Raster Procedures for Multi-Criteria/Multi-Objective Decisions

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Abstract
Decisions about the allocation of land typically involve the evaluation of multiple criteria according to several, often conflicting, objectives. With the advent of GIS, we now have the opportunity for a more explicitly reasoned environmental decision making process. However, GIS has been slow to develop decision support tools, more typically relying on procedures outside the GIS software. In this paper the issues of multi-criteria/multi- objective decision making are discussed, along with an exploration of a new set of decision support tools appropriate for the large data-handling needs of raster GIS. A case study is used to illustrate these tools as developed for the IDRISI geographic analysis software system.

Introduction
As a technology, GIS has evolved through three broad application domains. The first, and that which lends it its name, is the use of GIS as an information database—a means of coordinating and accessing geographic data. The second, and more recent, is the use of GIS as an analytical tool—a means of specifying logical and mathematical relationships among map layers (i.e., modeling) to yield new derivative maps. Building upon these two, we now see a third stage—the use of GIS as a decision support system—a means for deciding how to act upon the analyses produced.

With these later stages, we see the system evolving to accommodate the addition of new information to augment that in the database. With GIS as a database, we get nothing more from the system than what went in in the first place. Admittedly, we may access those data in new and novel combinations; but the fact remains that the system is little more than an automated data bank. As GIS evolved to take on a more analytical focus, we see the development of special tools for the addition of new information—knowledge of relationships and/or process. Derivative mapping and simulation modeling truly add new data to the database by combining existing data with knowledge of relations and process. Finally, as GIS evolves to accommodate decision making behavior, we will witness the development of specialized tools to specify how to act upon the outcomes of our analytical models. It is to this issue that the following paper is addressed, with special reference to raster GIS.

Making decisions about the allocation of land is one of the most fundamental activities of resource development (FAO, 1976). With the development of GIS, we now have the opportunity for a more explicitly reasoned process of land-use evaluation. However, despite the wide range of analytical tools these systems provide, they are typically weak in the provision of decision support procedures (Honea *et al.*, 1991). Over the past year, the Clark Labs have been involved in an exploration of decision making procedures for land allocation problems on behalf of the United Nations Institute for Training and Research. One of the difficulties we encountered was this lack of appropriate tools. As a result, we found the need to develop a series of new program modules for the IDRISI geographic analysis software system (Eastman, 1993). These are described in the following sections and will be illustrated by means of a hypothetical case study. A second difficulty we encountered was the broadly divergent use of decision terminology (e.g., see Rosenthal (1985)) that exists in the Decision/Management Science and Operations Research fields. 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.

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Definitions[1]

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 sets of features, and so on.

Criterion
A criterion is some basis for a decision that can be measured and evaluated. It is the evidence upon which a decision is based. Criteria can be of two kinds: factors and constraints.

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 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 (Fiering, 1986) and *structural variables* in the linear goal programming literature (Ignizio, 1985).

[1]This section is taken substantially from Eastman *et al.* (1993a) and Eastman *et al.* (1993b). Indeed, this paper is a modification and amplification of the former of these to give a broader treatment of Multi-Criteria Evaluation as well as Multi-Objective decision making.

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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 can proceed on slopes exceeding a 30 percent 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 final solution must possess. For example, we might require that the total area of lands selected for development be not less than 5000 hectares. Constraints such as this are often called *goals* (Ignizio, 1985) or *targets* (Rosenthal, 1985). Regardless, both forms of constraint have the same ultimate meaning—to limit the alternatives under consideration.

Decision Rule

The procedure by which criteria are 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 percent 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* or *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 for comparing alternatives. Because 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 (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 a result identical 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.

In general, two kinds of decision rules prevail—those in which the decision rule involves the evaluation of alternative hypotheses about individual features, and those in which it involves a decision about alternative features to include in a set. For example, a decision about whether areas are prone to landslides or not is indicative of the first type while one that selects the best regions for agriculture exemplifies the second. In essence, the first kind of decision is one of *classification* while the second is one of *selection*.

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 (i.e., 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.[2] 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 assign 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.

Multi-Criteria Evaluations

The actual process of applying the decision rule is called evaluation. To meet a specific objective, it is frequently the case that several criteria will need to be evaluated. Such procedures are called *Multi-Criteria Evaluations*. Another term that is sometimes encountered for this is *modeling*. However, this term is avoided here because the manner in which the criteria are combined is very much influenced by the objective of the decision, and thus explicitly influenced by personal perspectives.

Two of the most common procedures for multi-criteria evaluation are weighted linear combination and concordance-discordance analysis (Voogd, 1983; Carver, 1991). In the former, each factor is multiplied by a weight and then summed to arrive at a final suitability index. In the latter, each pair of alternatives is analyzed for the degree to which one out ranks the other on the specified criteria. Unfortunately, concordance-discordance analysis is computationally impractical when a large number of alternatives is present (such as with raster data where every pixel is an alternative). However, weighted linear combination is very straightforward in a raster GIS. Indeed, it is the derivation of the weights, within the context of the decision objective, that provides the major challenge. Accordingly, this will be examined in further detail.

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. These objectives may be complementary or conflicting (Carver, 1991, p. 322) in nature.

Complementary Objectives

With complementary or non-conflicting objectives, land areas may satisfy more than one objective. 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.

[2]It is important to note here that we are using a somewhat broader definition of the term objective than would be found in the goal programming literature (Ignizio, 1985). In goal programming, the term *objective* is synonymous with the term *objective function* in mathematical programming and *choice function* used here.

Conflicting Objectives

> With conflicting objectives, objectives compete for the available land because it can be used for one 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 indicating the degree to which areas meet all of the objectives considered (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 to 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 linear programming (Fiering, 1986) or goal programming (Ignizio, 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. However, we rarely have perfect information. This leads to uncertainty, for which two sources can be identified: *database* and *decision rule 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 (but not exclusive) source of such database uncertainty. Decision rule uncertainty is that which arises from the manner in which criteria are combined and evaluated to reach a decision. Both sources contribute to the *risk* that the decision reached will be incorrect.

When uncertainty is present, the decision rule will need to incorporate modifications to the choice function or heuristic to accommodate the propagation of uncertainty through the rule and replace the *hard* decision procedures of certain data with the *soft* ones of uncertainty. A variety of theoretical constructs have been developed to accommodate this uncertainty, including Bayesian Probability Theory, Fuzzy Set Theory, and Dempster-Shafer Theory (Lee *et al.*, 1987; Stoms, 1987). In this paper, the issues of uncertainty and risk are not addressed because they would detract from the main issue of decision rule structuring for multi-criteria/multi-objective problems.

Multi-Criteria Decision Making in GIS

As indicated above, the most prevalent procedure for multi-criteria evaluation is the weighted linear combination (Voogd, 1983, p. 120). 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.,

$$S = \Sigma w_i x_i \qquad (1)$$

where S is suitability, w_i is the weight of factor i, and x_i is the 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.,

$$S = \Sigma(w_i x_i)^* \Pi c_j \qquad (2)$$

where c_j is the criterion score of constraint j and Π is the 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. The primary issues, however, relate to the standardization of criteria scores and the development of the weights.

Standardizing Criterion Scores

Because of the different scales upon which criteria are measured, it is necessary that factors be standardized before combination in Equations 1 or 2, and that they be transformed, if necessary, such that all factors maps are positively correlated with suitability.[3] Voogd (1983, pp. 77-84) 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

$$x_i = (R_i - R_{\min})/(R_{\max} - R_{\min})^* \; m \qquad (3)$$

where R is the raw score and m is an an arbitrary multiplier.

Through standardization, criterion scores will be expressed according to a consistent numeric range (e.g., 0-99, 0-255, etc.). In the case of IDRISI, the STRETCH module is used to linearly scale all values to a 0 to 255, 8-bit integer range. Thus, each factor will have an equivalent measurement basis before any weights are applied.

Criterion Weights

Although a variety of techniques exist for the development of weights, one of the most promising would appear to be 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 GIS 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 1. In Saaty's technique (Saaty, 1977), 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 nine-point continuous scale (Figure 1). 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.

In developing the weights, an individual or group com-

[3]Thus, for example, if locations near a road were more advantageous for industrial siting than those far away, a distance map would need to be transformed into one expressing proximity.

1/9	1/7	1/5	1/3	1	3	5	7	9
extremely	very	strongly	moderatel	equally	moderatel	strongly	very	extremely

less important — more important

Figure 1. The continuous rating scale used for the pairwise comparison of factors in the multi-criteria evaluation.

pares every possible pairing and enters the ratings into a pairwise comparison matrix (Figure 2). Because 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, because the rating of slope gradient relative to road proximity is 1/7, the rating of road proximity relative to slope gradient will be 7). Note that, where empirical evidence exists about the relative efficacy of a pair of factors, this evidence can also be used.

The procedure then requires that the principal eigenvector of the pairwise comparison matrix be computed to produce a *best fit* set of weights (Figure 3). 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 averaging over all columns. For example, if we take the first column of figures, they sum to 1.78. Dividing each of the entries in the first column by 1.78 yields weights of 0.56, 0.07, 0.19, 0.11, and 0.07 (compare to the values in Figure 3). 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 case 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 this weighted linear combination procedure.

Because 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 3). 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. We have confirmed this by observing that re-evaluation only produces significant changes in the weights when the CR exceeds 0.1. As a result, the procedure accepts the weights when the CR is less than this threshold. Otherwise, the WEIGHT procedure analyzes the matrix to determine where logical inconsistencies arise. It does so by comparing direct pairwise comparison ratings with those implied by the eigenvector weights. Discrepancies indicate cases where the direct ratings are inconsistent with those derived from all indirect as well as direct ratings, and thus cases where re-evaluation would be productive in developing a consensus weight set.

Evaluation

Once the criteria maps (factors and constraints) have been developed, it is a fairly simple matter to multiply each factor map (i.e., each raster cell within each map) by its weight and then sum the results. Because the weights sum to 1, the resulting suitability map will have a range of values that matches that of the standardized factor maps that were used. After all of the factors have been incorporated, the resulting suitability map is then multiplied by each of the constraints to "zero out" unsuitable areas. In IDRISI, a special procedure named MCE has been created to undertake all of these steps with maximum efficiency.

Once a suitability map has been prepared, it is common to undertake a final step of deciding which cells belong to the set that meets a particular land allocation area target. 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 in 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 new module named RANK was developed to allow 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 been developed within GIS. The few examples one finds in the literature tend to concentrate on the use of linear 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. Because 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 rank ordered, the needs of higher ranked objectives are satisfied (through rank ordering of cells and reclassification to meet areal goals) before those of lower ranked ones. This is done by successively satisfying the needs of higher objectives and then removing (as a new constraint) areas taken from consideration by all remaining objectives. A prioritized solution is easily achieved with the use of the RANK and RECLASS modules in IDRISI. However, the instances where a *prioritized* solution makes sense are rare. More often, a *compromise* solution is required.

Compromise solutions to the multi-objective problem have most commonly been approached through the use of

	Proximity to Water	Proximity to Power	Proximity to Roads	Proximity to Market	Slope Gradient
Proximity to Water	1				
Proximity to Power	1/8	1			
Proximity to Roads	1/3	7	1		
Proximity to Market	1/5	5	1/2	1	
Slope Gradient	1/8	1/3	1/7	1/7	1

Figure 2. An example of a pairwise comparison matrix forassessing the comparative importance of factors.

Proximity to Water	0.51
Proximity to Power	0.05
Proximity to Roads	0.25
Proximity to Market	0.16
Slope Gradient	0.03
Consistency Ratio	0.08

Figure 3. The weights derived by calculating the principal eigenvector of the pairwise comparison matrix. The Consistency Ratio indicates the probability that the ratings were developed by chance.

mathematical programming tools outside the 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 diagrams in Figure 4. Each of the suitability maps may be thought of as an axis in a multidimensional space. Here we consider only two objectives for purposes of simple explanation. However, any number of objectives can be used.

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 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 most suitable land for it. As can be seen in Figure 4, 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—i.e., areas ofconflict.

To resolve these areas of conflict, a simple partitioning of the affected cells is used. As can be seen in Figure 4, 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. Because the conflict regions will be divided between the objectives, both objectives will initially 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 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. 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 because the logic outlined in Figure 4 is best achieved by reclassification of ranked suitability maps.

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

The Kathmandu Valley Case Study

To illustrate these multi-criteria/multi-objective procedures, we consider the hypothetical problem of developing a zoning map to regulate expansion of the carpet industry within agricultural areas of the Kathmandu Valley of Nepal. The problem is to zone 1500 hectares of current agricultural land outside the ring road of Kathmandu for further expansion of the carpet industry. In addition, 6000 hectares will be zoned for special protection of agriculture. The problem clearly falls into the realm of multi-objective/multi-criteria decision problems. In this case, we have two objectives: to protect lands that are best for agriculture, while at the same time finding other lands that are best suited for the carpet industry. Because land can be allocated to only one of these uses

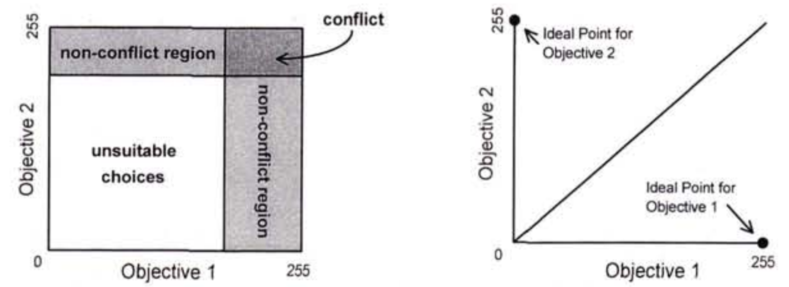

Figure 4. The decision space formed by treating suitabilities for each objective as a separate dimension. (Left) The decision lines isolating the best regions to meet areal goals for the objectives, in the case of two objectives, intersect to form four regions: two regions of choices desired by one objective and not the other (and thus not in conflict), a region of choices not desired by either, and a conflict region of choices desired by both. (Right) This conflict region is iteratively partitioned between objectives by means of a *minimum-distance-to-ideal-point* logic that partitions the decision space with a line whose angle is determined by the relative weight assigned to the objectives.

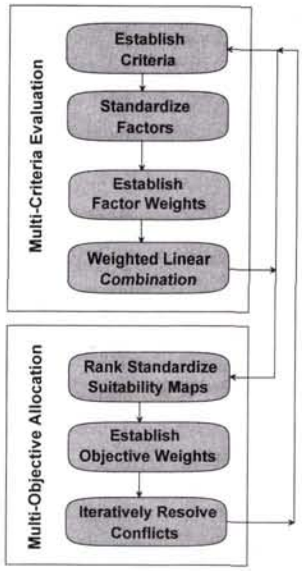

Figure 5. A flow diagram of the multi-critera/ *multi-objective decision making* process for cases of conflicting objectives as developed in the IDRISI software system.

at any one time, the objectives must be viewed as conflicting—i.e., they may potentially compete for the same lands. Furthermore, the evaluation of each of these objectives can be seen to require multiple criteria.

In the illustration that follows, a solution to the multi-objective/multi-criteria problem is presented as developed with a group of Nepalese government officials as part of an advanced seminar in GIS[4]. While the scenario was developed purely for the purpose of demonstrating the techniques used, and while the result does not represent an actual policy decision, it is one that incorporates substantial field work and the perspectives of knowledgeable decision makers. The procedure follows a logic in which each of the two objectives are first dealt with as separate multi-criteria evaluation problems. The result is two separate suitability maps (one for each objective) which are then compared to arrive at a single solution that balances the needs of the two competing objectives. The steps (as summarized in Figure 5) are as follows :

Solving the Single Objective Multi-Criteria Evaluations

Establishing the Criteria: Factors and Constraints

The decision making group identified five factors as being relevant to the siting of the carpet industry: proximity to water (for use in dying and the washing of carpets), proximity to roads (to minimize road construction costs), proximity to power, proximity to market, and slope gradient. For agriculture they identified three of the same factors: proximity to water (for irrigation), proximity to market, and slope gradient; and a fourth factor: soil capability. In both cases they identified the same constraints: either objective would be constrained to areas outside the ring road surrounding Kathmandu, existing agricultural lands, and slope gradients less than 100 percent.

[4]The seminar was hosted by UNITAR at the International Center for Integrated Mountain Development (ICIMOD) in Nepal, 28 September–2 October 1992.

Standardizing the Factors

Each of the constraints was developed as a Boolean map while the factors were standardized to a consistent range of 0 to 255. In addition, all factor maps were developed such that high values would indicate more suitable areas. Thus, for example, the proximity to market factor was developed as a cost distance surface (accounting for variable road class frictions) and then inverted after scaling to form the proximity map. Standardization was achieved by undertaking a linear rescaling of values using the minimum and maximum values as the scaling end points. The only exception to this was the slope gradient map where the scaling points were set at 0 and 100 percent (because slopes greater than 100 percent were ruled out by one of the constraints). Figure 6 illustrates these factor and constraint maps.

Establishing the Factor Weights

The next stage was to establish a set of weights for each of the factors. In the nature of a focus group, the GIS analyst worked with the decision makers as a group to fill out a pairwise comparison matrix. Each decision maker was asked in turn to estimate a rating and then to indicate why he or she felt that way. The group would then be asked if they agreed. Further discussion would ensue, often with suggestions for different ratings. Ultimately, if another person made a strong case for a different rating that seemed to have broad support, the original person who provided the rating would be asked if they were willing to change (the final decision would in fact rest with the original rater). Consensus was not difficult to achieve using this procedure. It has been found through repeated experimentation with this technique that the only cases where strong disagreements arise would be those in which new variables were eventually identified as needing to be incorporated. This is perhaps the greatest value of the pairwise comparison technique—it is very effec-

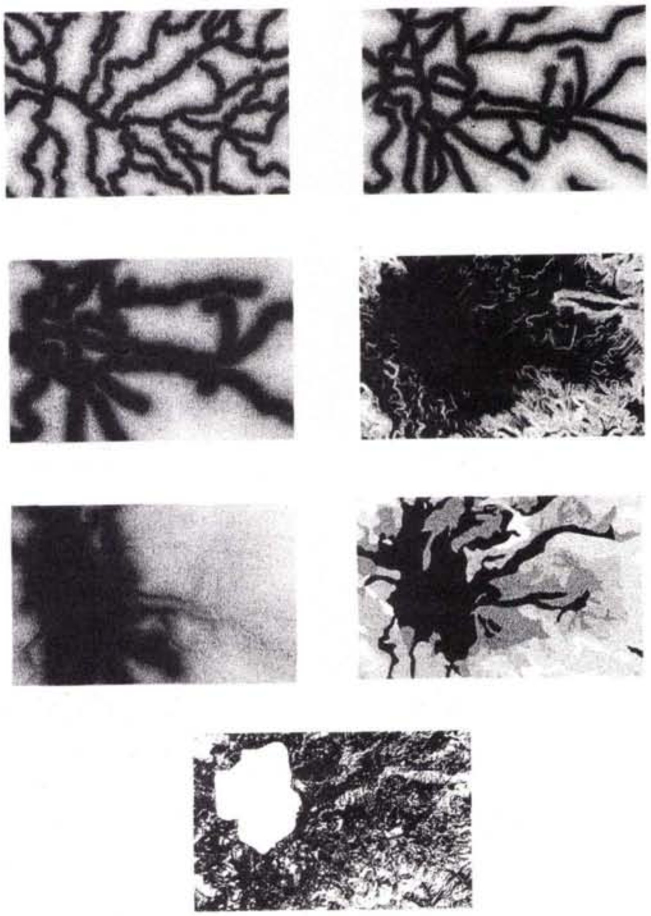

Figure 6. (Reading left to right and from top to bottom) The proximity to water, road proximity, proximity to power, slope gradient, proximity to market, and soil capability factors, and the Boolean constraints. With the factor maps, darker areas are those more suited to the objective in question. The Boolean constraint map illustrates regions that cannot be considered in white (areas within the urban ring road, forested areas, and areas on slopes with gradients greater than 100 percent).

tive in uncovering overlooked factors and reaching a consensus on weights through direct participation by decision makers.

Once the pairwise comparison matrices were filled out, the WEIGHT module was used to identify inconsistencies and to develop the best fit weights.

Undertaking the Multi-Criteria Evaluation

Once the weights were established, the module MCE (for Multi-Criteria Evaluation) was used to combine the factors and constraints in the form of a weighted linear combination. The procedure is optimized for speed and has the effect of multiplying each factor by its weight, adding the results, and then successively multiplying the result by each of the constraints. Because the weights sum to 1.0, and the factors are standardized from 0 to 255, the resulting suitability maps also have a range from 0 to 255. Figure 7 shows the result of separate multi-criteria evaluations to derive suitability maps for the carpet and agricultural industries.

Solving the Multi-Objective Land Allocation Problem

Once the multi-criteria suitability maps have been created for each objective, the multi-objective decision problem can be approached.

Standardizing the Single-Objective Suitability Maps

The first step was to use the RANK module to rank order the cells in each of the two suitability maps. This prepares the data for use with the MOLA procedure and has the additional effect of standardizing the suitability maps using a non-parametric histogram equalization technique. Ranks were developed in descending order (i.e., the best rank was 1). For both objectives, tied ranks were resolved by examining the other suitability map and ranking in reverse order to the suitability on that other map. This preserves the basic logic of the uncorrelated ideal points for conflicting objectives that is used in the resolution of conflicts.

Solving the Multi-Objective Problem

The second step was to submit the ranked suitability maps to the MOLA procedure. MOLA asks for the names of the objectives, the relative weight to assign to each, and the area to be allocated to each. The module then undertakes the iterative procedure of allocating the best ranked cells to each objective according to the areal goals, looking for conflicts, and resolving conflicts based on the weighted minimum-distance-to-ideal-point logic. Figure 8 shows the final result, achieved after six iterations.

Discussion and Conclusions

The result illustrated in Figure 8 is very satisfactory. Areas selected for each objective are geographically coherent and meaningful in terms of the criteria specified. The procedure is also suitable for use on large images (the analyses illustrated here took only seconds to perform). Perhaps most importantly, in testing with decision makers in both Nepal and Lithuania who have had no formal training in multi-objective procedures, the logic was easily understood and acted as an excellent vehicle for discussion of the criteria and objectives involved and their relative strengths.

Although we have not yet undertaken a systematic testing of this decision heuristic, it is logical to expect that the results should be very close to that which would be achieved through linear programming (assuming that a problem as large as this could be solved). The rank/reclass logic that underlies this process is one that is consistent with finding areas in which the sum of suitabilities is maximized. Only in the resolution of conflicts, where a local rather than global solution is used, would one expect that differences might occur. However, it should be noted that it was not our intention to duplicate the outcome of linear programming but, rather, to provide a logically coherent procedure that would be comprehensible to the majority of decision makers.

Another important feature of this heuristic is that, by specifically searching out areas of no conflict between the objectives, and by resolving conflicts only in areas where the land is suitable for all objectives, the cost of a mis-allocation will be minimized. In essence, we are pursuing a least-risk solution by proceeding in this manner. Clearly, further research is needed for a full evaluation of this procedure.

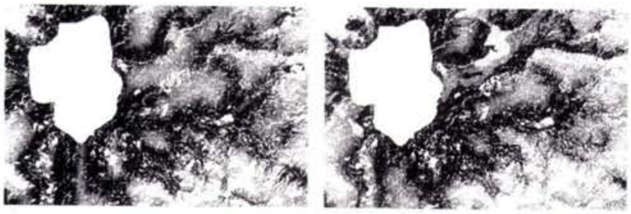

Figure 7. (Left) Suitability for the carpet industry. (Right) Suitability for Agriculture. Darker areas are those more suited to the objective in question.

Figure 8. The final land allocation (shown as two Boolean images for purposes of illustration in black and white). (Left) The best 1500 hectares allocated to the carpet industry. (Right) The best 6000 hectares allocated to agriculture.

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