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GIS AND UNCERTAINTY MANAGEMENT: NEW DIRECTIONS IN SOFTWARE DEVELOPMENT*

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RESUMEN

En este artículo se examinan algunas nuevas herramientas de software incorporadas a Sistemas de Información Geográfica como ayuda a los procesos de toma de decisiones en condiciones de incertidumbre.

ABSTRACT

This paper examines new software developments in GIS as a tool for supporting the decision making process under uncertainty conditions.

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INTRODUCTION

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 focussed 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 few years, the research staff at the IDRISI Project have been specifically concerned with the use of GIS as a direct extention of the human decision making process – most particularly in the context of resource allocation decisions. However, it has become clear greater attention to uncertainty is needed in these routines. 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 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.

In the discussion that follows, a broad overview is presented of the dimensions of uncertainty of critical importance to resource allocation decisions and the approach of the IDRISI research team in developing software modules to accommodate these elements.

THE DECISION MAKING PROCESS

A decision can be defined as a choice between alternatives:

(The terminology of this section is derived from Eastman et al, (1995)).

– alternative actions, hypotheses, locations, and so on. As such, the decision process is essentially a problem of set membership – does an alternative belong to the set to be chosen? The decision itself is based upon an evaluation of the attributes these alternatives possess. Based on these attributes a set of criteria is established.

Some of these criteria act as constaints that serve to limit the alternatives that may be considered. As such they are boolean in character. For example, it might be decided that all lands that are classified as forest must be excluded from consideration for industrial development.

Other criteria, however, are more continuous in character, and are commonly called factors. Thus, for example, we might decide that proximity to paved roads is an important factor in deciding whether land will be suitable for industrial development, the closer the better. Here, the decision about whether a location does or does not belong

to the chosen set is not an all-or-none proposition – it requires that some threshold of suitability be set. For example, all locations within a half kilometre of a paved road are suitable. The process of defining the criteria to be considered and the classes or thresholds which are indicative of the chosen set can be seen as the process of defining a decision rule. Some decision rules rely upon a single criterion. However, the majority require consideration of a group of criteria. One of the critical aspects of Multi-Criteria Evaluation (MCE) thus concerns the manner in which the criteria are combined into a single statement of set membership.

The manner in which a decision rule is constructed is guided partly by knowledge and partly by one's perspective or objective in making the decision – particularly in the choice of criteria to be evaluated and their weight in the decision rule developed. While most decisions involve only a single objective, some require consideration of multiple objectives

SOURCES OF UNCERTAINTY IN THE DECISION MAKING PROCESS

Considering the decision making process as a set membership problem is a useful perspective from which to understand the role of uncertainty in the decision making process. The decision process contains three basic elements within which uncertainty can occur – evidence, the decision set, and a relation that associates the two .

EVIDENCE

The measured attributes of alternatives constitute evidence by which set membership is determined. Thus to decide which areas would be inundated by a global rise in sea level, one might collect elevation data – evidence from which the decision can be made.

Clearly this is a major potential source of uncertainty, since all measurements are subject to error.

THE RELATION

The second basic element of a decision is the specification of the relationship between the evidence and the decision set. Uncertainty arises here from at least three sources.

1. The first is in cases where the "definition" of a criterion (as opposed to its measurement) is subject to uncertainty. Sets with clearly defined attributes are known as "crisp" sets and are subject to the logic of classical sets. Thus, for example, the set of areas that would be inundated by a rise in sea level is clearly defined. Disregarding measurement error, if an area is lower than the projected level of the sea, it is unambiguously a member of the set. However, not all sets are so clearly defined. Consider, for example, the set of areas with steep slopes. What constitutes a steep slope? If we specify that a slope is steep if it has a gradient of 10% or more, does this mean that a slope of 9.99999% is not steep? Clearly there is no sharp boundary here. Such sets are called "fuzzy" sets (Zadeh, 1965) and are typically defined by a set membership function. Although recognition of the concept of fuzzy sets is somewhat new in GIS, it

is increasing clear that such sets are prevalent (if not dominant) in land allocation decisions.

2. The second case where uncertainty arises is in cases where the evidence does not directly and perfectly imply the decision set under consideration. In the examples of inundated lands or steep slopes, there is a direct relationship between the evidence and the set under consideration. However, there are also cases where only indirect and imperfect evidence can be cited. For example, we may have knowledge that water bodies absorb infrared radiation. Thus we might use the evidence of low infrared reflectance in a remotely sensed image as a statement of the belief that the area is occupied by open water. However, this is only a belief since other materials also absorb infrared.

Statements of belief in the degree to which evidence implies set membership are very similar in character to fuzzy set membership functions. However, they are not definitions of the set itself, but simply statements of the degree to which the evidence suggests the presence of the set (however defined). Thus the logic of fuzzy sets is not appropriate here, but rather, that of “Bayes” and “Dempster-Shafer” theory.

3. The third area where uncertainty can occur in specifying the relation between the evidence and the decision set is most often called “model specification error” In some instances, decisions may be based on a single criterion, but commonly several criteria are required to define the decision set. Thus, for example, one might define areas suitable for development as being those on shallow slopes and near to roads. Two issues here would be of concern: are these criteria adequate to define suitable areas, and have we properly aggregated the evidence from these criteria? If membership in the set of shallow slopes is 0.6 and proximity to roads is 0.7, what is the membership in the decision set? Is it the 0.42 of probabilities, the 0.6 of fuzzy sets, the 0.78 of Bayes, the 0.88 of Dempster-Shafer, or the 0.65 of linear combination? Further, how well does this aggregated value truely predict the degree to which the alternative under consideration truely belongs to the decision set? Clearly the construction of the decision rule can have an enormous impact on the set membership value deduced.

THE DECISION SET

The final area of concern with respect to uncertainty in the decision process concerns the final set deduced. The process of developing the decision set consists of converting the evidence for each criterion into an elementary set statement, and then aggregating those statements into a single outcome that incorporates all of the criteria considered. Clearly, uncertainty here is some aggregate of the uncertainties which arose in acquiring the evidence and in specifying the relationship between that evidence and the decision set. However, in the presence of uncertainty about the degree to which any candidate belongs to the final set (as a result of the evidence gathered or its implications about set membership), some further action is required in order to develop the final set – a threshold of uncertainty will need to be established to establish which alternatives will be judged to belong to the decision set. To do so thus logically implies some likelihood that the decision made will be wrong – a concept that can best be described as “decision risk”. For example, given a group of locations for which the likelihood of being below a projected new sea level has been assessed, the final decision about which locations will be assumed to ultimately flood will be solved by establishing a threshold of likelihood. Clearly this threshold is best set in the context of decision risk – the likelihood that the decision made will be wrong.

IMPLICATIONS FOR SOFTWARE DEVELOPMENT

Over the past few years, the IDRISI Project has been striving to develop a suite of tools for land allocation decision problems (Eastman, and Jiang, 1996; Eastman, 1996, 1993; Eastman et al., 1995, 1993). The primary areas of concentration have been in the mechanics of multi-criteria and multi-objective decision making. However, as can be seen from these considerations, there is likely to be substantial uncertainty in the outcome from any such process. As a consequence, we have been striving to add a series of software modules that permit the management of uncertainty and its accommodation in the decision process. A number of these routines were available as part of the Decision Support group in the first release of the IDRISI for Windows software. However, Version 2 of that software, scheduled for release in late 1996, has a special emphasis on providing tools for uncertainty management, as will be noted in this review.

ERROR ASSESSMENT AND PROPAGATION

Following the logic set out above, it is clear that the first step in uncertainty management is the ability to assess measurement error associated with evidence and its subsequent propagation through an decision rule that might be developed. While systematic error might be assessed on theoretical grounds (such as that which arises from the projection process), random measurement error is usually assessed on the basis of re-measurement at a sample of locations. To facilitate the development of the sample, the software include the SAMPLE module that permits the determination of spatial sample points according to random, systematic or stratified random schemes. Once the test measurements have been made, error can either be characterized by means of database query and statistical modelling. This is easily done in the case of quantitative data using the EXTRACT query and statistical reporting tool. However, for qualitative data the procedure requires the analysis of an error matrix that is facilitated by use of the ERRMAT routine.

Once an assessment of error has been made, the next problem is that of propagating the error through the decision rule. While a small number of propagation formulas have been developed for very simple mathematical operations in GIS (see Burrough, 1986), none have been developed for the extensive range of mathematical and algorithmic operations that are typically encountered in GIS. As a consequence, we have chosen to provide the tools for “Monte Carlo Simulation” as an alternative approach to the assessment of error propagation (Heuvelink, 1993). Using the RANDOM module, the user can developed simulated error fields according to a group of common distribution models. These are then added into the appropriate input layers to allow the effects of that error to be assessed

(Normally, Monte Carlo Simulation requires that a large number of runs be used in order to derive an adequate sample for the statistical assessment of propagation error. However, in cases where each pixel can be assumed to be an independent trial, the many pixels of a single run can be used instead.)

The technique is simple and highly effective while maintaining generality to any analytical procedure that might be used. With Version 2 we have added the ability to define the source distribution independently for each pixel and we are currently wor-

king on a procedure that will allow simulation of spatially dependent error for a future release.

EXPRESSING SET MEMBERSHIP IN THE PRESENCE OF MEASUREMENT ERROR

As outlined above, the decision process initially requires that the evidence for each of the criteria considered be converted into an elementary statement of set membership – i.e., of whether each area belongs in the decision set or not on the basis of that specific criterion. When criteria are treated as crisp set functions, evidence is reclassified into boolean images of areas suitable for the decision under consideration. For example if we wish to identify residential areas subject to flooding as a result of a sea level rise, our first step would be to create a boolean image of areas below the projected level of the sea, and a second showing all areas occupied by a residential land use. However, in the presence of measurement error, these boolean images would be replaced by probability images. Thus, for example, the boolean image of inundated areas would be replaced with an image of the probability of being flooded and the boolean image of residential areas would be replaced by an image of the likelihood that the area is residential. In the case of qualitative data (such as the land use example here), this can be achieved with a simple reassignment of values. However, for quantitative data (such as the elevation data used to determine areas sucbject to inundation) a special software component is required.

In the IDRISI software system, the conversion of quantitative data to a probabilistic statement of set membership is achieved with the PCLASS module. PCLASS assumes a random model of measurement error, characterized by a Root Mean Square (RMS) error statement. In the IDRISI system, the metadata for each raster image contains a field where error in the attribute values can be stated, either as an RMS for quantitative data, or as a proportionl error for quantitative data. PCLASS uses the RMS recorded for a quantitative image to evaluate the probability that each value in the image lies either above or below a specified threshold. It does so by measuring the area delineated by that threshold under a normal curve with a standard deviation equal to the RMS . The result is a probability map, expressing the likelihood that each area belongs to the decision set (areas below the threshold of the new level of the sea).

EXPRESSING SET MEMBERSHIP IN THE PRESENCE OF CONCEPTUAL UNCERTAINTY

While measurement error is an important component of uncertainty management, the discussion earlier would suggest that a significant concern for uncertainty management is the conceptual uncertainty that arises from establishing the relationship between evidence and the decision set. This is particularly important in a context where the subjective opinions of experts or local community groups need to be accommodated in the decision process.

The key module for the implementation of set membership functions in IDRISI is the FUZZY module – a software component designed for the implementation of “fuzzy measures”. The term “fuzzy measure” refers to any set function which is monotonic with respect to set membership . Notable examples of fuzzy measures include “probabilities”, the “beliefs”and “plausibilities” of Dempster-Shafer theory, and the “possibilities” of fuzzy sets. The FUZZY module is specifically intended for use in those cases

where only a subjective definition of set membership is feasible, and can generate membership grades for each pixel based on the parameters set for a selection of prototypical set membership forms (linear, j-shaped and sigmoidal). Depending upon the context, the result may then be treated as an image of Fuzzy Set membership grades, or as Bayesian or Dempster-Shafer beliefs. In Version 2, the flexibility of FUZZY has been enhanced by allowing the output of non-normalized membership functions and the use of user-defined membership functions.

Interestingly, the development of fuzzified set membership statements is not new to GIS. Traditionally, this process has been called "standardization" with the predominant approach being to linearly transform variables to a [0-1] interval. Subsequent aggregation of standardized variables thus uses data with a common numeric basis. However, it has been widely recognized that a theoretical logic for the process of standardization has been lacking (Voogd, 1983; Eastman et al., 1993). But as noted by Eastman and Jiang (1996), if we consider the process of standardization to be one of transforming criterion scores into set membership statements, then standardized criteria are, by definition, fuzzy measures.

In a typical application of the FUZZY standardization procedure, the decision group first comes to an agreement about the shape of the set membership function. Then a decision is made about the minimum and maximum set membership values that can occur, followed by the critical values at which the curve changes shape. For example, a group might decide that an access factor is best described by proximity to roads. They might then decide that the factor smoothly approaches its limits, leading to a sigmoidal set membership function. They then might decide that suitability immediately falls off as distance from the road increases, reaching a limit at 2 km where the suitability is effectively zero. Such a set membership function is easily implemented using the FUZZY module.

EXPRESSING SET MEMBERSHIP IN THE CONTEXT OF INDIRECT EVIDENCE

As indicated above, the FUZZY module can be used to construct any Fuzzy Measure. Thus is is just as likely to be used in th context of expressing set membership in the context of indirect evidence as it is for true fuzzy sets. For example, one might believe that the farther one is away from permanent water, the less likely it would be to find an archaeological settlement. The set here is not ambiguous – either one exists or it does not. However, the relationship between distance from permanent water and the likelihood of a settlement is uncertain. The evidence here is indirect – there is a relationship, but not one that is certain. When subjective expertise is used to express such relationships, the FUZZY module is often well suited.

Although subjective expertise is very important in many participatory decision contexts, empirical evidence is also an important ingredient to the decision process. In Version 2 of IDRISI three new modules have been added to support the use of empirical evidence in substantiating and specifying indirect relationships. The first two are related – a multiple regression and a logistic regression procedure, both extending the simple regression procedure that has long been a part of the IDRISI system. Logistic regression has special significance in the context of boolean sets – it is specifically designed to establish the relationship between dichotomous dependent variables (e.g., sets) and a combination of quantitative and qualitative variables.

The third procedure for establishing the relationship between set membership and indirect evidence is one which is related to the problem of image classification in Remote Sensing. Perhaps the most commonly used procedure for classification of

remotely sensed imagey is the “maximum likelihood” procedure where samples of multi-spectral imagery for each cover class are used to develop multivariate normal probability models for each cover type. Software programs, such as the MAXLIKE module in IDRISI, are then used to assess the most likely interpretation for each pixel in an image based on its multi-spectal response pattern. However, the procedure typically does not evaluate the underlying Bayesian posterior probability, but rather, a monotonically related value that is more efficiently computed, and which allows a consistent choice between the alternatives being considered. However, for the purpose of accommodating non-spectral data, and the wide range of aggregation operators that are now becoming available (see below), we felt that it would be desirable to allow the full computation of posterior probabilities for each cover type. As a consequence, we are releasing with Version 2, a module named BAYECLAS that calculates the posterior probability of each covertype given the signature data provided.

The output from BAYECLAS can be very useful in monitoring the quality of the information from which a maximum likelihood classifier makes its decisions. For example, it can show quite directly the strength of the signature data in establishing the class of individual pixels. In addition, by decomposing the decision process into its individual components, it offers the prospect of merging these components with other information to achieve a stronger classification. However, Bayesian posterior probabilities do not directly address the issue of confusion between classes, such as that which arises from the presence of mixed pixels. Rather, it must be inferred from the fact that a pixel is assigned a non-zero probability of belonging to more than one class. As a consequence, the BAYECLAS module also outputs a “commitment” image expressing the degree of commitment to the maximum likelihood class .

In essence, the BAYECLAS module represents a form of “soft” classifier – soft in the sense that no hard decision is made, but rather, the degree of membership in each of the candidate sets is expressed. Version 2 also offers a second soft classifer based on a fuzzy set logic – FUZZCLAS, with similar outputs based on the distance of a pixel’s position in band space relative to the mean position of each of the signature classes being considered.

AGGREGATION OPERATORS

Unquestionably the area in which the greatest development has occurred with Version 2 is in the provision of aggregation operators. Aggregation of evidence is the very essence of Multi-Criteria Evaluation. However, the manner of aggregation varies in the context of uncertainty. As a consequence, a range of aggregation operators is needed.

AGGREGATION WITH MEASUREMENT ERROR

When criteria are treated as crisp (boolean), aggregation of evidence is achieved most typically with an intersection (logical AND) operator, but also sometimes with a union (logical OR) operator. The former is a very hard form of aggregation in that every criterion must be met for an area to be included in the final decision set, whereas the latter is a very lenient form of aggregation in that only one of the criteria needs to be met. In the presence of measurement error, these booelan statements are replaced with probabilistic statements (such as is produced from the PCLASS module). However, the basic aggregation operators remain the same – multiplication for the intersection operator and addition minus the intersection for the union operator .

AGGREGATION OF INDIRECT EVIDENCE

When criteria express conceptual uncertainty, a new set of aggregation operators is required. In the case of an indirect relationship between evidence and the decision set, two procedures have been provided – the BAYES and DEMPSTER modules. The former implements Bayes' Theorum for the aggregation of evidence:

$$p(i|x) = p(x|i) * p(i) / p(x) \quad \text{where} \quad x = \text{evidence and } i = \text{an hypothesis (the decision set)}$$

Here, new evidence is merged with prior information to develop a new statement of the probability that the hypothesis in question is true. Prior to Version 2, the BAYES module was only designed for the evaluation of dichotomous hypotheses. However with this release, multiple hypotheses are permitted.

With BAYES, lack of evidence for an hypothesis constitutes, by definition, evidence against that hypothesis. However, it is often the case that this is simply not appropriate. For example, in establishing the range and habitat for a bird species, evidence in the form of sightings might be used. However, the lack of sitings in an area may not constitute evidence against the presence of the species. It may be simply that conditions were not conducive to making a siting (e.g., perhaps the location was very far from a road or path). In cases such as this, a variant of Bayesian probability theory known as "Dempster-Shafer" theory is appropriate (Gordon and Shortliffe, 1985; Srinivasan and Richards, 1990).

Using the new IDRISI module named DEMPSTER, new evidence can be aggregated with existing information either as beliefs or disbeliefs in any of a set of hypotheses, including the basic classes and all their hierarchical combinations. Beliefs and disbeliefs are both expressed as probabilities. As a result of folding in this new information, inquiries can be made about any of these hypotheses in the form of three different types of output image – belief in the hypothesis, the plausibility of the hypothesis and ignorance concerning the hypothesis. Plausibility constitutes the degree to which the hypothesis cannot be disbelieved (i.e., 1 - disbelief), while ignorance represents the difference between the belief and disbelief. For example, consider the problem of estimating where an archaeological site of a particular culture might be found. Three lines of evidence are used in this illustration . The first is derived from a map of distances from existing sites of the same group. Based on the logic that one could believe the likelihood would be higher if other sites were present in the vicinity, the FUZZY module is used to transform this distance map into an image of belief. Although experience might be an adequate guide in doing so, the actual procedure used here was to develop a histogram of the frequency of distances between sites. This was then used to select the shape and critical inflection points of the belief function developed.

The second line of evidence is concerned with distance from permanent water. The location of this study is the arid Southwest of the United States. Water would thus represent a limiting factor on permanent human occupation. Again a histogram is used to develop the shape and parameters of the belief function. However, in this case what needs to be developed is a disbelief image. If one were near to water, there would be no reason to believe that a site would in fact be present. However, if one were far from water, there would be strong reason to disbelieve that one would "not" be present. Thus the output from the FUZZY module expresses low disbelief near to water and progressively higher disbelief as one moves away .

The third line of evidence concerns slope. Again, information from existing sites is used to determine the limiting slopes of settlement. This is then used to develop yet another disbelief image – i.e., disbelief in the possibility of finding a settlement because the slope is too high.

Once these belief and disbelief images have been produced, the DEMPSTER module is used to combine them into a single body of knowledge about the likelihood of finding an archaeological site. From this, separate belief, disbelief and ignorance images can be generated for the hypothesis that an archaeological site would be found. Several features are of particular interest in these images. First, in developing the evidence for this study only half of the existing sites were used. The other half were set aside as a control. These control sites are plotted to gauge the predictive capabilities of the model produced. Second, it is interesting to see that the igorance level is highest in those cases where belief is low but plausibility is high. In this illustration, plausibility expresses the degree to which the conditions are right for a site to exist. Thus areas of high ignorance and high plausibility are those where we would profit most from gathering new information. The Dempster-Shafer procedure thus tells us not only about the information we have, but also about the information that we do not have. As a consequence, we have a very direct sense of the value of information as we continue our quest.

AGGREGATION OF FUZZY SETS

The third area where uncertainty calls for a different aggregation operator is in the case of Fuzzy Sets. As indicated earlier the standardized criteria of Multi-Criteria Evaluation, when considered in the context of set membership, are, by definition, Fuzzy Measures. Indeed, it has been argued (Eastman and Jiang, 1996) that they can in fact be considered as statements of membership in Fuzzy Sets. For example, consider the case of where one of the criteria for establishing suitability for industrial development is proximity to roads. The closer to a road one is, clearly the more suitable the land (up to a limit – the actual membership function would most likely be sigmoidal, approaching 0 at some distance beyond which it would be unreasonable to build a connecting road). However, there is no crisp threshold between suitable and unsuitable areas. The transition in fuzzy. The normal aggregation operators for the intersection and union of fuzzy sets are the “minimum” and “maximum” functions respectively. However, Multi-Criteria Evaluation of continuous criteria in GIS is almost universally undertaken by means of a “weighted linear combination” (i.e., the standardized criteria are each multiplied by a weight to signify their importance to the solution, with the results being summed to determine the aggregate suitability for each location). As it turns out, the averaging process constitutes neither an intersection nor a union operator (Bonissone and Decker, 1986). Rather, it has been determined to fall midway between the extremes of a family of Fuzzy Measure intersection and union operators (known as “T-Norms” and “T-CoNorms” respectively) of which the most extreme representatives are the minimum and maximum operators of fuzzy sets (Eastman and Jiang, 1986). Thus the familiar weighted linear combination operation such as is found in the MCE module of IDRISI (Figure 13) constitutes neither an AND nor an OR operation, but rather, one that lies halfway in between – in essence an ANDOR operator (Yager, 1988). It possesses neither the extreme risk aversion of strict intersection (where every condition must be met), nor the risk acceptance of strict union (where only one condition must be met). In addition, it possesses the important quality of tradeoff that neither the minimum and maximum functions possess. Thus with weighted linear combination, one poor quality can be balanced by one or more good qualities.

This is not the case with Fuzzy intersection, where the aggregate quality is determined to be the minimum of the criteria considered, or Fuzzy union where the best quality is taken to represent the final result.

In common experience of multi-criteria decision problems, all of these options seem appropriate. In some cases tradeoff between criteria seems appropriate (such as in the aggregation of cost factors), and in some cases it does not (such as with personal risk factors). Similarly, in some cases one is concerned with the presence of limiting factors, for which a strict AND is appropriate while in other cases one is more concerned with establishing the highest potential (where the union operator would more likely be used). However, there is little doubt that the less extreme perspective of weighted linear combination often serves well in balancing the many issues considered in reaching the decision being considered. It was thus with considerable interest that we explored the application of a new module based on Yager's (1988) concept of an "Ordered Weighted Average".

This new aggregation operator (named OWA in IDRISI) is similar to the logic of the weighted linear combination operator, except that it employes two sets of weights (Figure 14). The first is the same as is traditionally used in weighted linear combination to establish the relative contribution of each factor to the solution achieved. However, the second set of weights controls the manner in which these weighted factors are aggregated (Eastman and Jiang, 1996). By varing these weights a continuum of aggregation operators can be produced, including, but not limited to, the minimum and maximum operators of Fuzzy Sets and the familiar averaging operator of weighted linear combination, spanning the dimensions of ANDORness and tradeoff between factors in the aggregation of decision criteria.

What is particularly interesting about the OWA module is the continuum of aggregation procedures it provides. At one extreme, criteria are considered as necessary (but not sufficient) conditions for inclusion in the decision set – the hard intersection (logical AND) operator provided by the minimum. As a consequence, the criteria are really being treated as constraints, althought the fact that they may be continuous in character yields a "fuzzy" or "soft" constraint. At the other extreme (the union operator), each criterion is treated as sufficient on its own to support inclusion in the decision set without modification by other factors. Thus the level of support for inclusion in the decision set is equal to the maximum support offered by the criteria considered. The position of the traditional weighted linear combination operator half way between these extremes is thus 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 perfect tradeoff. However, it is interesting to note that the OWA procedure offers not only a continuum of possibilities between these cases, but also, possibilities that suggest that the control is essentially two-dimensional in character . For example, a median operator is easily implemented which offers an equally intermediate position of ANDORness to that of weighted linear combination, but in this case there is no tradeoff.

RISK ASSESSMENT

As indicated earlier, to make a decision in the context of uncertainty implies some risk that the decision made will be wrong. In the context of measurement error, it is a fairly simple matter to relate this error to decision risk. As indicated earlier, the PCLASS module achieves this quite well by computing the area under the normal curve subtended by a decision threshold to determine what could be termed a Type 2

risk – the risk that the threshold would be exceeded if we were to assume that it would not . However, as we move from the strong frequentist interpretation of probability associated with measurement error, to the more indirect relationship of Bayesian and Dempster-Shafer beliefs, to the quite independently established concept of Fuzzy Sets, we move further and further away from the ability to be be able to establish risk in any absolute sense (Eastman, 1996). Indeed with a decision based on Fuzzy Sets, we can establish that the inclusion of an alternative is less risky than another, but not what the actual risk. Thus instead of calculating absolute risk, we need to be able to establish relative risk.

The concept of relative risk is one that is quite familiar. For example, in evaluating a group of candidates for employment, we might examine a number of quantifiable criteria – grades, rating charts, years of experience, etc., – that can permit the candidates to be ranked. We then attempt to hire the best ranked individuals on the assumption that they will perform well. However, there is no absolute scale by which to understand the likelihood that they will achieve the goals we set. In a similar manner, the RANK module in IDRISI can be used to rank the suitabilities achieved through a multi-criteria aggregation procedure. This result can then be divided by the maximum rank to produce an image of relative risk.. This result can then be thresholded to extract a specific percentage of the best (i.e., least risky) solutions available. The importance of this solution is that it can be applied to any decision surface regardless of the nature of the uncertainties involved.

IMPLICATIONS FOR THE ROLE OF UNCERTAINTY MANAGEMENT

Clearly the many forms of uncertainty the pervade the decision process have had strong implications for the development of decision support software. However, the availability of such programs also has implications for the role of uncertainty management in mainstram environmental decision making. In a cyclic fashion, however, these in turn have further implications for the course of software development.

The first implication concerns the use of expert and local knowledge in the decision making process. More often than not, local stakeholders hold a form of expert knowledge that is invaluable in the decision making process. They have insights into which criteria are relevant to the decision under consideration and the relative weight they should be assigned. They also have insights into the degree to which they can trade off attributes in the aggregation process and the strictness of the aggregation procedure that should be used. Furthermore, they have important insights into the levels of risk that are acceptable in the final solution that is reached. Given the many tools now becoming available for incorporating these perspectives, it there any reason not to include them more explicitly in the decision process? That such perspectives might be expressed as “beliefs” or inexact (i.e., “fuzzy”) parameters clearly does not present a methodological problem. The only significant issue is the process of developing those local perspectives in an efficient and quantifiable manner; although here too software can help. Consensus focussing tools such as the WEIGHT procedure in IDRISI based on Saaty’s pairwise comparison technique, can greatly facilitate the process of working with decision groups to develop a commonly agreed upon set of numeric parameters.

A second, and major, implication of these developments is that there is increasingly little justification for the development of decisions without some assessment of the decision risk involved. It would not be inappropriate to ask that any analysis that is

used to support a public decision be required to assess the total uncertainty budget of the procedure used to arrive at the decision. In some cases, very exacting assessments may be available, However, in the absense of this, one of the simplest and most effective techniques for uncertainty assessment is "sensitivity analysis". In this very simple procedure, high and low estimates (e.g., 90% and 10% subjective probability estimates) are made of each significant parameter that enters into the decision process. These are then systematically varied to produce a set of different runs of the analysis. The results can then be ranked and quantified in terms of their effect on the outcome to determine parameters that are particularly sensitive and for which uncertainties should be reduced by further data gathering. For any decision based upon these results, a map can also be generated of the proportion of cases in which each location was included in the decision set. This can then be used to develop a quantitative and very tangible sense of risk. The procedure here is not difficult. However, the amount of work involved is substantial since the number of runs required increases exponentially with the number of parameters considered. For example, the evaluation of a simple weighted linear combination with eight factors in which both the weights and the standardizations are varied can produce over 65,000 solutions. Such a brute force solution can be avoided if such uncertainties can be parameterized and propagated to the solution. However, with current computing power, a typical analytical run might take only a few seconds. If a higher order metaprogram could be created to systematically vary the parameters. execute the runs as a macro, and tabulate the results, many decision problems that could not be readily parameterized for uncertainty could be automatically assessed through sensitivity analysis given only limited involvement of the analyst and decision group.

Finally, it should be recognized that the many issues that have been raised in this review present a very complex set of considerations for the resource manager faced with uncertainty management in the decision process. At this stage, our purpose has been to explicate the many issues involved and to develop the low level tools that permit a reasoned management of the total uncertainty budget. However, it is clear that a set of higher-order navigation tools are required to steer the manager through the many procedures and issues involved. Given examples of such decision support tools (or "wizards" as they are sometimes called) in general office software suites, it is fair to say that such products are in their infancy. However, the scope for similar navigation tools in GIS is considerable, particularly in the context of uncertainty management and decision support.

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