options. The integration requires utility functions representing decision makers understanding (in form of expected utility) of the decision problem. Uncertainty management depends on decision model characteristics.

Finally, the outputs of the decision model are presented as decision aid maps using GIS processing and visualization. Decision proposals adjust to the requirements of the decision problem such as format, media, etc. Remote sensing images, digital cartography, tables and charts add context to these proposals.

2.2. Stakeholders

Six categories of stakeholders were identified as major players on the LSDSS. Local government and its policymakers, local stakeholders which are a group by themselves, third parties, experts, Decision Support Facilitator (DSF), and GIS Analysts (GIS–A). First two represent the local community as a whole, while the other four are related with decision support and GIS technology. An interaction model for those actors is included in Figure 1. The framework defines a close relationship between local Government and local Stakeholders, promoting inclusion and consensus as key factors for conflict resolution. It is important to note that the role covered by the DSF which isolates policymakers from software and data processing to the maximum extent possible.

2.3. IT

The LSDSS framework requires four IT modules: Environment Decision Support Database (EDSdb), Data Management, Decision Support, and Mapping. Their interactions with stakeholders define operational characteristics of any specific implementation of this framework. A generalized connection schema appears in Figure 1. The IT infrastructure for LSDSS is modular and object oriented by design.

2.4. A decision support module with spatial AHP and OWA

The SAHP model is a widely used GIS implementation of the AHP model ([26–28], [18]). AHP was introduced and later updated by Thomas Saaty ([29], [30]), it is extensively used in decision making. SAHP inherited from AHP the assumption of independent criteria and Pareto rational behavior of decision makers.

A typical application of SAHP uses spatial data in raster or vector formats interpreted as criterion maps.

Figure 1. Functional design of the LSDSS. Bold continuous lines indicates the decision flow, continuous lines the interactions among stakeholders and IT, and Dotted lines feedback cycles. IT modules are outlined in bold.
derived from attributes. These maps are used to build a
decision hierarchy. This hierarchy is synthesized eliciting
pairwise comparisons and Weighted Lineal Combination
(WLC) to rank decision options. Sensitivity analysis is
performed by variation of model parameters on a “one at
a time” basis. This method has been implemented to
mainstream GIS software, for example ARCGIS (31)
and IDRISI (32).

Despite the wide adoption of SAHP, the generation
of criterion maps and sensitivity analysis are usually
overlooked in software implementations. The LSDSS
framework addresses these issues using two fuzzy mea-
sures to extend the implementation of SAHP in the deci-
sion module. Fuzzy sets are used to create criterion
standardization maps, and WLC is substituted by OWA
operators in the synthesis.

Standardizing criterion maps is a common practice in
SAHP. However, it is usually performed choosing arbi-
trary values or by simple linear scaling. This module
treats criteria as a function of variable values \( V \) (envi-
ronment) and the decision goal \( v = f(V) \). Experts model
\( f(V) \) by using fuzzy membership functions. This
approach is similar to the knowledge discovery process
based on personal construct theory (33). Experts are able
to define piecewise lineal transformations which are easy
to understand and can approximate any function. See
Figure 4 for some examples.

The synthesis with OWA operators provide continu-
uous fuzzy aggregation operations between fuzzy intersec-
tion (MIN or AND) and union (MAX or OR), with
WLC falling midway in between. This effectively
expands the range of possible outcomes of a SAHP deci-
sion model without modification of pairwise compari-
sions.

An OWA operator can be represented by a triplet \([a, b, c]\) in which \( a \) and \( b \), called ANDness and ORness
are complementary \( a + b = 1 \). They represent both sides
of attitude toward risk. ANDness is the risk avoiding
attitude \( a = 1 \) reproduces Boolean AND overlap and
ORness represents positive attitude toward risks \( b = 1
\) reproduces Boolean OR overlap). The parameter \( c \) repre-
sents the amount of tradeoff that decision makers are
willing to accept, \( 0 \leq c \leq 1 \). The tradeoff is related with
the concept of entropy. Greater values of \( c \) indicate
higher degree of mixture among attributes. For example,
the maximum tradeoff \( c = 1 ([.5,.5,1]) \) is equivalent to
WLC. These concepts are extensively analyzed in(23,
34).

Maximum Entropy OWA (MEOWA) operators are
derived from Regular Increase Monotone (RIM) func-
tions that maximize entropy (35). They are more robust
than other RIM based operators for MCA decision mak-
ing using OWA (36).

The decision module proposed for this LSDSS imple-
ments MEOWA operators. It differs from the OWAHP
model (37) in that the users set ORness value directly,
and the process is independent from AHP hierarchy.
Consequently, this decision module is able to generate
multiple OWA scenarios with less effort. Accuracy
assessment relies on these scenarios to evaluate the sen-
sitivity of the model (38).

3. Case study

In this section, the implementation of the LSDSS frame-
work in a municipality of Cuba is described. It aims to
evaluate the technical feasibility and practical use for
local governments in developing countries. The case
study includes an example of decision problem and the
evaluation of its solution.

3.1. Study area

The municipality of Baracoa is located in the province
of Guantanamo, Cuba, 873 km east of Havana City
(see Figure 2). Its main gross domestic product sources
are Coconut, Cocoa, tourism and Coffee in this order.
Agriculture and local development in Baracoa are sub-
ject to interest for scientific community due to its
localization, environmental values and history. (39, 40)
Most of the municipality area fall under the classifica-
tion of class 1 mountains, more than 300.17 millions
of people live in similar environments. Globally, this
figure represents 48% of people living in mountainous
conditions (41).

3.2. EDSdb

Specifications for Baracoa’s EDSdb were delineated tak-
ing into account compatibility with Cuban standards and
further extensibility. Available standards from the
National Spatial Data Infrastructure (NSDI) were
included in the design. Additional personal communica-
tions with officers from different sectors of Cuban GIS
community were relevant sources of information. The
operational schema of the EDSdb enforced topology
rules before integrating or updating any spatial database.

At the moment, the EDSdb of Baracoa municipality
includes 40 primary data sets, each codifying a specific
geographical object or a variable. Working scales in this
spatial repository range from 1:2000 for city areas to
1:300,000 for climate variables. Maximum coverage area
for any data set was defined taking the physical bound-
aries of all hydrological basins discharging on municipal-
ity area. All spatial data except remote sensing was
projected to the south of Cuba Lambert Conformal Conic
projection codenamed “Cuba Sur”.

The locality limited IT resources conditioned that for
this EDSdb version, data warehousing was implemented in
local archives managed by the SuperMap SDX
driver. However, it is relatively straightforward to
upscale the data warehouse system using dedicated high
performance RDBMS since database drivers are transpar-
ent to GIS application layer.

3.3. Data manipulation

Data geoprocessing relied on SuperMap desktop 6R GIS
software. C# programming language and SuperMap Uni-
versal GIS Core (UGC) technology was used to complement UGC for solutions not covered by standard GIS functions.

3.4. Decision support module
The decision support module was organized in three layers: (a) Core AHP classes implementing AHP basics (for example, pairwise comparison matrices, closest discrete pairwise matrices, multiplicative and additive synthesis, etc.) (b) Visual components derived from windows forms classes, encapsulating the core AHP functions. (c) Graphical User Interfaces, integrating AHP modules with SuperMap Objects .Net 6R. The coding is Common Language Infrastructure compliant and was developed in C#.

3.4.1. Core AHP classes
The core classes fully implemented AHP multilevel hierarchy model as described in (29) and (42). Additional classes implemented auxiliary functions for the SAHP solver. For example decision options may be processed directly from multiband raster data. New classes supporting vector data model can be easily implemented. Several classes provide methods and storage for criteria standardization with fuzzy piecewise lineal transformation functions. Other fuzzy membership functions may be added deriving new classes for further versions.

3.4.2. Visual components
Visual components are interfaces to AHP core classes. They allow users to input pairwise evaluations, visual hierarchy building and interactive display of model statuses. Two kinds of visual components were designed for the LSDSS: Modular AHP components and Base AHP components.

Modular AHP components are building blocks to design complex AHP interfaces. They need base components to work properly. Base components encapsulate complete AHP decision models. Currently, the LSDSS implemented simple pairwise matrix solver, full AHP hierarchy solver and raster SAHP solver. All but the first supports multilevel hierarchies. The

Figure 2. Localization of the study area (A) Detail (B) includes a shaded relief of municipality area and administrative subdivisions.
SAHP solver supports OWA quantifiers for optimistic (no tradeoff) \([1,0,0]\), mostly optimistic \([.666,.333,.781]\) (high tradeoff), pessimistic (no tradeoff) \([0,1,0]\), mostly pessimistic \([.333,.666,.781]\) (high tradeoff) and WLC \([.5,.5,1]\) (full tradeoff). Other quantifiers may be added directly by users inputting individual vector values.

### 3.4.3. Interface layer

For this study we selected a standalone application for the interface layer, due to underdeveloped IT infrastructure in the municipality. The deployed application was named SuperMDS and was written in C#. This application implemented functions to: open a SuperMap workspace and browse maps from it, create GIS–AHP models from scratch or using a software wizard, and provide user interfaces to construct and solve raster GIS AHP hierarchies of unlimited levels. Figure 3 shows a general view with the open model used in this example. It offers visual interfaces to construct fuzzy membership functions (foreground in Figure 3) and perform other management tasks.

Users may interact with this layer in several ways conditional to IT infrastructure and operator expertise: Stand alone application, GIS services, and plug-in for Desktop GIS. SuperMDS includes common GIS analysis functions (background in Fig. 3). All visible interface objects float on a customizable reference map of the study area, which allow users to easily explore geographical data.

This software can be executed with reasonably low specifications of hardware, such as low power processors. Memory use is configurable by users. Furthermore, the modular approach shall simplify porting this application into other GIS platforms such as ARCMinfo or the open source GeoTools.

### 3.5. Mapping module

Mapping functions of this LSDSS relied on desktop GIS. This particular solution used predefined map templates designed for SuperMap Desktop 6R application. These base map templates includes standard office print sizes A4-A3 and large prints A0 with common scales.

### 3.6. Example: Coconut policy implementation

This example aims to highlight practical aspects of LSDSS framework. The coconut policy implementation was basically a Land Use Suitability Analysis (LUSA) focused in potential yield of actual or future coconut development areas. It was selected for three main reasons. First of all, coconut crops represent the 60% of the municipality’s gross income. Secondly, long cycle crops like coconut palms, which have 10–20 years of expected productive life, are difficult to address experimentally. Finally, due to the relevance of the matter, the government hired the best national experts in coconut crops, which gave us access to quality knowledge.

Local policymakers hosted the analysis. The local government summoned experts from the top ranked national institute on tropical fruits with large experience in coconut crop’s management. In addition, they...

![Figure 3. Screen of SuperMDS interface with coconut land suitability analysis and open standardization function dialog.](image-url)
recruited personnel from specialized government offices to help with GIS data management and train local staff. Same offices provided a DSF. The coconut farmers association and the local coconut company sent representatives. They supplied external opinions and helped experts evaluate the results.

4. Results and discussion

Six environmental factors were considered analyzing potential productivity of coconut palms: Cost distance to rivers (V1) which accounts for ground water availability; Incoming solar radiation (V2); Slope (V3); Annual average of accumulated rainfall (V4); Effective soil deep (V5); Annual average of minimal temperature (V6). Descriptive statistics of these variables appears in Table 1.

Data layers were adjusted using topological rules and vector to raster conversion. Variable maps were stored as a raster database with square pixels of 30 m. Each of these pixels is considered an option to rank.

A cross-correlation study of the data identified some unwanted relationships among variables. It is easy to observe in Table 2 that there are two groups of them with mild correlation. Both groups of variables V1, V2, V3 and V6, V4, V3 includes slope (V3). This kind of correlation is expected in highlands where usually high slopes are more common in higher altitudes. A principal component analysis could solve this issue. However, such analysis would complicate further elicitation of

Table 1. Variables for coconut crops.

| Var | Min  | Max    | Mean  | σ     | Unit |
|-----|------|--------|-------|-------|------|
| V1  | 0    | 20,663 | 3374.3| 3131.4| m    |
| V2  | $8.4 \times 10^5$ | $1.8 \times 10^6$ | $1.5 \times 10^6$ | $1.2 \times 10^5$ | Wm²/y |
| V3  | 0    | 53.29  | 16.48 | 9.93  | Deg  |
| V4  | 1000 | 3800   | 2644.5| 674.43| mm   |
| V5  | 0    | 155    | 58.52 | 37.32 | cm   |
| V6  | 16.5 | 21.5   | 19.22 | 1.27  | °C   |

Figure 4. Linear piecewise transformation functions for variable standardization. Dashed lines represent equivalent linear standardization.
pairwise judgments. Consequently, no further action was taken.

A linear piecewise transformation function was constructed for each variable with SuperMDS interactive interface. Those functions represented experts understanding of the relationship variable–coconut yield. The flexibility of this method is clearly visible in Figure 4. It shows that functions for each variable can be adjusted to approximate any profile considered by experts. The knowledge embedded in those tables was archived for further use or revision in a knowledge database (33).

Data fusion required two moments: Group sessions and data analysis.

| Code      | Area (m²) | Low suitability | Tolerable | High suitability |
|-----------|-----------|-----------------|-----------|------------------|
| (a) High suitability areas |
| HS_SITE_0 | 4680      | 0               | 52        | 0                |
| HS_SITE_1 | 3240      | 0               | 36        | 0                |
| HS_SITE_2 | 3690      | 0               | 35        | 0                |
| HS_SITE_3 | 41,490    | 0               | 400       | 61               |
| HS_SITE_4 | 8460      | 0               | 0         | 94               |
| HS_SITE_5 | 28,170    | 0               | 0         | 313              |
| HS_SITE_6 | 10,260    | 0               | 91        | 23               |
| HS_SITE_7 | 22,140    | 0               | 16        | 230              |
| HS_SITE_8 | 2880      | 0               | 0         | 32               |
| HS_SITE_9 | 2340      | 0               | 0         | 26               |
| HS_SITE_10| 1530      | 0               | 5         | 12               |
| HS_SITE_11| 10,440    | 0               | 103       | 13               |
| HS_SITE_12| 10,350    | 0               | 70        | 45               |
| HS_SITE_13| 14,760    | 0               | 53        | 111              |
| HS_SITE_14| 4950      | 0               | 7         | 48               |
| HS_SITE_15| 3690      | 0               | 6         | 35               |
| HS_SITE_16| 10,260    | 0               | 0         | 114              |
| HS_SITE_17| 3690      | 0               | 31        | 10               |
| HS_SITE_18| 9540      | 0               | 0         | 106              |
| HS_SITE_19| 1710      | 0               | 0         | 19               |
| HS_SITE_20| 14,490    | 0               | 22        | 139              |
| HS_SITE_21| 6840      | 0               | 23        | 53               |
| HS_SITE_22| 2610      | 0               | 28        | 1                |
| HS_SITE_23| 2610      | 0               | 29        | 0                |
| (b) Low suitability areas |
| LS_SITE_1 | 30,330    | 337             | 0         | 0                |
| LS_SITE_2 | 18,990    | 211             | 0         | 0                |
| LS_SITE_3 | 12,060    | 134             | 0         | 0                |
| LS_SITE_4 | 12,510    | 139             | 0         | 0                |
| LS_SITE_5 | 6660      | 74              | 0         | 0                |
| LS_SITE_6 | 9090      | 101             | 0         | 0                |
| LS_SITE_7 | 3330      | 37              | 0         | 0                |
| LS_SITE_8 | 22,140    | 246             | 0         | 0                |
| LS_SITE_9 | 9450      | 105             | 0         | 0                |
| LS_SITE_10| 7200      | 7               | 73        | 0                |
| LS_SITE_11| 5670      | 63              | 0         | 0                |
| LS_SITE_12| 7920      | 88              | 0         | 0                |

Table 2. Cross correlation matrix of decision variables.

| V1 | V2 | V3 | V4 | V5 | V6 |
|----|----|----|----|----|----|
| 0  | 0.1098 | 0.36799 | -0.10735 | -0.01623 | 0.17913 |
| 0.1098 | 0 | 0.59045 | -0.1228 | -0.0039 | 0.02774 |
| 0.36799 | 0.59045 | 0 | -0.37155 | 0.02052 | 0.38255 |
| -0.10735 | -0.1228 | -0.37155 | 0 | -0.15797 | -0.65976 |
| -0.01623 | -0.0039 | 0.02052 | -0.15797 | 0 | -0.03015 |
| 0.17913 | 0.02774 | 0.38255 | -0.65976 | -0.03015 | 0 |

Table 3. Weight vector.

| V1 | V2 | V3 | V4 | V5 | V6 |
|----|----|----|----|----|----|
| .1268 | .1108 | .1006 | .1598 | .1691 | .3325 |
Firstly, experts and local policymakers created a hierarchy describing relationships between variables with SuperMDS. One staff from an external government office assisted them as DSF. The local government sponsored these group sessions providing venues and official's time. The relative importance of each variable derived from policymakers and expert’s choices appear in Table 3.

Secondly, the DSF used these weights, fuzzy memberships in Figure 4 and MEOWA operators internally generated by SuperMDS to compute priority indexes for five scenarios. Two of those scenarios considered positive attitudes towards risk, two negative attitudes and a "neutral" one, equivalent to WLC. SuperMDS generated continuous priority maps, which are useful revealing relative suitability for each decision unit or pixel. However, policymakers required simplified maps. Each scenario in the Figs. 5(a–e) was segmented into three levels: Suitable areas, unsuitable areas, and a buffer zone in between (labeled "tolerable" areas). Thresholds for each level were defined by natural breaks with Jenks optimization.

Maps in Figure 5 clearly show the influence of MEOWA operators in the decision map. Optimistic attitudes toward risks, which rewarded the best ranked options, produced extensive suitable areas. Pessimistic attitudes, however, greatly reduced the extension of suitable areas as shown in Figure 5(b) and (c). It is noteworthy that in this example, pessimistic attitudes provoked higher variability in the definition of unsuitable areas.

The LSDSS provided two approaches to evaluate the accuracy of the coconut LUSA model: Sensibility evaluation to risk attitude and expert assessment.

In the first place, the five scenarios shown in Figure 5(e) were combined in a sensibility map. Those pixels equally classified in at least four scenarios were considered better candidates for each class. Correspondingly, areas of pixels with high class variability were recommended for careful pre-decision assessment.

The second approach used personal expert assessment of production areas. This is an extended practice in environmental modeling [43]. However, personal assessments are only practical for small and clustered areas. Local stakeholders with support from external experts visited selected locations and assessed their suitability for coconut crops. This assessment responded to available records and their subjective evaluation. Each location received a suitable Table 5a or unsuitable Table 5b label from these assessments.

Table 4 shows the classification derived from the map in Figure 5(d). Nine of the 37 sites were not clearly classified by the LSDSS model. However, it is clear from both tables that the computer model is close to the expert assessments.

5. Conclusion

This paper presents a framework for LSDSS developing countries. It implements a flexible approach to MCA decision making, complementing AHP model with modern fuzzy measurements. Deploying this framework in a
local government requires a standalone application in its first stages. The SuperMDSS integrates fuzzy criteria evaluation and MEOWA synthesis model to SAHP. This software does not require advanced IT infrastructure to analyze, in a short period of time, a decision problem under several scenarios.

One example of LUSA for coconut crops is presented. This example shows that the LSDSS framework is efficient solving spatial MCA decision problems. The accuracy analysis shows correspondence between the LSDSS decision model and personal expert assessment of production areas.

Despite the inclusion in MCA in general and AHP in particular, they are affected by special characteristics of GIS data in greater degrees than other methods such as SC models (20). The use of SC models in the context of LSDSS framework will be a matter of future research.

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**Note**

1. For all references to SuperMap software, please see http://www.supermap.com

**References**

(1) Ventura, S.J. The Use of Geographic Information Systems in Local Government. Public Admin. Rev. 1995, 55 (5), 461–467.

(2) Guoxin, T.; Shibasaki, R.; Matsumura, K. Development of a GIS-Based Decision Support System for Assessing Land Use Status. GIS 2004, 7, 72–78.

(3) Lane, D.; Michalowski, W.; Stephenson, R.; Page, F. Integrated Systems Analysis for Marine Site Evaluations and Multicriteria Decision Support for Coastal Aquaculture. In Aquaculture, Innovation and Social Transformation, 2009, i, 255–264.

(4) Chitsazan, M.; Akhthari, Y. GIS-based DRASTIC Model for Assessing Aquifer Vulnerability in Kheran plain, Khuzestan, Iran. Water Resour. Manage. 2008.

(5) Coutinho-Rodrigues, J.; Simão, A.; Henggele Antunes, C. A GIS-Based Multicriteria Spatial Decision Support System for Planning Urban Infrastructures. Decision Support Systems. 2011, 51 (3), 720–726.

(6) Thomas, M.R. A GIS-Based Decision Support System for Brownfield Redevelopment. Landscape and Urban Planning 2002, 59 (1), 1–18.

(7) Chih, T.; Kerkides, P. A Spatial Decision Support System for Water Resources Hazard Assessment: Local Level Water Resources Management with GIS in Kenya. J. Geogr. Inform. Decision Anal. 2003, 7 (1), 32–46.

(8) Huser, B.; Rutledge, D.T.; Van Delden, H.; Wedderburn, M.E.; Cameron, M.; Elliott, M.; Fenton, T.; Hurkens, J.; McBride, G.; McDonald, G.; O’Connor, M.; Phyn, D.; Poot, J.; Price, R.; Small, B.; Tait, A.; Vanhout, R.; Woods, R.A. In Development of an Integrated Spatial Decision Support System (ISDSS) for Local Government in New Zealand, Proceedings of the 18th World IMACS/MODSIM International Congress on Modelling and Simulation, Cairns, Australia, Jul 13–17 July, 2009.

(9) Sengupta, R.R.; Bennett, D.A. Agent-Based Modelling System for Spatial Decision Support. Int. J. Geographical Informat. Sci. 2003, 17 (2), 157–180.

(10) Sidler, J.U.; Gangopadhyay, A. Design and Implementation of a Web-Based Collaborative Spatial Decision Support System. Inform. Res. Manage. J. 2002, 15 (4), 33–47.

(11) Sugumaran, R. Web-based Spatial Decision Support Systems (WebSDSS): Evolution, Architecture, Examples and Challenges. Commun. Assoc. Inf. Syst. 2007, 19 (1).

(12) Simão, A.; Densham, P.J.; (Muki)Haklay, M. Web-based GIS for Collaborative Planning and Public Participation: An Application to the Strategic Planning of Wind Farm Sites. J. Environ. Manage. 2009, 90 (6), 2027–2040.

(13) Dragan, M.; Focil, E.; Fetnici, M.; Zerihun, W. Application of a Spatial Decision Support System (SDSS) to Reduce Soil Erosion in Northern Ethiopia. Environ. Modelling & Software 2003, 18, 861–868.

(14) Matthews, R.; Stephens, W.; Hess, T.; Mason, T.; Graves, A. Applications of Crop/Soil Simulation Models in Developing Countries; DFID NRSP Programme Development, Technical Report PD 82, Institute of Water and Environment Cranfield University, Silsoe, 2000.

(15) L.S. Willardson, Ed. Impact of Land Utilization Systems on Agricultural Productivity. The Asian Productivity Organization: Tokyo, 2003.

(16) Willis, E.; da CB Garman, C.; Haggard, S. The Politics of Decentralization in Latin America. Latin American Rev. 1999, 75–76.

(17) Nickson, R.A. Where is Local Government Going in Latin America? A Comparative Perspective. International Centre for Local Democracy, (Working Paper No. 6):1–36, 2011.

(18) Maleczewski, J. GIS and Multicriteria Decision Analysis; John Wiley & Sons: New York, NY, 1999.
(19) Jain, L.; Lim, C. Advances in Decision Making. In Recent Advances in Decision Making 2009, 222, 1–6.

(20) Openshaw, S. Some Suggestions Concerning the Development of Artificial Intelligence Tools for Spatial Modelling and Analysis in GIS. Ann. Reg. Sci. 1992, 26 (1), 35–51.

(21) Openshaw, S. Neural network, Genetic, and Fuzzy Logic Models of Spatial Interaction. Environ. Planning A 1998, 30, 1857–1872.

(22) Morris, A.; Jankowski, P. Spatial Decision Making Using Fuzzy GIS. In Fuzzy Modeling with Spatial Information for Geographic Problems 2005, 275–298.

(23) Jiang, H.; Ronald Eastman, J. Application of Fuzzy Measures in Multi-Criteria Evaluation in GIS. Inter. J. Geo. Infor. Sci. 2000, 14 (2), 173–184.

(24) Malczewski, J. Ordered Weighted Averaging with Fuzzy Quantifiers: GIS-Based Multicriteria Evaluation for Land-Use Suitability Analysis. Int. J. Appl. Earth Obs. Geoinf. 2006, 8 (4), 270–277.

(25) Malczewski, J.A. GIS-Based Approach to Multiple Criteria Group Decision-Making. Inter. J. Geo. Inform. Sci. 1996, 10 (8), 955.

(26) Malczewski, J.; Moreno-Sanchez, R.; Bojorquez-Tapia, L. A.; Ongay-Delhumeau, E. Multicriteria Group Decision-Making Model for Environmental Conflict Analysis in the Cape Region, Mexico. J. Environ. Planning Manage. 1997, 40 (3), 349.

(27) Malczewski, J.; Jackson, M. Multicriteria Spatial Allocation of Educational Resources: An Overview. Socio-Econ. Planning Sci. 2000, 34 (3), 219–235.

(28) Ying, X.; Zeng, G.-M.; Chen, G.-Q.; Tang, L.; Wang, K.-L.; Huang, D.-Y. Combining AHP with GIS in Synthetic Evaluation of Eco-Environment Quality—A Case Study of Hunan Province, China. Ecol. Model. 2007, 209 (2–4), 97–109.

(29) Saaty, T.L. The Analytic Hierarchy Process. Inter. Series in Opera. Res. Manage. Sci.; RWS Publications: Pittsburg, 1990.

(30) Saaty, T. Decision Making with the Analytic Hierarchy and Network Processes (AHP/ANP). J. Syst. Sci. Syst. Eng. 2004, 13 (1), 1–35.

(31) Marinoni, O. Implementation of the Analytical Hierarchy Process with VBA in ArcGIS. Comput. Geosci. 2004, 30 (6), 637–646.

(32) ClarkLabs. Clark Labs-IDRISI GIS and Image Processing Software, 2010. http://www.clarklabs.org/ (accessed Dec 21, 2010).

(33) Zhu, A.-X. A Personal Construct-Based Knowledge Acquisition Process for Natural Resource Mapping. Inter. J. Geo. Inform Sci. 1999, 13 (2), 119.

(34) Yager, R.R. Generalized OWA Aggregation Operators. Fuzzy Optim. Decis. Making March 2004, 3 (1), 93–107.

(35) Liu, X.; Da, Q. On the Properties of Regular Increasing Monotone (RIM) Quantifiers with Maximum Entropy††. Int. J. Gen Syst April 2008, 37 (2), 167–179.

(36) Makropoulos, C.K.; Butler, D. Spatial Ordered Weighted Averaging: Incorporating Spatially Variable Attitude Towards Risk in Spatial Multi-Criteria Decision-Making. Environ. Modelling Soft. January 2006, 21 (1), 69–84.

(37) Boroushaki, S.; Malczewski, J. Implementing an Extension of the Analytical Hierarchy Process Using Ordered Weighted Averaging Operators with Fuzzy Quantifiers in ArcGIS. Comput. Geosci. April 2008, 34 (4), 399–410.

(38) Arika, L.-Z.; Piotr, J.A. Framework for Sensitivity Analysis in Spatial Multiple Criteria Evaluation. In Geographic Information Science 2008, 217–233.

(39) Wezel, A.; Bender, S. Plant Species Diversity of Homegardens of Cuba and its Significance for Household Food Supply. Agrofor. Syst. January 2003, 57 (1), 39–49.

(40) Wezel, A.; Bender, S. Agricultural Land Use in the Coastal Area of the Alexander von Humboldt National Park, Cuba and its Implication for Conservation and Sustainability. GeoJournal 2002, 57 (4), 241–249.

(41) Huddleston, B.; Ataman, E.; de Salvo, P.; Zanetti, M.; Bloise, M.; Bel, J.; Franceschini, V.; Fé d’Ostiani, V. Towards a GIS-Based Analysis of Mountain Environments and Populations. Working paper Environment and Natural Resources Working paper no. 10, FAO, 2003.

(42) Saaty, T. Making and Validating Complex Decisions with the AHP/ANP. J. Syst. Sci. Syst. Eng. 2005, 14 (1), 1–36.

(43) Krueger, T.; Page, T.; Hubacek, K.; Smith, L.; Hiscock, K. The Role of Expert Opinion in Environmental Modeling. Environ. Modelling & Soft. 2012, 36, 4–18.