Multi-criteria decision analysis in spatial decision support: the ASSESS analytic hierarchy process and the role of quantitative methods and spatially explicit analysis

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Abstract

Decision support systems (DSS) that are simple, spatial, flexible, non-deterministic and have a long track record of practical application in a policy environment have until recently been uncommon. There has been a rapid expansion in the development and description of both quantitative and soft system methods that can be applied to decision-making processes and many of these have application in the spatial domain. This paper examines the case for inclusion of new methods in spatial systems for multi-criteria decision analysis (MCDA) in the context of the history and application of ASSESS (A System for Selecting Suitable Sites). As a spatial implementation of the Analytic Hierarchy Process (AHP), ASSESS has been used extensively for MCDA in a policy environment, but has not previously been described in peer-reviewed literature. ASSESS provides an interface in the ArcInfo Grid GIS environment that accesses GIS functionality and enables simple linear addition and combination of data layers, quantised into rankings from 1 to 5 corresponding to suitable/good to unsuitable/bad, for the development of output scenarios that may be constructed from different user viewpoints. Results from assessment of catchment condition for the intensive land use zone of Australia are used to illustrate issues surrounding incorporation of new methods and spatially explicit operations into the simple ASSESS AHP MCDA process. The knowledge and methods base is outlined diagrammatically using AHP MCDA as the core process, and new methods and spatial approaches as adjuncts or inputs at various stages. New methods can assist with correlation of input data layers, subjective weightings, and mixing of qualitative and quantitative data. The merits of the inclusion of quantitative methods based on logical empiricism for explicit definition of input errors and uncertainty, approaches to quantisation of input data, and optimisation of outputs are contrasted with soft systems approaches that incorporate more linguistic and information theory into landscape analysis. The potential role for spatial analysis both in providing static input factor layers and in dynamic optimisation and seamless integration in the decision process are explored.

Keywords: Multi-criteria analysis; Methods; Framework; Scenario analysis; Land use; Uncertainty; Site selection

1. Introduction

Integration of economic and ecological information in a spatial context is a valuable approach for strategic policy development and decision-making (e.g., Walker and Young, 1997; Tiwari et al., 1999; Turner et al., 2000; Sierra et al., 2002). Several conceptual frameworks encompassing the science, ways of capturing data and responses, and the human-biophysical dimension of problems, have recently arisen as a focus for interdisciplinary research and analysis for the 21st century. The
science element is addressed by Earth Systems Science (ESS) which is “the understanding of how the Earth is changing and the consequences for life on Earth with a focus on enabling prediction and mitigation of undesirable consequences” (Meeson, 2000). The ways of capturing data and responses are addressed by Environmental Informatics (EI) which is the “science and art of turning environmental data into information and understanding” (Lancaster University, 2003); or “research and system development focusing on the environmental sciences relating to the creation, collection, storage, processing, modelling, interpretation, display and dissemination of data and information” (NERC, 2004); or “an emerging field centering around the development of standards and protocols, both technical and institutional, for sharing and integrating environmental data and information” (Biosphere Data Project, 2004). The human-biophysical dimension is captured by the concept of Coupled Human Environmental Systems (CHES). These represent “a bounded, integrated unit on the land comprised of human, ecosystem/biological, and environmental components – they require analysis and assessment focused on the synergy and reciprocal relations among people, physical environment, and biota, emphasizing feedbacks between the human and natural subsystems” (Lourenco and Machado, 2003). In this discourse, we will refer principally to the latter term as it describes the kind of problem and decision envelope to which MCDA is particularly well suited. The development of these frameworks has expanded the domain of interdisciplinary analysis such that process models, scenario calculators, decision support systems (DSS), multi-criteria decision analysis (MCDA) and soft system methods need to be combined into integrated suites of analytical tools and approaches (Niskanen, 2002).

In recent years, there has been a rapid expansion of interest and research on “spatial” decision support systems (SDSS, e.g. Kangas et al., 2000; Store and Kangas, 2001; Walker and Veitch, 2001; Dragan et al., 2003; Fuller et al., 2003; Store and Jokimaki, 2003; Morari et al., 2004; Arampatzis et al., 2004; Giupponi et al., 2004). To varying degrees, these approaches attempt to capture the system dynamics; deliver outputs as spatial data that define biophysical, economic and social constraints (e.g. Dai et al., 2001); use new methods for translating factor layers into standardised inputs for problem criteria definition; use new methods for capturing uncertainty in ranking of alternatives; and explore options for quantitative optimisation with or without a spatial component. Two key issues are emerging from these endeavours. The first concerns the introduction of new quantitative methods at a number of stages in MCDA for landscape-scale problems and how these methods can be reconciled and assist with the human decision-making process in an iterative and user friendly way. The second concerns the utility and feasibility of incorporating spatial analysis into existing MCDA, or the redesigning of MCDA as a seamless spatially explicit process.

There has long been a desire to utilise multi-criteria decision analysis (MCDA) and GIS to make land allocation decisions that combine sophisticated decision theory with advanced spatial analysis. The European school of MCDA (Roy, 1991, 1996) has developed a large literature and diverse methodology for application of MCDA in industry and government (e.g. Ferrarini et al., 2001). This has lead to the development of a wide array of approaches to MCDA based on the analytical hierarchy process (AHP, Saaty, 1980; 2000; Ramanathan, 2001) on the one hand, and an array of cognitive methods on the other (Bisdorff, 1999; Niskanen, 2002; Mendoza and Prabhu, 2003). These approaches address the decision process in detail and deal with a limited and clearly defined set of alternatives. Many computer-based approaches have been developed to deliver MCDA, or elements thereof, in a range of forms; e.g. ELECTRE III (Opperhuizen and Hutzinger, 1982; Roy, 1991); ASSESS (Bowyer and Veitch, 1994); DEFINITE (Janssen and Herwijnen, 1994); routines in IDRISI GIS (Eastman and Jiang, 1995); GIWIN (Ren, 1997); MULINO-DSS (Giupponi et al., 2004); HERO for heuristic multi-objective optimisation (Kangas et al., 2000); FORM (Kazana et al., 2003); and MEACROS (Mazzetto and Bonera, 2003). Within this wide variety, various approaches are devised to limit alternatives to a feasible set when pairwise comparisons lead to an unmanageable number of alternatives (Maniezzo et al., 1998). Optimisation approaches do not constrain the possible set of alternatives, but may become computationally demanding with large numbers of alternatives (Aerts et al., 2002; Aerts and Heuvelink, 2002).

Most of the process models applied to CHES are based on a mechanistic approach and a deterministic paradigm – that a single optimal or correct solution to a problem exists. This is useful for identifying system dynamics, but there is a growing realisation that these process models are not a complete basis for decision-making in complex systems, no matter how complicated they are made (Krippendorff, 1986). Only in recent years have a number of spatially explicit approaches to these complex CHES problems been developed (e.g., Wu and Wang, 1998; White et al., 2000; Lees and Hafner, 2000; Bousquet, 2001; Bousquet et al., 2001). Historically, most models have dealt with the spatial data aspatially. The important spatial interactions between elements were usually not dealt with; and in MCDA spatial influence or requirements have not often been an explicit criteria in developing the solution. Approaches to problems and decision-making in CHES must be able to deal with spatially distributed, interacting factors at the level of resolution required for spatially explicit decision support.

In this paper, we examine the recent expansion in the development of systems for multi-criteria decision
analysis in the context of the history and application of ASSESS, A System for Selecting Suitable Sites, as spatial implementation of the analytic hierarchy process. ASSESS has not previously been documented in peer-reviewed literature; a brief description here provides structure around which discussion of recent advances in MCDA methodology and incorporation of spatial analysis into data layers, optimisation and the decision process itself. Some analyses with a recent version of ASSESS for assessment of continental scale catchment condition for the intensive land use zone of Australia are used as a context for discussion of the merits and drawbacks of incorporation of more quantitative analytical methods and soft systems approaches into an ASSESS-style AHP.

2. Genesis of ASSESS

ASSESS represents an implementation of the ordinal combination method (Hopkins, 1977) as applied by McHarg (1969). This was translated into the GIS domain in an approach pioneered by Davis et al. (1988) in their GEM system. GEM was an expert system with primitive spatial operators. It developed, through GEM2, into the more sophisticated ARX (Whigham and Davis, 1989) and LMAS (Land Management Advice System; Cuddy et al., 1990a,b) an operational, explicitly spatial expert system. Though developed independently, the ARX approach has been applied to multi-criteria land evaluation over the past 10 years under the name of ASSESS (A System for Selecting Suitable Sites). ASSESS implements the AHP in an operational spatial decision support system, but ranks criteria in relation to an absolute scale rather than undertaking pairwise comparison. It has been committed to tasks of considerable economic and political sensitivity at a national level. Despite its simplicity, it has been highly effective. ASSESS has been adapted to address a very wide range of decision contexts including: selection of a low level radiative waste repository (Veitch, 1997a); land use decision support for the Murray Darling Basin (Bui, 1999); assessment of the condition of hydrological catchments in the intensive land use zone of Australia (Walker and Veitch, 2001).

The interface has also been adapted as a hybrid calculator incorporating knowledge-based indices and quantitative data for catchment-scale assessment of tree planting effects on the water table (Braaten, unpublished) and continental scale assessment of potential carbon sequestration responses from Australia’s rangelands with changes in management (Hill et al., 2002, 2003).

The MCDA approach of ASSESS remains a simple implementation of AHP without explicit spatial operations although it has incorporated static factor layers derived from spatial analysis to define proximity. The ASSESS approach has maintained a balance between logical empiricism and soft systems approaches to decision-making, allowing many views to be represented. There are potential analytical benefits for this process in the recent development of quantitative methods for capture of uncertainty, input data quantisation, and optimisation, and of the evolution of soft systems based on linguistic relations, decision theory and agents. However, the balance of determinism and flexibility is important in addressing complex problems in coupled human environmental systems and AHP has the advantage of allowing tradeoffs (Ramanathan, 2001).

Within the ArcInfo® GIS, ASSESS performs a simple multi-criteria analysis on input data layers which may be selected by the user (Veitch and Bowyer, 1996). ASSESS uses a simple linear additive procedure, or an ordinal combination method with some option for deciding on rules and hierarchies for combination (Jankowski, 1995). The input data, whether categorical, ordinal or numerical, are converted to relative ratings from 1 to 5 representing high to low suitability or quality. These rating layers may be added or combined by the user to create an integrated suitability or relative value map. The process does not involve optimisation of any sort. It has been suggested that the absence of a modelled optimum avoids over-determining the modelling process where input data are of variable quality and mixed type (Veitch, 1997a). The operations and outcomes are very much dependent upon the user. However, the relative rankings of input data depend heavily upon how these data are quantised and on what basis the quantitative data are allocated to subjective categories like good and poor.

Output rating layers represent a range of scenarios. Input data may be grouped on the basis of themes based on biases, paradigms, goals, prejudices and objective categorisation. These groups may form the basis for the development of scenarios representative of particular viewpoints or sub-groupings according to the nature of inputs or the philosophical views of the users. This enables the decision tension between particular viewpoints to be examined and visualised. A process of comparison of scenarios from different viewpoints reveals redundancies, correlations and interrelationships between the data, but no attempt at quantification is made. ASSESS is an implementation of the general model of multi-criteria decision-making (Jankowski, 1995) through a process often previously described (Veitch, 1997a,b; Luria and Aspinall, 2003).

3. Program structure

ASSESS provides an interactive interface for display and analysis built on the geographical analysis capability of the ArcInfo GRID module. It is written in the Arc Macro Language (AML®) and is made up of a series of interlinked AML and MENU routines which provide the
interface, selection buttons, display capability, additive and combinatorial capability for suitability indices, functional operators for calculator systems, interrogation capability, and file management. The program is started by execution of “assess.aml” (Fig. 1). From this point the ArcInfo workspaces, directory paths, environment variables, theme definition names and variables for selection widgets and display parameters and map extents are set, and the main tools menu is made available within the interface. The user can select specific projects from the NATIONAL or REGIONAL menu. A specific project will have an individual widget interface constructed to gather together the basic input grid data and provide access to additive or combinatorial functions for suitability layers. This may be accessed through the national or regional menus, or the interface may be designed such that this project widget appears when the program is started.

4. Example applications

The ASSESS concept has been used in a wide range of analytical tasks within the area of scientific advice and analysis for the policy-making process (Table 1). In this section, we briefly describe several example MCDA applications. The MCDA systems involve the combination of many different data types standardised into suitability indices ranked from 1 (most suitable) to 5 (least suitable) and used to create an index based on addition or combination using linear weighting. Examples given here are Radwaste ASSESS, MDBSIS and CatCon.

4.1. RADWASTE – disposal sites for low level radioactive waste

The selection of repositories for various forms of radioactive waste was the first major issue for which ASSESS was developed (Veitch and Caughley, 1993; Bowyer and Veitch, 1994; Veitch, 1995; Veitch and Bowyer, 1996; Veitch, 1997a). Here, the focus was on selection of high suitability sites, hence the genesis of the name ASSESS – A System for Selecting Suitable Sites. The premise was that a range of biophysical, economic and infrastructure suitabilities would determine the most suitable areas. A similar siting problem and approach for waste disposal is outlined by Maniezzo et al. (1998). Much depends in this analysis on the way suitability is defined for each theme grid, what the levels of uncertainty are in the underlying data, and in the definition of suitability. Another key issue is how themes are ranked in order of importance as determinants.

![Fig. 1. Diagram showing the basic menu and tool structure for ASSESS.](image-url)
4.2. MDBSIS – Murray Darling Basin Soils Information System

The MCDA version of ASSESS was used for evaluation of soil characteristics for agricultural suitability within the Murray Darling Basin (Bui et al., 1998, Bui, 1999). In MDBSIS (Murray Darling Basin Soil Information System), a list of theme grids is displayed and the suitability ratings for these can be adjusted prior to addition or combination to make an output suitability grid for a particular crop or agricultural enterprise. In addition, different landscape elements throughout the study area can be examined in annotated photographs displayed in the viewing window by selection from a menu. A demonstration version of the MDBSIS version of ASSESS is accessible on the Internet at http://www.brs.gov.au/mdbsis/assess/assess2.html.

4.3. CatCon – biophysical assessment of catchment condition

As part of the National Land and Water Resources Audit for Australia, ASSESS was used to establish the current, relative biophysical condition of Australia’s surface water catchments within the intensive land use zone (Catchment Condition Project – CatCon, Walker and Veitch, 2000, 2001; Braaten et al., 2001; Walker et al., 2002b). The approach used an indicator set chosen to reflect the key information about the structure, function and biophysical composition of catchments (Walker et al., 2002a). The CatCon project produced an Online Mapping System that can be accessed at http://www.affa.gov.au/CatCon. Fig. 2 shows the structure of the CatCon version of ASSESS. Fig. 3 shows the CatCon interface as an example of a typical ASSESS interface. The menu structure shows the 21 indicators used to compile three sub-indices, for water, land and biota that were combined to form a Catchment Condition Index (CCI; Fig. 2). In the absence of quantifiable threshold values, relative catchment condition classes were based on the shape of the frequency distribution for each indicator or index. Distributions for indicators were skewed and classes were based on an equal area classification; distributions for sub-indices and the overall index were closer to normal and an equal interval classification was used (Walker et al., 2002a,b).

Summing all the rated values for the selected indicators and reclassifying the results back into five equal interval classes provided the basis for calculation of the overall catchment condition index and the sub-indices. The CCI was calculated on three minimum mapping units: a 5 km grid cell; small, approximately 500 km² catchments delineated from hydrological processing of a national digital elevation model; and a national coverage of “basins” incorporating multiple catchments.
Catchment condition can be compared to other catchment attributes via cross-comparisons – e.g. scaled catchment condition (good, moderate and poor) can be compared with scaled product/goods/services (good, moderate, poor) to give a $3 \times 3$ cross comparison matrix (Walker et al., 2002b). This approach provides insights on sustainability, suitability and targeting of funds to high priority areas for rehabilitation and structural adjustment. The cross comparison provides a basis for visualisation of the relationship between catchment goods/services and catchment condition with the colour coding and mapping of the potential interpretations (Walker et al., 2002b).

5. The integrated framework for analysis of coupled human environmental systems

The development of new methods and new spatially explicit paradigms poses some interesting issues for future application of MCDA to analysis of complex natural resource management issues in CHES. In this section, we explore the issues surrounding incorporation of new quantitative methods, and new soft system methods in the AHP MCDA. A diagram that summarises these methods and outlines their interaction with MCDA provides the framework for this discussion (Fig. 4).

The diagram has a number of components (Fig. 4). (1) The central core is made up of a standard AHP MCDA process. (2) This is paralleled on one hand by a complementary empirical process involving spatial data processing feeding into process modelling as a system surrogate for CHES experiments, scenario analysis and quantification of dynamics and effects. (3) On the other hand, AHP MCDA is paralleled by a soft systems approach incorporating cognitive methods and linguistic constructs. (4a) New methods can address quantisation, fuzzy membership of classes in factor layers, and fuzzy approaches to uncertainty in weighting, pairwise comparison, preferences and ranking feed into the AHP MCDA. (4b) The AHP MCDA is also influenced by fuzzy methods, Bayesian regressions and goodness criteria for ranking and rating criteria – this connects to soft systems approaches and the use of Dempster-Shafer probability theory. (5) The combined process leads to solutions based on ranking alone (no optimisation) or a variety of alternatives for optimisation, including procedures involving coupling to scenario outputs from modelling. This represents the methodological issue framework surrounding AHP MCDM including coupling with process modelling. (6) Shadowing the whole framework at various points is the issue of spatial explicitness. It is injected at the beginning in the use of spatial analysis in the generation of factor...
layers that incorporate information about the neighbourhhood of a pixel that should influence criteria ranking. It may be embedded in data layers and scenario inputs from process models if these contain spatially explicit operations such as those in catchment hydrology models. There is also potential for optimisation that includes a spatial constraint. (7) The whole coupled modelling-MCDA process is potentially modified by new spatially explicit methods such as cellular automata and decision systems such as agent-based modelling that incorporate decision theory and spatial operations in different ways. (8) Hybrid systems that incorporate new methods and spatial analysis for factor layer generation represent the current situation.

The successful application and flexibility of the ASSESS AHP MCDA provides a good reference for examination of the above analytical framework. ASSESS deals with the human decision process in a readily understandable way, but it does not utilise quantitative methods to any great degree. In the following section, we discuss this framework using the CatCon ASSESS AHP MCDA to illustrate some of the aspects of analysis where quantitative methods may help, and we explore the development of optimisation and other completely new analytical approaches.

5.1. AHP MCDA operations

5.1.1. Correlation of datasets

High correlation in spatial pattern between datasets can lead to heavy redundancy in input data, and minimal actual improvement in map definition from inclusion of data layers that should conceptually be major determinants. In an example using CatCon ASSESS, interdependence of indicators derived from the same base data can result in some bias. For example, for a CCI calculated at the scale of 500 km² catchment units (Walker et al., 2002b; Fig. 5), there was a

![Image](image_url)
correlation of 0.88 between a 21 indicator grid and a grid based only on the three indicators with the highest correlation with the 21 indicator grid – native vegetation density (0.69). This problem can be overcome to some extent using cross correlation analysis. For example, in CatCon, cross correlation analysis was used to develop rules to exclude strongly inter-dependent attributes (Walker et al., 2002b). It is therefore possible to use this form of MCDA for a type of sensitivity analysis, to test for interdependence and for redundant input data, either by spatially comparing outputs or by cross correlation analysis. An analysis of correlation should be performed before selecting factors or indicators for use in the creation of suitability or quality indices, or particular analytical viewpoints.

5.1.2. Scale of minimum mapping unit

In a multi-scale MCDA, different scales of application require different indicator sets and different class boundaries (Walker et al., 2002a,b). Depending upon the scale and level of spatial averaging involved, an analysis may not generate coherent spatial areas (Pullar, 1999). The scaling issue is illustrated here by comparing example CCIs generated at grid cell scale, 500 km² catchment scale and basin scale for two basins (Fig. 6). Differences in the way fine resolution catchment condition is represented at coarser resolution can be seen from looking at the composition of catchment level CCI 5 and CCI 4 in terms of grid cell level values in the two basins. For CCI 5, in one basin the predominant CCI at grid cell level is 5 whilst in the other it is 4. For CCI 4, in one basin CCIs 3, 4 and 5 occur almost equally, whilst in the other, CCIs 3 and 4 predominate. In low intensity land use areas, the indicator set developed in the CatCon project was not always compatible with the large spatial dimensions of the catchment or basin units of aggregation. This tended to cause a bias toward relatively better condition thereby expanding the size of areas with relatively poorer condition under a five class equal area or equal interval classification (Walker and Veitch, 2001).
5.1.3. Trade-off and substitutability

Substitutability or trade-off occurs when a high score on one criterion compensates for a low score on another criterion (Jiang and Eastman, 2000). This effect can be illustrated using the CatCon system by looking at the condition scores obtained from calculating CCI from two different sets of indicators. The best 18 indicators were sorted alphabetically and then CCI was calculated using the first nine and the second nine. The effect of substitution is illustrated in Fig. 7 for a catchment where the indicators sum to the same aggregate value of 16, a CCI of 1. The two CCIs were subtracted to give a difference shown in the histogram, indicating a considerable degree of similarity on a grid cell by grid cell basis. Yet, the CCI was based on completely different sets of input indicators. Analysis might not normally be

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Fig. 5. An example of the effect of correlation between input datasets on output index maps. A significant amount of the variation in a catchment condition index map based on 21 indicators can be captured by a map based upon the three indicators that are most highly correlated with the map based upon 21 indicators.

Fig. 6. An illustration of the effect of minimum mapping unit in MCDA with ASSESS using the CatCon system. The analysis looks at the three mapping scales: basins, 500 km² catchments, and 1 km² grid cells. On the right-hand side of the figure, for two basins, with overall CCIs of 4 and 2, the figure shows the frequency distribution of 500 km² CCIs and 1 km² CCIs in each basin-level CCI. On the left-hand side, the figure shows the frequency distribution of CCI values at 1 km² within each catchment level CCI. Differences in the way fine resolution catchment condition are represented at coarser resolution can be seen from looking at the composition of CCI 5 and CCI 2 in the two basins.
carried out without ranking the indicators for importance in relation to a particular view. When the same analysis is carried out with indicators ranked for environmental significance, the aggregate value and CCI remain the same at catchment scale (Fig. 7). However, there is a broader spread in difference between the indices at 5 km pixel scale. Hence ranking indicators or input themes will not necessarily eliminate substitutability if the scale of application involves considerable averaging. Linear additive or multiplicative models may become impractical where there are a large number of alternatives for complex environmental systems (Tkach and Simonovic, 1997).

5.1.4. Slicing and ranking

Criteria possess a level of difficulty in understanding; over-aggregation and use of direct units may lead to a lack of understanding and a need to explain their basis (Arondel and Girardin, 2000). Approaches to mixing ordinal and cardinal information in MCDA ranking are needed (Hinloopen et al., 2004). The method and assumptions used to convert quantitative data layers into ordinal data layers with ranking 1–5 can have large effect on the output from an ASSESS MCDA. It is possible to get rank reversal with addition of another alternative, but this may be offset by including an absolute measurement so that ratings are absolute (Ramanathan, 2001). This procedure represents a standardization of factors. The recast criteria express suitability or value. In many cases it may be more appropriate for criterion scores to asymptotically approach the maximum or minimum (Jiang and Eastman, 2000). Outranking methods use a partial aggregation of suitability indices and are not suited to problems with a large number of alternatives (Joerin et al., 2001). The resulting maps are sensitive to spatial division and the description of the territory is rough because of the limited zonation (Joerin et al., 2001). In the CatCon analysis, the class thresholds within a frequency distribution of a single indicator had more effect on the

Fig. 7. The figure illustrates the effect of substitution. On the left is a frequency distribution of difference between two CCIs at 5 km grid cell scale for the same area, each based on a different set of indicators and summing to the same aggregate score of 16, and a CCI of 1 at catchment scale. The CCIs show a considerable degree of similarity on a grid cell by grid cell basis. This may be compared with another frequency distribution on the right where indicators were ranked for environmental significance. This still results in the same overall aggregate score, this time 35, and CCI of 1 at catchment scale, but provides more pixel by pixel differences at 5 km grid cell scale. The indices were based on an alphabetical split of the 18 best indicators as shown in the table.

<table>
<thead>
<tr>
<th>CRES catchments</th>
<th>CCI A</th>
<th>S</th>
<th>W</th>
<th>S</th>
<th>CCI B</th>
<th>S</th>
<th>W</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acid Hazard</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>Nutrient Point Sources</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Agriculture on Steep Slopes</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>Pesticide Hazard</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>Erosion Index</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>Population Density</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Feral Animals</td>
<td>3</td>
<td>2</td>
<td>6</td>
<td>Protected Areas</td>
<td>1</td>
<td>3</td>
<td>3</td>
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<td>2</td>
<td>3</td>
<td>6</td>
<td>Road Density</td>
<td>1</td>
<td>2</td>
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<td>3</td>
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<td>Sediment Loads</td>
<td>4</td>
<td>2</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>Intensive Agriculture</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>Predicted 2050 Salinity</td>
<td>1</td>
<td>2</td>
<td>2</td>
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<tr>
<td>Industrial Point Sources</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>Soil Structural Hazard</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Native Vegetation Cover</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>Weed Density</td>
<td>4</td>
<td>2</td>
<td>8</td>
<td></td>
</tr>
</tbody>
</table>

Aggregate Score 16  35 Aggregate Score 16  35

CCI 1  CCI 1

*S = score; W = weight; WS = weighted score
condition output layer than the choice between indicators (Walker et al., 2002b). This can be illustrated by the following example using CatCon. An equal area slice of catchment condition based on 21 indicators has a similarity of only 42% to an equal interval slice (Fig. 8). However, there is a high similarity between catchment condition layers based on different but highly correlated inputs.

5.1.5. Error propagation

In traditional MCDA, the decision or result risk is not easy to represent. In weighted linear combination, the uncertainty cannot be easily estimated, as there is no real threshold that allows a value to be regarded as good or poor (Jiang and Eastman, 2000). In a Boolean procedure, measurement error may be propagated through the decision rule providing a measure of risk (Jiang and Eastman, 2000). One way to approach explicit error propagation in these systems is to create a reliability index. For example, a catchment condition index is created based on three indicators for which reliability information is available (Fig. 9, top). The three indicators have reliability rankings scaled into five classes from good to poor. Soil degradation has reliability derived from map information on scale of original data sources from the Australia Soil Resources Information System (ASRIS; NLWRA, 2000). Projected landscape salinity in 2050 has a reliability ranking assigned by state according to method of mapping used, e.g. aerial photo interpretation, modelling, field work, etc.). The map of intensive agriculture area has reliability based on the ‘affinity’ dataset accompanying the 1996 National Land Use (NLWRA, 2000) data set, i.e. error level of satellite data interpretation model (Fig. 9, middle). A reliability map is created by combining the individual indicator reliabilities by adding the classes and re-slicing into five reliability classes for the index (Fig. 9, bottom). The outcome may be dependent on the way the error is defined and quantised.

5.1.6. Attaching reasons to rankings

In a process where different combinations of data input can provide very similar suitability outputs in terms of both ranking score and spatial definition, assignment of reasons to ranking could provide more useful information for discrimination. One approach for examining reasons behind the ranking results is cluster analysis (e.g. Ottaviani et al., 2003) which also provides an approach to complex problems where major groups of factors can be defined as potential organising axes in multi-variate space. An example is shown in Fig. 10 for CatCon scenarios based on five key indicators at the large catchment scale: salinity, native vegetation extent, protected areas, weeds and road density. A k-means approach based on Euclidean distances was applied to standardised values of the five indicators for each catchment to produce five clusters. The result was two clusters in good condition for different reasons, two clusters in poor condition for different reasons and one cluster in moderate condition.

Average indicator scores for the clusters are shown in the Cluster Profile Plots in Fig. 11. Cluster 3 contains catchments in good condition primarily because they have large areas under protection. Cluster 5 also contains catchments in good condition with high areas of native vegetation, low weed density and low road density. However these catchments are in good condition primarily because they are remote and not highly developed. Cluster 4 catchments, located mainly in Western Australian and southern Victoria are in poor condition due to the overriding influence of salinity. Cluster 1 catchments are also in poor condition but
mainly because of intensive development as evidenced by the high road density. Finally, cluster 2 contains catchments with lower intensity agricultural development that are generally in moderate condition with average values for most indicators.

5.2. Integration of MCDA with process modelling

Validated simulation models provide an effective means of delivering biological dynamics of the system and its components into MCDM processes (Herrero

Fig. 9. An example of error propagation with the CatCon version of ASSESS. The figure shows a catchment condition index based on three indicators for which reliability information is available. The three indicators are shown with reliability rankings scaled into five classes from good to poor: soil degradation; predicted 2050 salinity extent; and intensive agriculture area. A reliability map is created by combining the individual indicator reliabilities by adding the classes and re-slicing into five reliability classes for the index.
et al., 1999; Hjortsø and Stræde, 2001; Rose and Adiku, 2001; Morari et al., 2004; Giupponi et al., 2004). These models may be used to calculate consequences on their own, but a broader perspective can be provided using multi-objective programming and MCDA (Hjortsø and Stræde, 2001). Processes can be set up so that MCDA reads ascii files generated from simulations of the system and chooses from runs by optimising an objective function subject to constraints (Herrero et al., 1999), or MCDA can simply be run on alternative simulation

Fig. 10. An example of using cluster analysis to assign reasons to rankings. A k-means clustering approach based on Euclidean distances was applied to standardised values of the five indicators for each catchment to produce five clusters. Standardised rankings for five indicators for each of five clusters showing the major influence on the catchment condition.
outputs based on criteria, such as sustainability, economic returns and soil surface protection (Rose and Adiku, 2001). Nested structures may be developed such that models for simulating environmental impacts of land use change in terms of point and non-point source pollution produce quantitative indicators for MCDA, operate on land use changes in response to alternative management from another suite of models, and in turn utilise a hydrological model to determine how water dynamics are affected by land use (Giupponi et al., 2004).

5.3. Cognitive mapping

Cognitive mapping works towards improved communication between an artificial formal decision system and the human expert decision-maker (Bisdorff, 1999). These models are difficult to construct in abstract code and need a symbolic coding allowing formal expression of the behaviour of the decision-maker; the decision reference or extension; capture of cognitive strategies and creation of a feedback system to validate and evolve the decision model (Bisdorff, 1999). Complex problems are rarely amenable to quantitative optimisation as the desirable outcome may not necessarily be the optimum one based on objective input criteria, and there may be too many alternatives for spatial optimisation. Cognitive mapping can reveal cross-criterion and cross-indicator interactions (Mendoza and Prabhu, 2003). MCDA is used to provide a structure for generation of indicators, and interactions are analysed through graphs and influence diagrams wherein arrows represent the trajectory of impact or nature of causality relationship (Mendoza and Prabhu, 2003). The elements of a problem are represented as nodes and connections with relationships among elements represented as arrows with the head representing the direction of causality. Criticality of indicators in example studies are assessed on the basis of: (a) domain – the number of indicators directly linked to one indicator; (b) centrality – the overall cumulative impact of an indicator beyond its direct impacts; and (c) criticality – the number of critical indicators linked to an indicator (Mendoza and Prabhu, 2003). Cognitive mapping may be used to identify and relate factors – fundamental points of view (FPV) – in an interactive learning process integrated with MCDA (Bana e Costa et al., 1999). The plausible impact levels of FPVs are

![Map showing the classification of CCI based on the cluster analysis in Fig. 10. The result was two clusters in good condition for different reasons, two clusters in poor condition for different reasons and one cluster in moderate condition.](image-url)
described by descriptors that are provided with attractiveness measures from expert evaluation. The decision tools are used in an interactive process with human facilitators enabling iterative definition of ill-structured decision-making processes. Marriage of this soft systems methodology to spatially explicit GIS-based approaches is an important area of development.

5.4. Dealing with uncertainty

In a recent review of uncertainty in integrated assessment modelling, the authors assert that not all uncertainties can be adequately addressed by existing methods and tools (such as behavioural and societal variability), that uncertainty is mainly resolved in terms of quantitative estimation or probability distribution, and that it is difficult to construct aggregated uncertainty measures that are understandable (to clients and stakeholders) (Van Asselt and Rotmans, 2002). The AHP MDDA approach utilising the development of scenario outputs constructed from different views and paradigms attempts to capture the behavioural and societal variability. In addition, attribute quality can be estimated. Walker et al. (2002a,b) defined 10 selection criteria for using an attribute as an indicator in the system: functional relevance; application relevance; sensitivity to change; standard method used; application across space and time; low error in measure; reliable data; interpretable data; data validated; and intelligible to the end user. The input data layers were scored on the basis of these criteria and the score was provided as a measure of the reliability of the indicator data layers (Walker et al., 2002a,b).

Fuzzy measures (Munda, 1995) can incorporate uncertainty into generation of factor classes and maps (Gogus and Boucher, 1997; Hall and Arnberg, 2002; Ceballos-Silva and Lopez-Blanco, 2003; Rashed and Weeks, 2003), pairwise comparison (Gogus and Boucher, 1997; Espelta et al., 2003), ranking, dominance and similarity measures (Anand Raj and Nagesh Kumar, 1998; Schneider and Pontius, 2001; Khadam and Kaluarachchi, 2003), optimisation (Kozerska et al., 2004) and spatial queries and operations associated with MCDA (Davis and Keller, 1997; de Bruin, 2000; Jiang and Eastman, 2000). The issues surrounding establishment of standardised suitability ratings and procedures for combination can be addressed by incorporation of methods that address the uncertainty surrounding discretization of quantitative, continuous data into rankings from 1 to 5. A combination of fuzzy sets and probability theories can be applied. Fuzzy sets have been used (Lees and Hafner, 2000) to separate spatial patterns of salinization on the Liverpool Plains of New South Wales, and in conjunction with neural nets (Lees, 1996) to model species importance levels in forests. Combination of fuzzy membership grades and probabilities enables the capture of fuzzily qualified probability of an event, and membership of a fuzzy set defined on a stochastic variable (de Bruin, 2000). An example of catchment condition assessment using fuzzy ranking instead of discrete classes is given in Fig. 12. Instead of quantising inputs into five classes, continuous standardised grids were created for each of the 21 input datasets (at the small catchment scale). These were combined and the output was re-standardised. The result is a continuous grid that ranks catchment condition between three standard deviations below to five standard deviations above an average level.

Bayesian probabilities through Dempster-Shafer theory provide a means to represent judgements in a decision process as a set of exact beliefs with a body of evidence constructed for each criterion using preference judgements on groups of decision alternatives with critical priority values, and assigning basic probabilities to these (Beynon, in press). The probabilities represent the level of exact belief in one focal element (group of decision alternatives) within frame of discernment (all decision alternatives) and also possess plausibility and commonality measures, and measures based around the Shannon-entropy measure such as discord, confusion, dissonance, non-specificity and total uncertainty (Beynon et al., 2001). Bayesian regression may also be used to analyse pairwise comparisons (Kangas et al., 2000).

In the spatial domain, Bayesian inference has been used to analyse pattern in spatial data (Aspinall, 1992) using conditional probabilities of association with other spatial entities to map distribution of plant species (Hill et al., 1997, 2000), and likely spread of urbanisation (Aspinall and Hill, 2000) and is being applied for derivation of land use maps from satellite time series data (Simon Barry, unpublished, personal communication). Bayesian networks extend this capability further by capturing both uncertainty in the reasoning process and uncertainty in the data (Stassopoulou et al., 1998). Incomplete knowledge, uncertainty in data, overlaps in membership, confusion in rankings and vagueness or truthfulness in assignment of optimal or selected spatial regions may be best addressed via a variety of methods, since single methods may be more or less well suited to particular problem types and decision processes, e.g. subjective probability theory was better than Dempster-Shafer Theory or fuzzy logic for handling vagueness in assignment of geological provenance in basin systems (Ferrier and Wadge, 1997).

5.5. Optimisation

Although the flexibility of the AHP MCDA process has major advantages, exploration of outcomes might be aided if non-optimised scenarios could be compared with scenarios resulting from a range of optimisation approaches. Optimisation methods involve formulation
of multi-objective functions, which are then maximized as defined by decision, control and constraint variables. These functions may be solved for the optimum solution using a variety of techniques (Whitley, 2001), some examples of which are described below.

1. Multi-objective programming (Berbel, 1993) using stochastic dominance with no restriction on decision maker’s preference. This describes a broad category, some more specific examples of which are listed below.

2. Linear programming using a spatial compactness objective (Aerts et al., 2002). Currently there are solution-time limitations when compared with heuristic techniques – only a linear integer model using buffer cells would reach a solution for a $30 \times 30$ grid. If compactness requirement is increased, solution times expand.

3. Coupled non-linear differential equations (Seppelt and Voinov, 2003) solved on a daily time step in grid-based spatially explicit simulation where aspects of topology and connectivity between cells are included. Optimisation distinguishes between local and global optima by basing simulation on locally optimal control maps. Results are evaluated by inventory and correlation of output maps in moving windows to create distance scores.

4. Region growing algorithms (Brookes, 1997) are designed to locate sites with particular spatial characteristics on raster suitability maps. The algorithm trades off optimum cell suitability and optimum region shape. It enhances traditional suitability analysis based on weighted summation by enabling selection of highest ranked cells clustered into suitable regions.

5. Simulated annealing causes the system realisation to converge towards a specified state using probability to admit ascent steps (Lockwood and Moore, 1993; Muttilah et al., 1996; Wu and Wang, 1998; Yang, 2000; Aerts and Heuvelink, 2002). Solution times increase with grid size but $300 \times 300$ grids reached solution within several hours (Aerts and Heuvelink, 2002).

6. Tabu search uses memory to avoid local optima and continue searching for global optima (Bland and Baylis, 1997; Boston and Bettinger, 1999), although problems may arise in real world systems where response surfaces are irregular and unconstrained (Mayer et al., 1998).

7. Genetic algorithms act as function optimisers using selection, recombination and mutation on simple data structures (Whitley, 2001; Schmitt, 2001). The algorithms convert the numbers to binary strings,
randomly change individual values, divide and recombine segments, or select subsets, convert the results back to the number and test against an objective function.

8. Compromise programming (Tkach and Simonovic, 1997; Kazana et al., 2003) uses a distance metric to identify solutions closest to the ideal, and which becomes spatially explicit when embedded within a GIS by incorporating spatial dependence and spatial optimisation using a distance metric for each pixel (Tkach and Simonovic, 1997). The metric is a function of the criteria, their relative importance to decision makers and the importance of the largest deviation from the ideal solution i.e., the tolerance for non-idealness.

Regardless of the merits and difficulties of optimisation for particular problems, methods such as these should be more readily available so that outcomes from analysis may be compared and decisions are not reliant on single approaches.

5.6. Spatial dependencies

Spatial analysis can provide a range of important information for landscape-based MCDA. Filters applied at different kernel sizes can provide scale-dependent layers for MCDA. Spatial correlation analysis can be used to assess the suitability of relevant factor layers for land use targets (Ren, 1997). Spatial filters can be used to capture spatial properties within a minimum mapping unit tailored to average size of target types of land use area (Schneider and Pontius, 2001). Spatial dependencies may be accounted for in MCDA using a location allocation model to define allocations expressed as constraints that are satisfied as part of the decision evaluation (Pullar, 1999) – in the MCDA, a spatially dependent indicator is included. Proximity layers e.g. for roads (Walker et al., 2002a,b) are frequently used. Outputs from spatially explicit modelling introduce spatially derived factor layers to MCDA.

5.7. Decision processes – an aspatial and spatial mixture

Modern inquiry into complex CHES decision-making should include both quantitative approaches from the tradition of logical empiricism, and qualitative approaches applying human explanations, understanding and interpretations (Niskanen, 2002). In many cases the methods involving linguistic system construction and decision-making are able to translate the process into semi-quantitative measures (Niskanen, 2002). Comparison of decision algorithms within such systems suggested that fuzzy and neuro-fuzzy systems were simple, fairly comprehensible, non-parametric and amenable to optimisation. The problems associated with analysis of complex CHES might be described as “wicked” – their definition co-evolves with the exploration of options, there is no correct or best solution, the decision may be successful because it gets implemented and is respected in the long run (Voss et al., in press). This is a political reality outcome. This is the context for the development of participatory GIS – wherein GIS with visualisation and MCDA functions is combined with a cognitive/linguistic instrument for knowledge transfer through complex text-based discussion (Voss et al., in press). This represents the integration of the logical empirical quantitative paradigm with the soft systems cognitive/linguistic approach (Niskanen, 2002) and points to sophisticated systems that provide iterative and interactive dialog between human and artificial decision-making systems.

5.7.1. Spatially explicit operation

MCDA and other approaches may benefit from the incorporation of behaviour-oriented rules of transition for cells in a raster space using, for example, cellula automata to provide more complete application of spatial dependence in decision systems (White and Engelen, 1993, 1997; Fulong, 1998; White et al., 2000). Modelling processes and optimisation processes involving spatial operations are also important here (e.g., Brookes, 1997). Since spatial optimisation can be computationally demanding, there may be a good case for segmentation of spatial MCDA so that the dimension of the decision frame are successively reduced by creating a subset of feasible solutions, or a series of sub-alternative paths that can be separately processed.

5.7.2. Multi-agent systems

Agent-based modelling shows potential as a method for capture of the interaction between biophysical and social aspects of a problem and aiding decision processes whilst incorporating explicitly spatial relationships. Comparison of alternatives in AHP MCDA could be enhanced if biophysical and human systems could be captured in a dynamic simulation wherein relations between land units, process elements, human operations and economic inputs may be represented as agents with behaviour. Such capability is provided by multi-agent systems (MAS) that divide the necessary knowledge into subunits, associate an intelligent, independent agent with each subunit, and coordinate the agent’s activity (Bousquet, 2001; Lynam et al., 2002). A range of programming platforms is available including generic systems such as SWARM (Minar et al., 1996); ecosystem-oriented platforms such as CORMAS (Bousquet et al., 1998); and specific tools. These MAS systems provide for spatial, social and passive entities with time-steps for behaviour and change, and specified viewpoints. They allow the study of human behaviour in
a spatial context at a specified level (Otter and van der Veen, 2001; Le Page et al., 2001) and illustration of the outcomes of policy decisions in a range of problem contexts (Le Bars and Attonay, 2001; Otter and van der Veen, 2001; Chivers et al., 2001; Becu et al., 2001; Kuper et al., 2001).

6. Conclusions – integrated systems

The research community is showing signs of answering the pressing need to develop methods for addressing uncertainty and the interaction of human behaviour with biophysical outcomes in the increasingly complex natural resource management policy area of CHES. Traditional AHP MCDA as applied through ASSESS and its derivatives has served many problems well. However, new integrated systems are emerging that combine GIS processing and spatial analysis with MCDA techniques (Store and Kangas, 2001) and handle expert knowledge, as a substitute for process modelling together with empirical evaluation models in the evaluation process (Store and Jokimaki, 2003). There is ample opportunity to build on the use of MCDA in natural resource policy decision making for CHES by development, investigation, comparison, and implementation of methods to address uncertainty and social/biophysical interaction within a combined academic and government policy environment and using real, current issues as the example problems for testing.

A wide array of methods and approaches to uncertainty, optimisation, data scaling and quantisation, and interactions between human and biophysical domains in decision-making have been developed. Whilst there has been a frustrating deficiency in the implementation of these methods within practical frameworks for decision-making, and in a form that makes them accessible to the lay policy analyst or regional planner, this is now beginning to be redressed (e.g. Kangas et al., 2000; Store and Kangas, 2001; Store and Jokimaki, 2003; Seppelt and Voinov, 2003; Voss et al., in press). The AHP MCDA approach has many advantages including its simplicity and flexibility, and as a result it has been highly successful (Ramanathan, 2001). However, MCDA could be greatly improved by having a suite of different methods and approaches available to the user such that uncertainty could be explicitly propagated, various fuzzy and probabilistic approaches could be applied, optimisation could be chosen, and the stakeholder/client environment could be simulated using intelligent agents. The application of various approaches is often determined by the problem – is it one of exploration (tensions and tradeoffs); selection (suitability); assessment (i.e., good or bad); finding an optimal solution (quantitative best); or a combination of these.

The AHP MCDA approach is very suitable for exploration of tensions and tradeoffs and providing assistance to heuristic processes. However, decisions based on quantitative criteria may require inclusion of quantitative error and uncertainty in the analysis, and a quantitative basis for decision through optimisation. Widespread realisation of this improved capability depends upon multi-disciplinary approaches by biological and physical scientists, mathematicians and programmers, and sociologists and economists with a passionate interest in the way humans are affecting their terrestrial environment. The global initiatives in the area of CHES are providing infrastructure and science resources to enable a rapid expansion in this field of endeavour. The development of advance MCDA and participatory GIS promises truly spatially explicit, artificial systems-aided human decision-making processes in the near future.

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