MOONRISES

INTEGRATED MONITORING SYSTEM FOR DESERTIFICATION RISK ASSESSMENT

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ΟΛΟΚΛΗΡΩΜΕΝΟ ΣΥΣΤΗΜΑ ΠΑΡΑΚΟΛΟΥΘΗΣΗΣ ΓΙΑ ΤΗ ΕΚΤΙΜΗΣΗ ΤΟΥ ΚΙΝΔΥΝΟΥ ΕΡΗΜΟΠΟΙΗΣΗΣ

WP 7: Development of the Decision Support System software

7.1. Development of the Decision Support System

1. **Requirements Analysis / Algorithm description**
2. **Decision Support System**
3. **Documentation for**
   a) **Data input**
   b) **Data output**
   c). **Expected results**

LEAD PARTNER:

REGION OF PELOPONESSE

PARTNERS

ARISTOTLE UNIVERSITY

REGION OF CENTRAL MACEDONIA

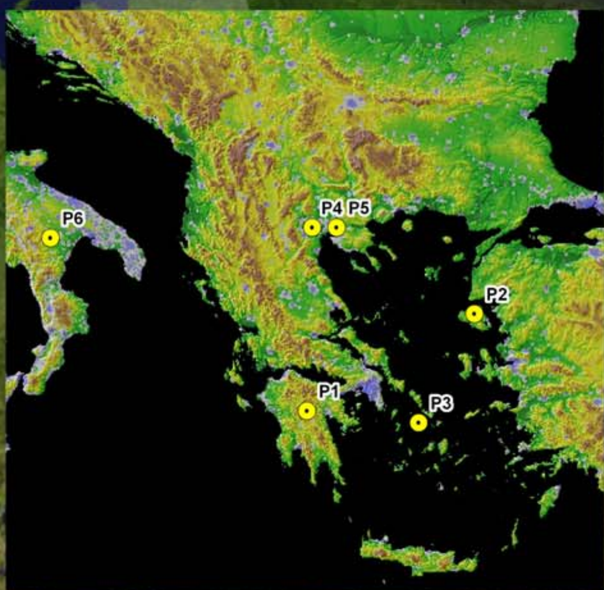
REGION OF NORTH AEGEAN

REGION OF SOUTH AEGEAN

UNIVERSITY OF BASILICATA (ITALY)

SCIENTIFIC RESPONSIBLE:

PROF. DR. N. SILLEOS



COFINANCED BY THE EUROPEAN REGIONAL DEVELOPMENT FUND

MOONRISES

INTEGRATED MONITORING SYSTEM FOR DESERTIFICATION RISK ASSESSMENT

MOONRISES PROJECT

INTEGRATED MONITORING SYSTEM FOR DESERTIFICATION RISK ASSESSMENT

Program	**Interreg III B - Archimed**
Measure	**3.3 - Management, prevention and reduction of natural risks**
Call for Proposals	**1st Call – June 2005**
Project Acronym	**Moonrises**
Project Title	**Integrated Monitoring System For Desertification Risk Assessment**
Date of Approval	**May 2006**
Agreement ref. No	**A.1.083/3.3**

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CHAPTER 1: IDENTIFICATION SHEET

Identification Sheet

Work Package	**WP 7: Development of the Decision Support System software**
Action	**7.1. Development of the Decision Support System**
Deliverable	1. Requirements Analysis / Algorithm description 2. Decision Support System 3. Documentation for a) Data input b) Data output c) Expected results
Type	RTD
Version	finished
Responsible Partner	P1
Involved Partners	P2, P3, P4, P5, P6
Authors	PROF. DR. N. SILLEOS
Date of completion	**03/2007 - 07/2007** **IN PROGRESS**
Distributed to Partners	Lead partner
Published to Web Collaboration System	

CHAPTER 2: Introduction

This action's objective is the development of a Desertification Decision Support System. This system will combine the knowledge acquired through all previous actions and will be based on the rules and guidelines depicted in the Desertification Risk Monitoring Model, in order to provide support to any decision-making body, planning to take actions against desertification.

The Decision Support System that includes the Spatial Multi-criteria Weighed Model will be developed in order to describe the above-mentioned methodology and depict the Driving Forces, the Pressures and the Impacts on Desertification Risks.

This action will start by analyzing decision requirements and describing the Decision Support Algorithm based on the Model's standardized procedures and rules.

With rapid increases in population and continuing expectations of growth in the standard of living, pressures on natural resource use have become intense. For the resource manager; the task of effective resource allocation has thus become especially difficult. Clear choices are few and the increasing use of more marginal lands puts one face-to-face with a broad range of uncertainties. Add to this a very dynamic environment subject to substantial and complex impacts from human intervention, and one has the ingredients for a decision making process that is dominated by uncertainty and consequent risk for the decision maker.

In recent years, considerable interest has been focused on the use of GIS as a decision support system. For some, this role consists of simply informing the decision making process. However it is more likely in the realm of resource allocation that the greatest contribution can be made.

Over the past several years, the research staff at the Clark Labs have been specifically concerned with the use of GIS as a direct extension of the human decision making process--most particularly in the context of resource allocation decisions. However our initial investigations into this area indicated that the tools available for this type of analysis were remarkably poor. Despite strong developments in the field of Decision Science, little of this had made a substantial impact on the development of software tools. And yet, at the same time, there was clear interest on the part of a growing contingency of researchers in the GIS field to incorporate some of these developments into the GIS arena. As a consequence, in the early 1990s, we embarked on a project, in conjunction with the United Nations Institute for Training and Research (UNITAR), to research the subject and to develop a suite of software tools for resource allocation. These were first released with Version 4.1 of the MS-DOS version of IDRISI, with a concentration on procedures for Multi-Criteria and Multi-Objective decision making-an area that can broadly be termed Decision Strategy Analysis. Since then, we have continued this development, most particularly in the area of t Uncertainty Management.

Uncertainty is not simply a problem with data. Rather, it is an inherent characteristic of the decision making process itself. Given the increasing pressures that are being placed on the resource allocation process, we need to recognize uncertainty not as a flaw to be regretted and perhaps ignored, but as a fact of the decision making process that needs to be understood and accommodated. Uncertainty Management thus lies at the very heart of effective decision making and constitutes a very special role for the software systems that support GIS. The following discussion is thus presented in two parts. This chapter explores Decision Strategy Analysis and the following chapter discusses Uncertainty Management.

Decision Theory is concerned with the logic by which one arrives at a choice between alternatives. What those alternatives are varies from problem to problem. They might be alternative actions, alternative hypotheses about a phenomenon, alternative objects to include in a set, and so on. In the context of GIS, it is useful to distinguish between policy decisions and resource allocation decisions. The latter involves decisions that directly affect the utilization of resources (e.g., land) while the former is only intended to influence the decision behavior of others who will in turn make resource commitments. GIS has considerable potential in both arenas.

In the context of policy decisions, GIS is most commonly used to inform the decision maker However; it also has potential (almost entirely unrealized at this time) as a process modeling tool, in which the spatial effects of predicted decision behavior might be simulated. Simulation modeling, particularly of the spatial nature of socio-economic issues and their relation to nature, is still in its infancy. However; it is to be expected that GIS will play an increasingly sophisticated role in this area in the future.

Resource allocation decisions are also prime candidates for analysis with a GIS. Indeed, land evaluation and allocation is one of the most fundamental activities of resource development (FAO 1976). With the advent of GIS we now have the opportunity for a more explicitly reasoned land evaluation process. However. without procedures and tools for the development of decision rules and the predictive modeling of expected outcomes, this opportunity will largely go unrealized. GIS has been slow to address the needs of decision makers and to cope with the problems of uncertainty that lead to decision risk In an attempt to address these issues, the Clark Labs has worked in close collaboration with the United Nations Institute for Training and Research (UNITAR) to develop a set of decision support tools for the IDRISI software system.

Although there is now fairly extensive literature on decision making in the Management Science~ Operations Research and Regional Science fields (sometimes linked together under the single name *Decision Science),* there is unfortunately a broadly divergent use of terminology (e.g., see Rosenthal, 1985). Accordingly, we have adopted the following set of operational definitions which we feel are in keeping with the thrust of the Decision Science literature and which are expressive of the GIS decision making context.

CHAPTER 3. Requirements Analysis / Algorithm description

Deliverable	Requirements Analysis / Algorithm description

Abstract

This action will start by analyzing decision requirements and describing the Decision Support Algorithm based on the Model's standardized procedures and rules.

DSS, ALGORITHM

Definitions Decision

Decision

A decision is a choice between alternatives. The alternatives may represent different courses of action, different hypotheses about the character of a feature, different classifications, and so on. We call this set of alternatives the decision frame. Thus, for example, the decision frame for a zoning problem might be commercial residential industrial. The decision frame, however, should be distinguished from the individuals to which the decision is being applied. We call this the candidate set. For example, extending the zoning example above, the set of all locations (pixels) in the image that will be zoned is the candidate set. Finally, a *decision set is* that set of all individuals that are assigned a specific alternative from the decision frame. Thus, for exammple all pixels assigned to the residential zone constitute one decision set Similarly, those belonging to the commercial zone constitute another. Therefore, another definition of a decision would be to consider it the act of assigning an individual to a decision set Alternatively, it can be thought of as a choice of alternative characterizations for an individual.

Criterion

A criterion is some basis for a decision that can be measured and evaluated. It is the evidence upon which an individual can be assigned to a decision set. Criteria can be of two kinds: factors and constraints, and can pertain either to attributes of the individual or to an entire decision set.

Factors

A factor is a criterion that enhances or detracts from the suitability of a specific alternative for the activity under consideration. It is therefore most commonly measured on a continuous scale. For example a forestry company may determine that the steeper the slope the more costly it is to transport wood. As a result, better areas for logging would be those on shallow slopes -the shallower the better. Factors are also known as *decision variables* in the mathematical programming literature (see Feiring, 1996) and structural *variables* in the linear goal programming literature (see Ignizio, 1985).

Constraints

A constraint serves to limit the alternatives under consideration. A good example of a constraint would be the exclusion from development of areas designated as wildlife reserves. Another might be the stipulation that no development may proceed on slopes exceeding a 30% gradient. In many cases, constraints will be expressed in the form of a Boolean (logical) map: areas excluded from consideration being coded with a 0 and those open for consideration being coded with a 1. However, in some instances, the constraint will be expressed as some characteristic that the decision set must possess. For example, we might require that the total area of lands selected for development be no less than 5000 hectares, or that the decision set consist of a single contiguous area. Constraints such as these are often called goals (Igniziq 1985) or targets (Rosenthal, 1985). Regardless, both forms of constraints have the same ultimate meaning--to limit the alternatives under consideration.

Although factors and constraints are commonly viewed as very different forms of criteria, material will be presented later in this chapter which shows these commonly held perspectives simply to be special cases of a continuum of variation in the degree to which criteria tradeoff in their influence over the solution, and in the degree of conservativeness in risk (or alternatively, pessimism or optimism) that one wishes to introduce in the decision strategy chosen. Thus, the very hard constraints illustrated above will be seen to be the crisp extremes of a more general class of fuzzy criteria that encompasses all of these possibilities. Indeed, it will be shown that continuous criteria (which we typically think of as factors) can serve as soft constraints when tradeoff is eliminated. In ecosystems analysis and land suitability assessment this kind of factor is called a limiting factor, which is clearly a kind of constraint.

Decision Rule

The procedure by which criteria are selected and combined to arrive at a particular evaluation, and by which evaluations are compared and acted upon, is known as a decision rule. A decision rule might be as simple as a threshold applied to a single criterion (such as, all regions with slopes less than 35% will be zoned as suitable for development) or it may be as complex as one involving the comparison of several multi-criteria evaluations.

Decision rules typically contain procedures for combining criteria into a single composite index and a statement of how alternatives are to be compared using this index. For example, we might define a composite suitability map for agriculture based on a weighted linear combination of information on soils, slope, and distance from market. The rule might further state that the best 5000 hectares are to be selected. This could be achieved by choosing that set of raster cells, totaling 5000 hectares, in which the sum of suitabilities is maximized. It could equally be achieved by rank ordering the cells and taking enough of the highest ranked cells to produce a total of 5000 hectares. The former might be called a choice function (known as an objective function of performance index in the mathematical programming literature-see Diamond and Wright, 1989) while the latter might be called a choice heuristic.

Choice Function

Choice functions provide a mathematical means of comparing alternatives. Since they involve some form of optimization (such as maximizing or minimizing some measurable characteristic), they theoretically require that each alternative be evaluated in turn. However; in some instances, techniques do exist to limit the evaluation only to likely alternatives. For example, the Simplex Method in linear programming (see Feiring 1986) is specifically designed to avoid unnecessary evaluations.

Choice Heuristic
Choice heuristics specify a procedure to be followed rather than a function to be evaluated. In some cases, they will produce an identical result to a choice function (such as the ranking example above), while in other cases they may simply provide a close approximation. Choice heuristics are commonly used because they are often simpler to understand and easier to implement.

Objective
Decision rules are structured in the context of a specific objective. The nature of that objective, and how it is viewed by the decision makers their motives} will serve as a strong guiding force in the development of a specific decision rule. An objective is thus a perspective that serves to guide the structuring of decision rules. For example we may have the stated objective to determine areas suitable for timber harvesting. However; our perspective may be one that tries to minimize the impact of harvesting on recreational uses in the area. The choice of criteria to be used and the weights to be assigned to them would thus be quite different from that of a group whose primary concern was profit maximization. Objectives are thus very much concerned with issues of motive and social perspective.

Evaluation
The actual process of applying the decision rule is called evaluation. Mufti-Criteria

Evaluations
To meet a specific objective, it is frequently the case that several criteria will need to be evaluated. Such a procedure is called Multi-Criteria Evaluation (Voogd, 1983; Carver, 1991). Another term that is sometimes encountered for this is modeling. However; this term is avoided here since the manner in which the criteria are combined is very much influenced by the objective of the decision.

Mu1ti-criteria evaluation (MCE) is most commonly achieved by one of two procedures. The first involves Boolean overlay whereby all criteria are reduced to logic-at statements of suitability and then combined by means of one or more logical operators such as intersection (AND) and union (OR). The second is known as Weighted Linear Combination (WLC) wherein continuous criteria (factors) are standardized to a common numeric range, and then combined by means of a weighted average. The result is a continuous mapping of suitability that may then be masked by one or more Boolean constraints to accommodate qualitative criteria, and finally thresholded to yield a Final decision.

While these two procedures are well established in GIS, they frequently lead to different results, as they make very different statements about how criteria should be evaluated. In the case of Boolean evaluation, a very extreme form of decision making is used. If the criteria are combined with a logical AND (the intersection operator), a location must meet every criterion for it to be included in the decision set. If even a single criterion fails to be met, the location will be excluded. Such a procedure is essentially risk averse, and selects locations based on the most cautious strategy possible-a location succeeds in being chosen only if its worst quality (and therefore all qualities) passes the test On the other hand, if a logical OR (union) is used, the opposite applies-a location will be included in the decision set even if only a single criterion passes the test. This is thus a very gambling strategy, with (presumably) substantial risk involved.

Now compare these strategies with that represented by weighted linear combination (WLC). With MLC, criteria are permitted to tradeoff their qualities. A very poor quality can be compensated for by having a number of very favorable qualities. This operator represents neither an AND nor an OR-4t lies somewhere in between these extremes. It is neither risk averse nor risk taking.

For reasons that have largely to do with the ease with which these approaches can be implemented, the Boolean strategy dominates vector approaches to MCE, while WLC dominates solutions in raster systems. But clearly neither is better they simply represent two very different outlooks on the decision process----what can be called a decision strategy. IDRISI also includes a third option for multi-criteria evaluation, known as an Ordered Weighted Average (OWA) (Eastman and Jiang, 1996). This method offers a complete spectrum of decision strategies along the primary dimensions of degree of tradeoff involved and degree of risk in the solution.

Multi-Objective Evaluations

While many decisions we make are prompted by a single objective, it also happens that we need to make decisions that satisfy several objectives. A multi-objective problem is encountered whenever we have two candidate sets (i.e., sets of entities) that share members. These objectives may be complementary or conflicting in nature (Carver, 1991: 322).

Complementary Objectives

With complementary or non-conflicting objectives, land areas may satisfy more than one objective, i.e., an individual pixel can belong to more than one decision set. Desirable areas will thus be those which serve these objectives together in some specified manner. For example, we might wish to allocate a certain amount of land for combined recreation and wildlife preservation uses. Optimal areas would thus be those that satisfy both of these objectives to the maximum degree possible.

Conflicting Objectives

With conflicting objectives, competion occurs for the available land since it can be used for one objective or the other but not both. For example, we may need to resolve the problem of allocating land for timber harvesting and wildlife preservation. Clearly the two cannot coexist. Exactly how they compete, and on what basis one will win out over the other, will depend upon the nature of the decision rule that is developed.

In cases of complementary objectives, multi-objective decisions can often be solved through a hierarchical extension of the multi-criteria evaluation process. For example, we might assign a weight to each of the objectives and use these, along with the suitability maps developed for each, to combine them into a single suitability map. This would indicate the degree to which areas meet all of the objectives considered (see Voogd, 1983). However, with conflicting objectives the procedure is more involved.

With conflicting objectives, it is sometimes possible to rank order the objectives and reach a prioritized solution (Rosenthal, 1985). In these cases, the needs of higher ranked objectives are satisfied before those of lower ranked objectives are dealt with. However; this is often not possible, and the most common solution for conflicting objectives is the development of a *compromise* solution. Undoubtedly the most commonly employed techniques for resolving conflicting objectives are those involving optimization of a choice function such as mathematical programming (Fiering, 1986) or goal programming (Igniziq 1985). In both, the concern is to develop an allocation of the land that maximizes or minimizes an objective function subject to a series of constraints.

Uncertainty and Risk

Clearly, information is vital to the process of decision making. Howeve~ we rarely have perfect information. This leads to uncertainty, of which two sources can be identified: *database* and *decision rule uncertainly.*

Database Uncertainty

Database uncertainty is that which resides in our assessments of the criteria which are enumerated in the decision rule. Measurement error is the primary source of such uncertainty. For example, a slope of 35% may represent an important threshold However, because of the manner in which slopes are determined, there may be some uncertainty about whether a slope that was measured as 34% really w 34%. While we may have considerable confidence that it is most likely around 34%, we may also need to admit that there is some finite probability that it is as high as 36%. Our expression of database uncertainty is likely to rely upon probability theory.

Decision Rule Uncertainty

Decision rule uncertainty is that which arises from the manner in which criteria are combined and evaluated to reach a decision. A very simple form of decision rule uncertainty is that which relates to parameters or thresholds used in the decision rule. A more complex issue is that which relates to the very structure of the decision rule itself. This is sometimes called *specification error* (Alonsq 1968), because of uncertainties that arise in specifying the relationship between criteria (as a model) such that adequate evidence is available for the proper evaluation of the hypotheses under investigation.

Decision Rule Uncertainty and Direct Evidence: Fuzzy versus Crisp Sets

A key issue in decision rule uncertainty is that of establishing the relationship between the evidence and the decision set. In most cases, we are able to establish a direct relationship between the two, in the sense that we can define the decision set by measurable attributes that its members should possess. In some cases these attributes are crisp and unambiguous. For example, we might define those sewer lines in need of replacement as those of a particular material and age. However; quite frequently the attributes they possess are fuzzy rather than crisp. For example, we might define suitable areas for timber logging as those forested areas that have gentle slopes and are near to a road. What is a gentle slope? If we specify that a slope is gentle if it has a gradient of less than 5%, does this mean that a slope of 5.0001 °lo is not gentle? Clearly there is no sharp boundary here. Such classes are called fuzzy sets (Zadeh, 1965) and are typically defined by a set membership function. Thus we might decide that any slope less than 2% is unquestionably gentle, and that any slope greater than 10% is unquestionably steep, but that membership in the gentle set gradually falls from 1.0 at a 2% gradient to 0.0 at a

10% gradient. A slope of 5% might then be considered to have a membership value of only 0.7 in the set called "gentle." A similar group of considerations also surround the concept of being "near" to a road.

Fuzzy sets are extremely common in the decision problems faced with GIS. They represent a form of uncertainty, but it is not measurement uncertainty. The issue of what constitutes a shallow slope is over and above the issue of whether a measured slope is actually what is recorded It is a form of uncertainty that lies at the very heart of the concept of factors previously developed. *The continuous-factors of* multi-criteria *decision* making are thus fuzzy set membership functions, whereas Boolean constraints are crisp set membership *functions.* But it should be recognized that the terms factor and constraint imply more than fuzzy or crisp membership functions. Rather, these terms give some meaning also to the manner in which they are aggregated with other information.

Decision Rule Uncertainty and Indirect Evidence: Bayes versus Dempster Shafer

Not all evidence can be directly related to the decision set. In some instances we only have an indirect relationship between the two. In this case, we may set up what can be called a belief function of the degree to which evidence implies the membership in the decision set. Two important tools for accomplishing this are Bayesian Probability Theory and Dempster-Shafer Theory of Evidence. These will be dealt with at more length later in this chapter in Part B on Uncertainty Management.

Decision Risk

Decision Risk may be understood as the likelihood that the decision made will be wrong. Risk arises as a result of uncertainty, and its assessment thus requires a combination of uncertainty estimates from the various sources involved (database and decision rule uncertainty) and procedures, such as Bayesian Probability theory through which it can be determined.

A Typology of Decisions

Given **these definitions, it is possible to set** out awry broad typology of decisions.

	Single Criterion	Multi-Criteria
Single Objective		
Multi-Objective		

Decisions may be characterized as ***single-*** or ***multi-objective*** in nature, based on either a single criterion or multiple criteria. While one is occasionally concerned with single criterion problems, most problems approached with a GIS are multi-criteria in nature. For example, we might wish to identify areas of concern for soil erosion on the basis of slope, land use, soil type and the like. In these instances, our concern lies with how to combine these criteria to arrive at a composite decision. As a consequence, the first major area of concern in GIS with regard to Decision Theory is Multi-Criteria Evaluation.

Most commonly, we deal with decision problems of this nature from a single perspective. However; in many instances, the problem is actually multi-objective in nature (Diamond and Wright, 1988). Multi-objective problems arise whenever the same resources belong to more than one candidate set. Thus, for example, a paper company might include all forest areas in its candidate set for consideration of logging areas, while a conservation group may include forest areas in a larger candidate set of natural areas to be protected Any attempt, therefore, to reconcile their potential claims to this common set of resources presents a multi-objective decision problem.

Despite the prevalence of multi-objective problems, current GIS software is severely lacking in techniques to deal with this kind of decision. To date, most examples of multi-objective decision procedures in the literature have dealt with the problem through the use of linear programming optimization (e.g., Janssen and Rietveld 1990; Carvei; 1991; Campbell et. al., 1992; Wright et. al., 1983). However in most cases, these have been treated as choice problems between a limited number (e.g., less than 20) of candidate sites previously isolated in a vector system. The volume of data associated with raster applications (where each pixel is a choice alternative) clearly overwhelms the computational capabilities of today's computing environment. In addition, the terminology and procedures of linear programming are unknown to most decision makers and are complex and unintuitive by nature. As a consequence, the second major area of Decision Theory of importance to GIS is Multi-Objective Land Allocation. Here, the focus will be on a simple decision heuristic appropriate to the special needs of raster GIS.

CHAPTER 4. Decision Support System

Deliverable	Decision Support System
Abstract	
This action's objective is the development of a Desertification Decision Support System. This system will combine the knowledge acquired through all previous actions and will be based on the rules and guidelines depicted in the Desertification Risk Monitoring Model, in order to provide support to any decision-making body, planning to take actions against desertification. The Decision Support System that includes the Spatial Multi-criteria Weighed Model will be developed in order to describe the above-mentioned methodology and depict the Driving Forces, the Pressures and the Impacts on Desertification Risks.	
DSS, ALGORITHM	

Multi-Criteria Decision Making in GIS

As indicated earlier, the primary issue in multi-criteria evaluation is concerned with how to combine the information from several criteria to form a single index of evaluation. In the case of Boolean criteria (constraints), the solution usually lies in the union (logical OR) or intersection (logical AND) of conditions. However, for continuous factors, a weighted linear combination (Voogd, 1983: 120) is most commonly used. 'With a weighted linear combination, factors are combined by applying a weight to each followed by a summation of the results to yield a suitability map, i.e.:

$S = \Sigma w_i x_i$ where S = suitability
w_i = weight of factor i
x_i = criterion score of factor i

This procedure is not unfamiliar in GIS and has a form very similar to the nature of a regression equation. In cases where

Boolean constraints also apply, the procedure can be modified by multiplying the suitability calculated from the factors by the product of the constraints, i.e.:

$S = \Sigma wixi * \Pi ci$ where c = criterion score of constraint j
Π = product

All GIS software systems provide the basic tools for evaluating such a model. In addition, in IDRISI, a special module named MCE has been developed to facilitate this process. However, the MCE module also offers a special procedure called an Ordered Weighted Average that greatly extends the decision strategy options available. The procedure will be discussed more fully in the section on Evaluation below. For now, however; the primary issues relate to the standardization of criterion scores and the development of the weights.

Criterion Scores

Because of the different scales upon which criteria are measured, it is necessary that factors be standardized before combination using the formulas above, and that they be transformed, if necessary, such that all factors maps are positively correlated with suitability. Voogd (1983: 77-$4) reviews a variety of procedures for standardization, typically using the minimum and maximum values as scaling points. The simplest is a linear scaling such as:

$Xi = (Ri-R_{min)}) / (Rmax.-Rmin) *$ standardized range where R= raw score

However; if we recognize that continuous factors are really fuzzy sets, we easily recognize this as just one of many possible set membership functions. In IDRISI, the module named FUZZY is provided for the standardization of factors using a whole range of fuzzy set membership functions. The module is quick and easy to use, and provides the option of standardizing factors to either a 0-1 real number scale or a 0-255 byte scale. This latter option is recommended because the MCE module has been optimized for speed using a 0-255 level standardization. Importantly, the higher value of the standardized scale must represent the case of being more likely to belong to the decision set

A critical issue in the standardization of factors is the choice of the end points at which set membership reaches either 0.0 or 1.0 (or 0 and 255). Our own research has suggested that blindly using a linear scaling (or indeed any other scaling) between the minimum and maximum values of the image is ill advised In setting these critical points for the set membership function, it is important to consider their inherent meaning. Thus, for example, if we feel that industrial development should be placed as far away from a nature reserve as possible, it would be dangerous to implement this without careful consideration. Taken literally if the map were to cover a range of perhaps 100 km from the reserve, then the farthest point away from the reserve would be given a value of 1.0 (or 255 for a byte scaling). Using a linear function, then, a location 5 km from the reserve would have a standardized value of only 0.05 (13 for a byte scaling). And yet it may be that the primary issue was noise and minor disturbance from local citizens, for which a distance of only 5 kilometers would have been equally as good as being 100 km away. Thus the standardized score should really have been 1.0 (155). If an MCE were undertaken using the blind linear scaling, locations in the range of a few 10s of km would have been severely devalued when it fact they might have been quite good. In this case, the recommended critical points for the scaling should have been 0 and 5 km. In developing standardized factors using FUZZY, then, careful consideration should be given to the inherent meaning of the end points chosen.

Criterion Weights

A wide variety of techniques exist for the development of weights. In very simple cases, assigning criteria weights may be accomplished by dividing 1.0 among the criteria. (It is sometimes useful for people to think about "spending" one dollar, for example, among the criteria). However, when the number of criteria is more than a few, and the considerations are many it becomes quite difficult to make weight evaluations on the set as a whole. Breaking the information down into simple pairwise comparisons in which only two criteria need be considered at a time can greatly facilitate the weighting process, and will likely produce a more robust set of criteria weights. A pairwise comparison method has the added advantages of providing an organized structure for group discussions, and helping the decision making group hone in on areas of agreement and disagreement in setting criterion weights.

The technique described here and implemented in IDRISI is that of pairwise comparisons developed by Saaty (1977) in the context of a decision making process known as the Analytical Hierarchy Process (AHP). The first introduction of this technique to a G IS application was that of Rao et. al. (1991), although the procedure was developed outside the GIS software using a variety of analytical resources.

In the procedure for Multi-Criteria Evaluation using a weighted linear combination outlined above, it is necessary that the weights sum to one. In Saaty's technique, weights of this nature can be derived by taking the principal eigenvector of a square reciprocal matrix of pairwise comparisons between the criteria. The comparisons concern the relative importance of the two criteria involved in determining suitability for the stated objective Ratings are provided on a 9-point continuous scale (Figure 12-2). For example, if one felt that proximity to roads was very strongly more important than slope gradient in determining suitability for industrial siting, one would enter a 7 on this scale. If the inverse were the case (slope gradient was very strongly more important than proximity to roads), one would enter 1/7.

1/9	1/7	1/5	1/3	1	3	5	7	9
extremely	very strongly	strongly	moderately	equally	moderately	strongly	very strongly	extremely
	less important						more important	

SAATY SCALE

In developing the weights, an individual or group compares every possible pairing and enters the ratings into a pairwise comparison matrix (Figure 12-3). Since the matrix is symmetrical, only the lower triangular half actually needs to be filled in. The remaining cells are then simply the reciprocals of the lower triangular half (for example, since the rating of slope gradient relative to town proximity is 4, the rating of town proximity relative to slope gradient will be 1/4). Note that where empirical evidence exists about the relative efficacy of a pair of factors, this evidence can also be used.

Rating of the Row Factor Relative to the Column Factor

	Road Proximity	Town Proximity	Slope Gradient	Small Holder Settlement	Distance from Park
Road Proximity	1				
Town Proximity	1/3	1			
Slope Gradient	1	4	1		
Small Holder Set.	1/7	2	1/7	1	
Distance from Park	1/2	2	1/2	4	1

An example of a pairwise comparison matrix for assessing the comparative importance of five factors to industrial development suitability

The procedure then requires that the principal eigenvector of the pain.vise comparison matrix be computed to produce a tiest,fit set of weights (Figure 12-4). If no procedure is available to do this, a good approximation to this result can be achieved by calculating the weights with each column and then azreraging over all columns. For example, if we take the first column of figures, they sum to 2.98. Dividing each of the entries in the first column by 2.98 yields weights of 0.34, 0.11, 0.34, 0.05, and 0.17 (compare to the values in Figure 12-4). Repeating this for each column and averaging the weights over the columns usually gives a good approximation to the values calculated by the principal eigenvector. In the ,sase of IDRISI, however a special module named WEIGHT has been developed to calculate the principal eigenvector directly. Note that these weights will sum to one, as is required by the weighted linear combination procedure.

RoadProx	0.33
TownProx	0.08
Slope	0.34
SmalHold	0.07
ParkDist	0.18

Consistency Ratio 0.06

Weights derived by calculating the principal eigenvector of the pairwise comparison matrix

Since the complete pairwise comparison matrix contains multiple paths by which the relative importance of criteria can be assessed, it is also possible to determine the degree of consistency that has been used in developing the ratings. Saaty (1977) indicates the procedure by which an index of consistency, known as a consistency ratio can be produced (Figure 124). The consistency ratio (CR) indicates the probability that the matrix ratings were randomly generated. Saaty indicates that matrices with CR ratings greater than 0.10 should be re-evaluated. In addition to the overall consistency ratio, it is also possible to analyze the matrix to determine where the inconsistencies arise. This has also been developed as part of the WEIGHT module in IDRISI.

Evaluation

Once the criteria maps (factors and constraints) have been developed, an evaluation (or aggregation) stage is undertaken to combine the information from the various factors and constraints. The MCE module offers three logics for the evaluation/aggregation of multiple criteria: Boolean intersection, weighted linear combination (WLC), and the ordered weighted average (OWA).

MCE and Boolean Intersection

The most simplistic type of aggregation is the Boolean intersection or logical AND. This method is used only when factor maps have been strictly classified into Boolean suitable/unsuitable images with values 1 and 0. The evaluation is simply the ultiplication of all the images.

MCE and Weighted Linear Combination

The derivation of criterion (or factor) weights is described above. The weighted linear combination (WLC) aggregation method multiplies each standardized factor map (i.e, each raster cell within each map) by its factor weight and then sums the results. Since the set of factor weights for an evaluation must sum to one, the resulting suitability map will have the same range of values as the standardized factor maps that were used This result is then multiplied by each of the constraints in turn to "mask out" unsuitable areas. All these steps could be done using either a combination of SCALAR and OVERLAY, or by using the Image Calculator However, the module MCE is designed to facilitate the process.

The WLC option in the MCE module requires that you specify the number of criteria (both constraints and factors), their names, and the weights to be applied to the factors. All factors must be standardized to a byte (0-255) range. (If you have factors in real format, then use one of the options other than MCE mentioned above) The output is a suitability map masked by the specified constraints.

MCE and the Ordered Weighted Average

In its use and implementation, the ordered weighted average approach is not unlike WLC. The dialog box for the OWA option is almost identical to that of WLC, with the exception that a second set of weights appears. This second set of weights, the order weights controls the manner in which the weighted factors are aggregated (Eastman and Jiang, 1996; Yagm 1988). Indeed, WLC turns out to be just one variant of the OWA technique. To introduce the OWA technique, let's first review WLC in terms of two new concepts: tradeoff and risk

Tradeoff

Factor weights are weights that apply to specific factors, i.e., all the pixels of a particular factor image receive the same factor weight They indicate the relative degree of importance each factor plays in determining the suitability for an objective. In the case of WLC the weight given to each factor also determines how it will tradeoff relative to other factors. For example, a factor with a high factor weight can tradeoff or compensate for poor scores on other factors, even if the unweighted suitability score for that highly-weighted factor is not particularly good. In contrast, a factor with a high suitability score but a small factor weight can only weakly compensate for poor scores on other factors. The factor weights determine how factors tradeoff but; as described below, order weights determine the overall level of tradeoff allowed

Risk

Boolean approaches are extreme functions that result either in very risk-averse solutions when the AND operator is used or in risk taking solutions when the OR operator is used. In the former a high aggregate suitability score for a given location (pixel) is only possible if a11 factors have high scores. In the latter a high score in any factor will yield a high aggregate score, even if all the other factors have very low scores. The AND operation may be usefully described as the *minimum*, since the minimum score for any pixel determines the final aggregate score. Similarly the OR operation may be called the *maximum*, since the maximum score for any pixel determines the final aggregate score. The AND solution is risk-averse because we can be sure that the score for every factor is at least as good as the final aggregate score. The OR solution is risk-taking because the final aggregate score only tells us about the suitability score for the single most suitable factor.

The WLC approach is an averaging technique that softens the hard decisions of the boolean approach and avoids the extremes. In fact, given a continuum of risk from minimum to maximum, %LC falls exactly in the middle; it is neither risk averse nor risk taking.

Order Weights, Tradeoff and Risk

The use of order weights allows for aggregation solutions that fall anywhere along the risk continuum between AND and OR Order weights are quite different from factor weights. They do not apply to any specific factor. Rather, they are applied on a pixel-by-pixel basis to factor scores as determined by their rank ordering across factors at each location (pixel). Order weight 1 is assigned to the lowest ranked factor for that pixel (i.e., the factor with the lowest score), order weight 2 to the next higher-ranked factor for that pixel, and so forth. Thus, it is possible that a single order weight could be applied to pixels from any of the various factors depending upon their relative rank order.

To examine how order weights alter MCE results by controlling levels of tradeoff and risk, let us consider the case where factor weights are equal for three factors A, B~ and C. (Holding factor weights equal will make clearer the effect of the order weights.) Consider a single pixel with factor scores A= 187, B=174, and C=201. The factor weights for each of the factors is 0.33. When ranked from minimum value to maximum value, the order of these factors for this pixel is [B,A,C]. For this pixel, factor B will be assigned order weight 1, A order weight 2 and C order weight 3.

Below is a table with thirteen sets of order weights that have been applied to this set of factor scores [174,187,201]. Each set yields a different MCE result even though the factor scores and the factor weights are the same in each case.

Order Weights			Result
Min (1)	(2)	Max (3)	
1.00	0.00	0.00	174
0.90	0.10	0.00	175
0.80	0.20	0.00	177
0.70	0.20	0.10	179
0.50	0.30	0.20	183
0.40	0.30	0.30	186
0.33	0.33	0.33	187
0.30	0.30	0.40	189
0.20	0.30	0.50	191
0.10	0.20	0.70	196
0.00	0.20	0.80	198
0.00	0.10	0.90	200
0.00	0.00	1.00	201

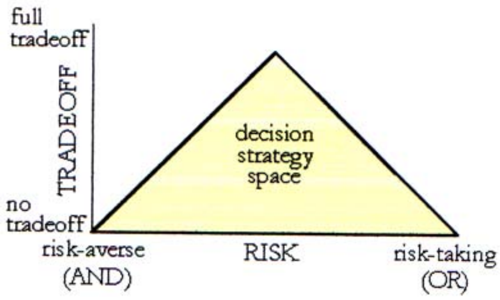
The first set of order weights in the table is [1, 0, 0]. The weight of factor B (the factor with the minimum value in the set [B, A, C]) will receive all possible weight while factors A and C will be given no weight at all. Such a set of order weights make irrelevant the factor weights. Indeed, the order weights have altered the evaluation such that no tradeoff is possible. As can be seen in the table, this has the effect of applying a minimum operator to the factors, thus producing the traditional intersection operator (AND) of fuzzy sets.

Similarly the last set of order weights [0, 0, 1] has the effect of a maximum operator, the traditional union operator (OR) of fuzzy sets. Again, there is no tradeoff and the factor weights are not employed.

Another important example from the table is where the order weights are equal, [.33, .33, .33]. Here all ranked positions get the same weight; this makes tradeoff fully possible and locates the analysis exactly midway between AND and OR Equal order weights produce the same result as WLC.

In all three cases the order weights have determined not only the level of tradeoff but have situated the analysis on a continuum from (risk-averse, minimum, AND) to (risk taking, maximum, OR).

As seen in the table, the order weights in the OWA option of MCE are not restricted to these three possibilities, but instead can be assigned any combination of values that sum to 1.0. Any assignment of order weights results in a decision rule that falls somewhere in a triangular decision strategy space that is defined by the dimensions of risk and tradeoff as shown in Figure 12-5.



Whether most of the order weight is assigned to the left, right or center of the order weights determines the position in the risk dimension. The logical AND operator is the most risk averse combination and the logical OR is the most risk-taking combination. When order weights are predominantly assigned to the lower-ranked factors, there is greater risk aversion (more of an AND approach). 'When order weights are more dominant for the higher-ranked factors, there is greater risk taking (more of an OR approach). As discussed above, equal order weights yield a solution at the middle of the risk axis.

The degree of tradeoff is governed by the relative distribution of order weights between the ranked factors. Thus, if the sum of the order weights is evenly spread between the factors, there is strong tradeoff, whereas if all the weight is assigned to a single factor rank, there is no tradeoff. (It may be helpful to think of this in terms of a graph of the order weights, with rank order on the X axis and the order weight value on the Y axis. If the graph has a sharp peak, there is little tradeoff. If the graph is relatively flat, there is strong tradeoff).

Thus, as seen from the table, the order weights of [0.5 0.3 0.2] would indicate a strong (but not perfect) degree of risk aversion (because weights are skewed to the risk averse side of the risk axis) and some degree of tradeoff (because the weights are spread out over all three ranks). Weights of [0 1 0], however, would imply neither risk aversion nor acceptance (exactly in the middle of the risk axis), and no tradeoff (because all the weight is assigned to a single rank).

The OWA method is particularly interesting because it provides this continuum of aggregation procedures. At one extreme (the logical AND), each criterion is considered necessary (but not sufficient on its own} for inclusion in the decision set At the other extreme (the logical OR), each criterion is sufficient on its own to support inclusion in the decision set without modification by other factors. The position of the weighted linear combination operator halfway between these extremes is therefore not surprising. This operator considers criteria as neither necessary nor sufficient strong support for inclusion in the decision set by one criterion can be equally balanced by correspondingly low support by another. It thus offers full tradeoff.

Using OWA
Given this introduction, it is worth considering how one would use the OWA option of MCE. Some guidelines are as follows:

1. Divide your criteria into three groups: hard constraints, factors that should not tradeoff and factors that should tradeoff. For example, factors with monetary implications typically tradeoff, while those associated with some safety concern typically do not.
2. If you find that you have factors that both tradeoff and do not tradeoff, separate their consideration into two stages of analysis. In the First, aggregate the factors that tradeoff using the OWA option. You can govern the degree of tradeoff by manipulating the order weights. Then use the result of the first stage as a new factor that is included in the analysis of those that do not tradeoff.
3. If you run an analysis with absolutely no tradeoff, the factor weights have no real meaning and can be set to any value.

Completing the Evaluation

Once a suitability map has been prepared, it is common to decide, as a final step~ which cells should belong to the set that meets a particular land allocation area target (the decision set). For example, having developed a map of suitability for industrial development, we may then wish to determine which areas constitute the best 5000 hectares that may be allocated. Oddly, this is an area where most raster systems have difficulty achieving an exact solution. One solution would be to use a choice function where that set of cells is chosen which maximizes the sum of suitabilities. However, the number of combinations that would need to be evaluated is prohibitive in a raster GIS. As a result, we chose to use a simple choice heuristic--to rank order the cells and choose as many of the highest ranks as will be required to meet the area target In IDRISI, a module named RANK is available that allows a rapid ranking of cells within an image. In addition, it allows the use of a second image to resolve the ranks of ties. The ranked map can then be reclassified to extract the highest ranks to meet the area goal.

Multi-Objective Decision Making in GIS

Multi-objective decisions are so common in environmental management that it is surprising that specific tools to address them have not yet been further developed within GIS. The few examples one finds in the literature tend to concentrate on the use of mathematical programming tools outside the GIS, or are restricted to cases of complementary objectives.

Complementary Objectives

As indicated earlier, the case of complementary objectives can be dealt with quite simply by means of a hierarchical extension of the multi-criteria evaluation process (e.g., Carver, 1991). Here a set of suitability maps, each derived in the context of a specific objective, serve as the factors for a new evaluation in which the objectives are themselves weighted and combined by linear summation. Since the logic which underlies this is multiple use, it also makes sense to multiply the result by all constraints associated with the component objectives.

Conflicting Objectives

With conflicting objectives, land can be allocated to one objective but not more than one (although hybrid models might combine complementary and conflicting objectives). As was indicated earlier, one possible solution lies with a prioritization of objectives (Rosenthal, 1985). After the objectives have been ordered according to prior# the needs of higher priority objectives are satisfied (through rank ordering of cells and reclassification to meet areal goals) before those of lower priority ones. This is done by successively satisfying the needs of higher priority objectives and then removing (as a new constraint) areas taken by that objective from consideration by all remaining objectives. A prioritized solution is easily achieved with the use of the RANK, RECLASS and OVERLAY modules in IDRISI. However, instances are rare where a prioritized solution makes sense. More often a compromise solution is required.

As noted earlier, compromise solutions to the multi-objective problem have most commonly been approached through the use of mathematical programming tools outside GIS (e.g., Diamond and Wright, 1988; Janssen and Rietveld, 1990; Campbell, et. al., 1992). Mathematical programming solutions (such as linear or integer programming) can work quite well in instances where only a small number of alternatives are being addressed. However, in the case of raster GIS, the massive data sets involved will typically exceed present-day computing power In addition, the concepts and methodology of linear and integer programming are not particularly approachable to a broad range of decision makers. As a result, we have sought a solution to the problem of multi-objective land allocation under conditions of conflicting objectives such that large raster datasets may be handled using procedures that have an immediate intuitive appeal.

The procedure we have developed is an extension of the decision heuristic used for the allocation of land with single objective problems. This is best illustrated by the diagram in the below Figure 12a. Each of the suitability maps may be thought of as an axis in a multi-dimensional space. Here we consider only two objectives for purposes of simple explanation. However any number of objectives can be used.

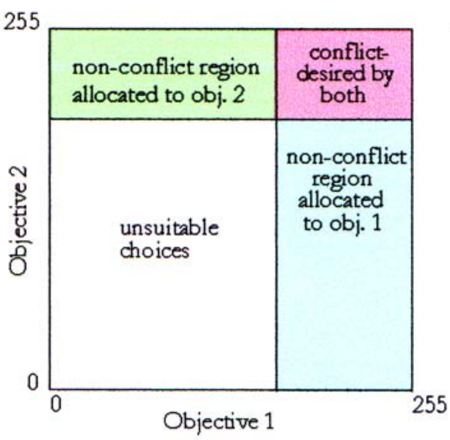


Figure 12a

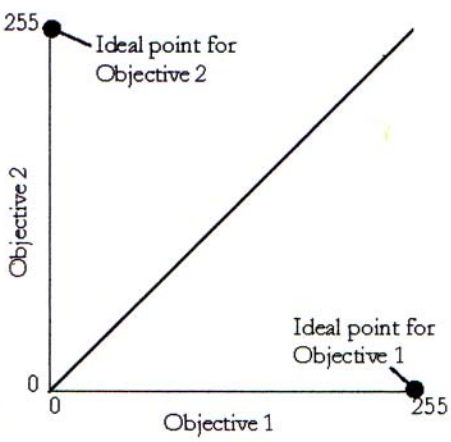


Figure 12a

Every raster cell in the image can be located within this decision space according to its suitability level on each of the objectives. To find the best x hectares of land for the Objective 1, we simply need to move a decision line down from the top (i.e., far right) of the Objective 1 suitability axis until enough of the best raster cells are captured to meet our area target. We can do the same with the Objective 2 suitability axis to capture the best **y** hectares of land for it As can be seen in Figure 12a, this partitions the decision space into four regions-areas best for Objective 1 and not suitable for Objective 2. areas best for Objective 2 and not suitable for Objective 1, areas not suitable for either, and areas judged best for both. The latter represents areas of conflict.

To resolve these areas of conflict, a simple partitioning of the affected cells is used. As can be seen in Figure 12b the decision space can also be partitioned into two further regions: those closer to the ideal point for Objective 1 and those closer to that for Objective 2. The ideal point represents the best possible case-a cell that is maximally suited for one objective and minimally suited for anything else. To resolve the conflict zone, the line that divides these two regions is overlaid onto it and cells are then allocated to their closest ideal point. Since the conflict region will be divided between the objectives, both objectives will be short on achieving their area goals. As a result, the process will be repeated with the decision lines being lowered for both objectives to gain more territory. The process of resolving conflicts and lowering the decision lines is iteratively repeated until the exact area targets are achieved.

It should be noted that a 45-degree line between a pair of objectives assumes that they are given equal weight in the resolution of conflicts. However, unequal weighting can be given. Unequal weighting has the effect of changing the angle of this dividing line In fact, the tangent of that angle is equal to the ratio of the weights assigned to those objectives.

It should also be noted that just as it was necessary to standardize criteria for multi-criteria evaluation, it is also required for multi-objective evaluation. The process involves a matching of the histograms for the two suitability maps. In cases where the distributions are normal, conversion to standard scores (using the module named STANDARD) would seem appropriate. However, in many cases, the distributions are not normal. In these cases, the matching of histograms is most easily achieved by a non-parametric technique known as histogram equalization. This is a standard option in many image processing systems such as IDRISI. However; it is also the case that the ranked suitability maps produced by the RANK module are also histogram equalized (i.e., a histogram of a rank map is uniform). This is fortuitous since the logic outlined in Figure 12a is best achieved by reclassification of ranked suitability maps.

As a result of the above considerations, the module named MOLA (Multi-0bjective Land Allocation) was developed to undertake the compromise solution to the multi-obiective problem. MDLA requires the names of the objectives and their relative weights, the names of the ranked suitability maps for each, and the areas that should be allocated to each. It then iteratively reclassifies the ranked suitability maps to perform a first stage allocation, checks for conflicts, and then allocates conflicts based on a minimum-distance-to-ideal-point rule using the weighted ranks.

CHAPTER 5 . Desertification Decision Support System

Requirements Analysis

Introduction

Purpose of this document

Purpose of this document is to provide an analysis of the requirements of the Desertification Decision Support System (DSS).

Overview

The system's objective is to combine the knowledge acquired through all previous actions and to provide support to any decision-making body, planning to take actions against desertification, based on the rules and guidelines depicted in the Desertification Risk Monitoring Model.

General Description

Product functions

The produced system will comprise of three main components:

1. A Multicriteria Decision Support component based on the Analytic Hierarchy Process (AHP) by Thomas Saaty.
2. A site location component that will enable the user to locate a site, based on a series of criteria.
3. A site location component that will enable the user to locate a site, based on weighted criteria.

User characteristics

The system aims to any decision-making body planning to take action against desertification. The system users should have at least a basic knowledge of Geographical Information Systems (GIS) and GIS related software.

Functional Requirements

Application Requirements

- The application should work as an extension to the existing GIS software, enabling thus the user to directly observe and manipulate the produced results.
- The user should be able to use all the tools provided by the GIS software before and after using the Desertification Decision Support System.
- Compatibility with raster files: The available data (criteria) will be available in raster file format.

AHP Component

- Criteria comparison through a pair-wise comparison matrix. Criteria weighting will use the Saaty scale[1] as a scale of comparison.
- Normalization of the comparison results through a process of principal component analysis.
- Option to filter the final result with the use of a constraint map. A constraint map is a raster format file with values 0 and 1. The areas with value 0 are to be excluded from the final result while the areas with value equal to 1 will remain intact.
- The output of the application should be maps in raster format that will depict the result.

Site Location Component

- A criteria selection component will enable the user to choose from a list of available criteria.
- A criteria definition component will enable the user to define the specific constrains for each criterion.
- The output of the application should be maps in raster format. Areas with higher values represent areas the satisfy the largest number of criteria.

Weighted Site Location Component

- Criteria selection component
- Criteria definition component.
- Criteria weighting component.
- The output of the application should be maps in raster format. Areas with higher values represent areas the satisfy the largest number of criteria.

Non-Functional Requirements

Design Constraints

Standards Compliance

- The application should be developed as an extension to the ArcMap software by ESRI.
- The data to be manipulated from the system should be in raster file format. Both output and input maps should be in the raster file format.

Hardware limitations

- The application should work on PC systems with Microsoft Windows 2000 or later operating system.

[1] Saaty, T.L., (1977). "*A scaling method for priorities in hierarchical structures*". Journal of Mathematical Psychology, 15, pp. 231-281

Algorithm Description

General Description

The developed application should function as an extension to the existing GIS software. The user should be able to activate the application through a link in the Graphical User Interface (GUI) of the existing GIS software. The main screen of the application should allow the user to choose one of the three available functions: AHP Multicriteria application, site location application and weighted site location application. The results of the application should appear on the GIS software user interface enabling thus the user to directly access and process them through the GIS software. Figure 1 depicts the relationships between the components of the system and the existing GIS software.

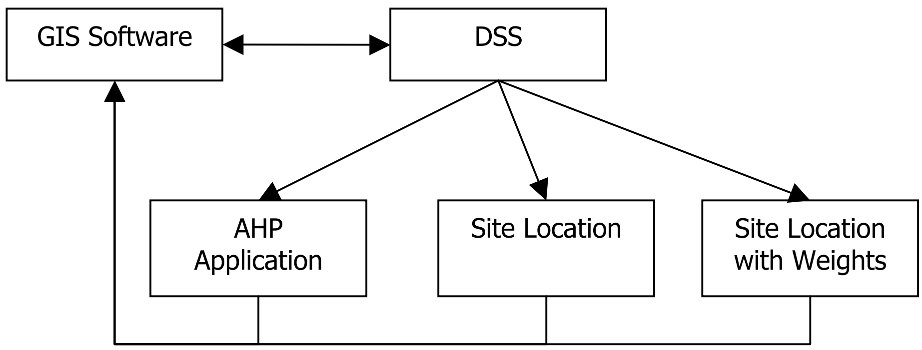


Figure 1: The architecture of the system

The Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a Multi-Criteria Decision support method that was developed by Prof. Thomas Saaty. AHP uses paired comparisons in order to calculate the weights of multiple criteria. It has an advantage over other multi-criteria methods as it can also calculate the consistency ratio, which detects the possible inconsistencies in the comparison. The weights of the criteria are derived from the principal Eigen Vectors and the consistency ratio is derived from the principal Eigen value.

Process Description

All criteria that take part in the analysis are compared pair-wise with the use of a comparison matrix allowing the user to express the relative preference of one factor against another by using numerical values. The numerical values that are used in the comparison are values emerging from the SAATY scale (Table 1). Saaty proposed a scale of comparison consisting of values ranging from 1 to 9 which describe the importance of one factor against another.

Table 1: The SAATY Scale

Value	Importance
1	Equal
3	Moderate
5	Strong
7	Very strong
9	Extreme
2,4,6,8	Intermediate values
Reciprocals	Values for inverse comparison

Table 2 shows an example of a comparison matrix that depicts the comparison of three criteria C1, C2 and C3. C1 is set to have strong importance (value 5) against C2 and moderate to strong importance (value 4) against C3. C2 is set to have equal to moderate importance against C3 (value 2). The inverse positions of the table automatically get a reciprocal value (0.2, 0.25 and 0.5)

Table 2: The Comparison Matrix

Criteria	C1	C2	C3
C1	1	5	4
C2	0.2	1	2
C3	0.25	0.5	1

The next step in the Analytic Hierarchy Process involves applying an algorithm that yields similar results to that of the principal component analysis. The algorithm consists of the following steps:

1. Sum each column of the comparison matrix
2. Divide each element of the matrix with the sum of its column in order to calculate the normalized relative weight
3. Calculate the average value of each row in order to get the principal Eigen value
4. Sum each row and divide by the number of criteria in order to calculate the criteria weights.

Considering the possible number of comparisons in the comparison matrix it is possible that inconsistencies may arise mostly due to human error. The AHP process offers a consistency ratio (CR) which is a numerical index that aims to detect such inconsistencies. CR is defined as the ratio of consistency index (CI) to an average consistency index (RI):

$$CR = \frac{CI}{RI}$$

The values for RI are related to the order of the comparison matrix. Table 3 shows the RI values for a matrix of an order up to 8.

Table 3: Values for RI (n=order of matrix)

n	2	3	4	5	6	7	8
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41

The consistency index can be calculated from the comparison matrix using the following formula:

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

where

λ_{max}: greatest Eigenvalue of the preference matrix
n: order of matrix

A revision of the preference matrix is recommended if the consistency ratio (CR) exceeds a value of 0.1.

Architecture

Figure 2 depicts the AHP component architecture and the relationships between each individual component.

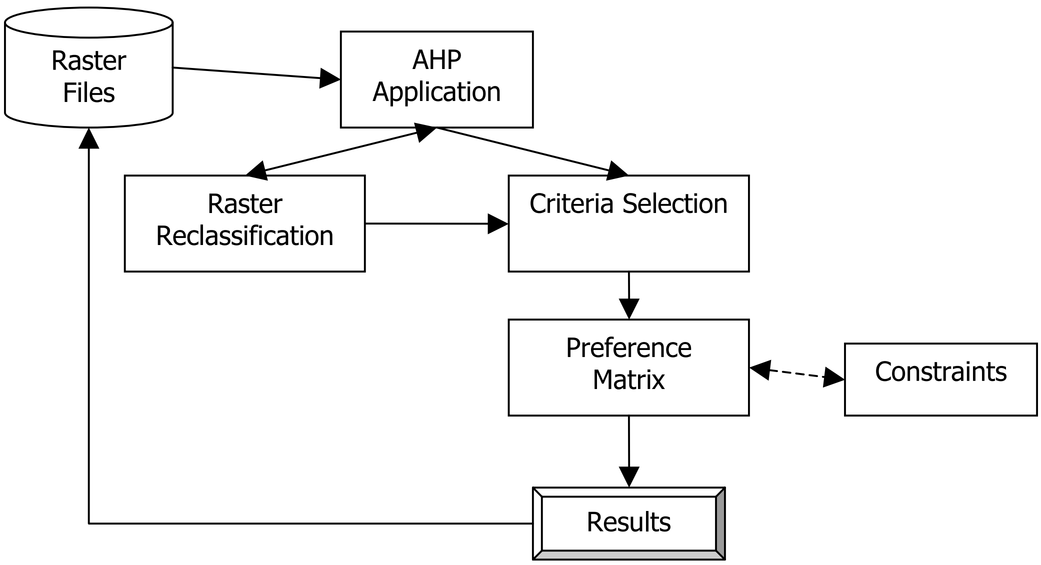


Figure 2: AHP component architecture

Site Location

The site location application should work with maps in raster format. Each map represents an attribute (e.g. rainfall, slope etc.). The user should be able to select a number of attributes and a selection of criteria for each attribute (e.g. rainfall>10, slope <20 etc.). The areas that satisfy the criteria should be valued with 1 whereas the areas that do not satisfy the criteria should be numbered with zero. The application should perform an addition of the maps that are selected and a new map should be produced (figure 3). The final result should be normalized in a scale of 0 to 1 such as 1 represents areas that meet all the criteria and 0 represents areas that do not meet any of the criteria whereas intermediate numbers represent partial satisfaction of the criteria.

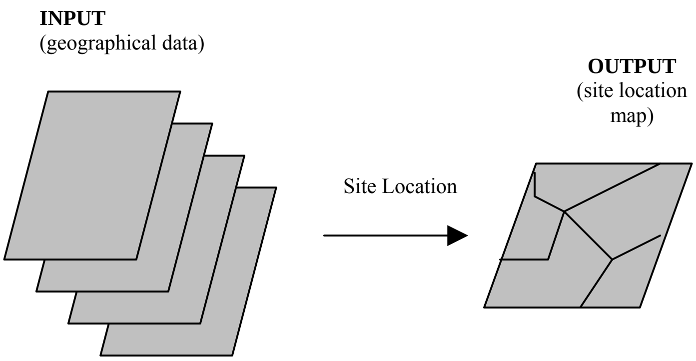


Figure 3: Site location application results

Figure 4 depicts the architecture of the site location component.

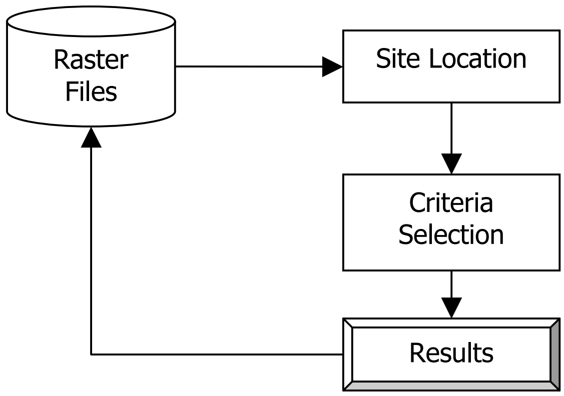


Figure 4: Site Location component architecture

Weighted Site Location

The Weighted Site Location application follows the same steps as the Site Location application until the criteria weighting stage. Criteria weighting is achieved through a process similar to that of the Analytic Hierarchy Process. The user is prompter with a pair-wise comparison matrix in order to define the degree of preference of the criteria against each other. The final results are normalized on a scale of 0 to 1, with 0 representing areas that do not meet any criteria, and 1 satisfying the criteria and the preferences defined by the user.

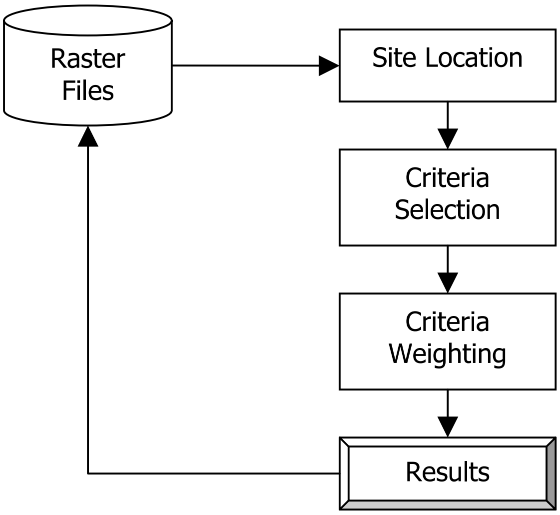


Figure 4: Weighted Site Location component architecture

CHAPTER 6. Documentation for

- Data input
- Data output
- Expected results

Deliverable	Documentation for, Data input, Data output, Expected results
Abstract	
This deliverable includes the documentation for the data input and output, as well as the expected results	
Data output, input	

Data Input

The application takes as an input a varied number of criteria. Each criterion is represented by a map in raster format compatible with the ESRI ArcMap raster definition. ESRI defines a raster map as a map that "represents features as a matrix of cells in continuous space" and proposes the following guidelines:

- The cell size you use for a raster layer will affect the results of the analysis and how the map looks.
- The cell size should be based on the original map scale and the minimum mapping unit.
- Using too large a cell size will cause some information to be lost.
- Using a cell size that is too small requires a lot of storage space and takes longer to process without adding additional precision to the map.

Raster files that could be used on the application can be either primary raster files or maps in vector format that have been converted to raster format.

Data Output / Expected Results

The output of the application dependents on the features of the application that are going to be used (AHP, Site Location or Detailed Site Location). All of the results however are produced in ESRI raster file format. More specifically:

- AHP produces a map in raster format that displays the relative importance of each area on the map (according to the scale provided by the user).
- Site Location produces a raster map that depicts the number of criteria each area satisfies.
- Detailed Site Location produces a raster map that depicts in detail which criteria each area of map satisfies.

All the produced maps are on the same scale, resolution and map unit size as the input maps.