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Decision-making in environmental management is complex due to the multiplicity and diversity of management objectives and technological choices. This suggests that modelers and experts could utilize (1) multiple-criteria decision-making (MCDM) approaches to assist stakeholder groups in integrating and synthesizing relevant data and information to address ecological and socio-economic concerns and (2) uncertainty approaches to quantify the risks related to the impact of decision alternatives. Since decisions made under uncertainty and MCDM methods have been studied almost independently, most of the MCDM approaches do not address the uncertainties of real world decision situations.

This dissertation presents the use of a MCDM methodology and its related decision-making tool, RESTORE. RESTORE is an integrative geographical information system-based decision-making tool that was developed to help watershed councils prioritize and evaluate restoration activities at the watershed level. RESTORE's deterministic performance evaluation module is developed from experts' knowledge and experiences. However, to fully address the complexity of the various landscape processes and human subjectivity, RESTORE should involve uncertainties inherent to experts' knowledge. No single method is able to model all types of uncertainty, therefore the examination of various uncertainty theories is critical before selecting one best suited to a specific decision context. This work explores three uncertainty theories: certainty factor model, Dempster-

Shafer theory, and fuzzy set theory. To evaluate these methods in a MCDM watershed restoration context, we (1) identified criteria to assess the suitability of a method for a specific MCDM context, (2) characterized each theory in terms of the identified criteria using RESTORE, and (3) applied each theory using RESTORE. Special emphasis was given to the development of a comprehensive fuzzy MCDM methodology.

Uncertainty-based MCDM approaches provide a valuable tool in analyzing complex watershed management issues. When used properly, the proposed MCDM methodology allows decision-makers (DMs) to explore a broader range of drivers and consequences. The inclusion of uncertainty analysis provides DMs with meaningful information on the quality of the evidence supporting the impact of a decision alternative, allowing them to make more informed decisions.

Development and Evaluation of Multiple Criteria Decision-Making Approaches to Watershed Management

by
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France Lamy, Author

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John P. Bolte was the key investigator responsible for the development and implementation of the decision support system RESTORE. John P. Bolte and Jian-Bo Yang provided many useful suggestions for the development of multiplecriteria and uncertainty approaches.

Mary Santelmann and Court Smith provided useful comments in reviewing manuscripts.

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CHAPTER 1

GENERAL INTRODUCTION

Nowadays, most environmental decision-making bodies must use a decision process that is consistent, open, and transparent to ensure that sound and high quality decisions are made in accordance with the various and often conflicting decision-makers (DMs') objectives. In Oregon, Watershed Councils offer a good example. Their mission is to involve the local population in a consultation and decision process toward the design of watershed management plans that meet the objectives of their members. Such decision-making contexts typically contend with the following challenges (Janssen, 1992): (1) consideration of a variety of often conflicting management objectives representative of stakeholders' multiple interests, (2) understanding of ecosystem processes and functions within a socio-economic context, (3) multiple and diverse technological choices for restoration, (4) qualitative and quantitative evaluation criteria, (5) inability to provide exact assessment of alternatives which may originate from uncertainty in experts' knowledge and/or data errors, and (6) need of transparent and quantitative methods for evaluating and selecting restoration options.

Because of these difficulties, uncertainty is almost always present in the decision process. Consequently, experts may have difficulty to evaluate and distinguish between decision alternatives with respect to their ability at addressing multiple DMs' objectives. Most watershed management decision-making situations suggest that modelers and experts could utilize (1) multiple-criteria decision-making (MCDM[1]) approaches to assist

[1] In this contribution MCDM can be distinguished from Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM). In a MODM method, such as the one presented in Chapter 2, decision alternatives are not predetermined, a mathematical algorithm is used for selecting the decision alternatives. Each decision alternative, once identified, is judged against its ability at meeting DMs' objectives. A MADM approach entails that the selection of a decision alternative is made among predetermined decision alternatives using attribute as criteria (Hwang and Yoon, 1981). Proposed MCDM ranking methods presented in Chapter 3 and 4 can also be seen as MADM methods.

stakeholder groups in integrating and synthesizing relevant data and information, and in addressing ecological, economic, and sociological concerns (Salminen et al., 1998) and (2) uncertainty approaches to quantify the risks related to the impact of decisions alternatives, allowing DMs to make more informed decisions.

MCDM methods offer a structured approach, in which decision-making is a process-oriented activity that must be able to deal with qualitative, quantitative, and uncertain information. However, decisions under uncertainty and MCDM methods have been studied almost independently (Dubois et al., 2000). A lot of efforts have been put on knowledge capture and inference, yet uncertainty assessments are the most poorly understood and implemented in nearly all decision-support systems (DSSs) and more specifically in MCDM-based DSSs. Decision-making approaches that include uncertainty analysis can be seen as more credible approaches since they recognize that uncertainty occurs at many points in the modeling process (e.g. models assumptions, parameters, experts' knowledge, system definitions). Additionally, uncertainty analysis provides critical information to DMs about the quality of the evidence supporting the impacts of a decision alternative.

To assist watershed councils to prioritize and evaluate restoration activities both at the site and the watershed scales, RESTORE, a spatially-explicit DSS was developed. RESTORE uses MCDM methods, knowledge base, evaluative models, and geographical information system resources. It includes a rule-based system that models the experts' perception of restoration options performance at meeting DMs' multiple objectives. Objectives considered include water quality, water storage, habitat quality, social concerns, and economics that often conflict. A deterministic MCDM performance evaluation leads to the ranking of restoration alternatives that are used as building blocks for the design of watershed restoration plans. Rankings, which reflect restoration alternatives impacts on the

objectives described above, are determined through the application of a set of rules developed from experts' knowledge and experience. However, the complexity of the various landscape processes and human subjectivity suggest that a robust performance evaluation module would involve the modeling of the inherent uncertainties in experts' knowledge, including partial belief, conflicting evidence, ignorance, and/or ambiguity.

This dissertation endeavors to address these issues. Chapter 2 presents the use of a multiple-objective decision-making methodology and its related tool, RESTORE.

Chapter 3 aims to (1) describe each step of a proposed fuzzy MCDM approach using RESTORE, (2) characterize the types of uncertainty in experts' knowledge that the approach could address, (3) introduce a novel ranking method for fuzzy performance evaluation, and (4) evaluate the ability of the approach at exploiting the knowledge provided by DMs and experts. The ranking method is based on a MCDM algorithm that captures the properties of the fuzzy solutions through seven decision variables combined into four criteria: (1) expected performance of the restoration option at meeting DMs' objectives, (2) vagueness of the expected performance, (3) ambiguity of the expected performance, and (4) accumulation of evidence.

Chapter 4 explores the use of uncertainty assessments in the RESTORE decision-making process, three uncertainty theories are investigated: (1) certainty factors model, (2) Dempster-Shafer theory, and (3) fuzzy set theory. To facilitate the evaluation of the utility of these three methods in a MCDM watershed restoration context, we (1) examine the basic mechanisms for reasoning under uncertainty advocated by each theory, (2) identify criteria to assess the suitability of a theory for a specific MCDM context, (3) characterize each theory in terms of the identified criteria using RESTORE, and (4) apply each theory using RESTORE. Decision-making issues in the certainty factors model and the Dempster-

Shafer theory frameworks have not been much investigated in the literature (Dubois et al., 1996). To address this gap, new avenues for ranking decision alternatives are proposed.

Chapter 5 concludes with a brief summary and suggestions for future research.

CHAPTER 2

DEVELOPMENT AND EVALUATION OF MULTIPLE OBJECTIVE DECISION-MAKING METHODS FOR WATERSHED MANAGEMENT PLANNING

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2.1 INTRODUCTION

Human-dominated land uses have resulted in extensive loss, fragmentation, and degradation of natural habitats (Freemark 1995; Vitousek et al. 1997). As an example, in the two hundred years after 1780, the United States lost more than half of its wetlands. These losses can be attributed to many causes (Dahl, 1990; Johnson, 1994). Fresh water is becoming increasingly limited in many parts of the world as industry, expanding cities, and agriculture compete for limited supplies. The stress on the environment can lead to a decline in biodiversity, disrupting the balance of natural ecosystems, and ultimately threaten the foundation on which all living organisms depend (Gliessman, 1990; Naeem et al. 1994, Sala et al. 2000). A growing awareness of the environmental impacts of human development activities resulted in the concept of sustainable development as a general development policy (Janssen, 1992; ASCE, 1998). The Brundtland Commission's report (WCED, 1987) offers this characterization:

> *"Development is sustainable if it satisfies present needs without compromising the ability of future generations to meet their own needs."*

Managing natural resources in a sustainable way and in observance of environmental regulations dictates considering the variety of management objectives and management practices that are most appropriate to achieve these objectives (Kangas and Pukkala 1996; Nijkamp and van der Bergh, 1997). Objectives may refer to biodiversity, water quality, water storage, habitat quality, social, and economic issues, which often conflict. One approach to reconcile these conflicts lies in a systems approach to land use planning. Such an approach combines information from hydrologists, agronomists, economists, sociologists, communities, farmers, landowners, and other sources (Jensen et al., 1996; Santelmann et al. 2001). In Oregon, an example is a watershed council that addresses conflicting values using an ecosystem approach to management at the local scale. Councils

involve local people in a consultation process intended to yield a watershed management plan that meets community objectives. Social scientists have shown that effective natural resource management is community-based and includes participation of stakeholders such as landowners and other resource users (Western and Wright, 1994; USEPA/OWOW, 1997; Marriot et al., 1999).

Since watershed councils are quite new, they form a useful test for assessing the utility of decision-making approaches. Many watershed councils have completed a process to assess the conditions in their watershed. The purpose of these assessments is to prioritize problems and identify areas for restoration activities. To date, councils have identified restoration projects opportunistically. Leadership, funds, a cooperating landowner, and ease of getting permits typify the selection of projects. However, the watershed assessment processes have demonstrated the benefits of a more holistic approach to restoration planning. Consequently, councils identified a need for tools integrating scientific and technical knowledge for prioritizing actions. These tools should assist the decision-makers (DMs) in selecting restoration options at the site level that satisfy watershed level ecological and socio-economic goals.

Evaluating efficacy of restoration activities at addressing restoration goals and setting priorities are complex tasks. They require an understanding of ecosystem processes and functions in the context of the landscape and restoration option characteristics. The reality of most decision-making situations suggests that modelers and experts could utilize multiple-objective decision-making (MODM) tools to assist community groups, integrate and synthesize their knowledge, and address concerns relating to ecological, economic, and sociological issues (Karacapilidis et al., 1997; Moreno-Jiménez et al., 1999; ReVelle, 2000). Without such tools, DMs and stakeholder groups will have difficulty integrating

multiple objectives into watershed-level plans for restoration and cannot realistically assess the potential success of restoration strategies to meet watershed restoration objectives (Moualek, 1997; Stam et al., 1998; Crist et al., 2000).

We describe the development of the RESTORE decision support system (DSS); a tool designed to assist stakeholders and DMs in watershed restoration planning and prioritization. The DSS was developed with two watershed councils, from Oregon's Willamette Valley. This paper presents the rationale for integrating the elements mentioned previously into a decision-making methodology and its related decision-making tool, RESTORE. RESTORE uses MODM methods, evaluative models, and GIS-based (geographical information system) resources. It offers a platform that supports interactive analysis of the restoration decision-making. The aim of RESTORE is to compare different restoration options and watershed restoration plans at meeting the DMs' objectives and to rank them in terms of their utility at addressing these objectives. The questions we address here are: (1) What are the socio-economic and environmental impacts of the different restoration options as a function of landscape position? and (2) What is the mix of restoration options (watershed restoration plan) that creates the preferred solution responding to the DMs' objectives at the watershed level?

2.2 MULTIPLE-OBJECTIVE DECISION-MAKING METHODS

Practitioners and the scientific community's view of effective watershed restoration strategies has evolved over the last two decades from a focus on localized restoration projects to the adoption of holistic approaches. Such approaches address spatial patterns and processes, the interrelationships among landscape elements and reconcile conflicting management objectives. For example, the United States Environmental Protection Agency

(USEPA) asserts that restoration requires a design based on the entire watershed, not just on the section(s) of the watershed that may be the most degraded (USEPA, 2000). Decision-making in a watershed restoration context is a complex activity. It may include both social and environmental guidelines, models, methods, and tools that allow the DMs to choose between several alternatives that address conflicting objectives and different sources of uncertainties. The emergence of intelligent systems makes accessible valuable resources to practitioners, scientists, and DMs to deal with the intricacy of the decision-making process (Zhu et al., 1998).

Effective decision-making requires DMs to assess the potential success of different restoration options in meeting watershed restoration objectives. This assessment generally requires the simultaneous consideration of different objectives that are often in conflict; thus it is inadequate to use a traditional single-objective planning approach (Janssen, 1992; Avogadro et al., 1997). Public agencies generally look for a preferred solution that trades off the achievement of one objective against another objective (Salminen et al., 1998; Martell et al., 1998; Al-Rashdan et al., 1999). The tradeoff assessment often becomes a personal value question and requires the subjective judgment of the DMs (Keeney and Raiffa, 1993; Clemen, 1996). When objectives are conflicting, the suitable framework for the formulation of the decision problem should involve MODM methodologies (Bogetoft and Pruzan, 1991; Sen and Yang, 1998). In the context of our study, we use a MODM method classified as a prior articulation of preferences method (Chankong and Haimes, 1983; Mollaghasemi and Pet-Edwards, 1997). The information required by the DM is obtained before the formulation of the mathematical model. These methods are fairly simple to use, since typically the multiple-objective problem is reduced to a single-objective problem (Mollaghasemi and Pet-Edwards, 1997). Several methods exist for prior

articulation of preferences MODM, such as the Simple Additive Weighted method (Hwang and Yoon, 1981), goal programming (Charnes and Cooper, 1971), value and utility theory (Keeney and Raiffa, 1993), and outranking methods such as ELECTRE (Roy, 1968).

The Simple Additive Weighted method (SAW) was selected as our MODM model. SAW has few input requirements from the DMs; it is flexible and easy to interpret. It is one of the simplest MODM methods and one of the most popular (Triantaphyllou and Lin, 1996; Mollaghasemi and Pet-Edwards, 1997).

Different MODM methods have been widely applied to environmental management decision problems in areas including environmental disaster planning (Jenkins, 2000), planning of water resources sharing (Avogadro et al., 1997), urban waste management (Haastrup et al., 1998), and tactical forest planning (Kangas and Pukkala, 1996; Church, 2000). The spatial nature of environmental management problems suggests that a DSS be developed and implemented using GIS technology combined with models and decision-making techniques.

While similar to environmental management DSSs, DSSs for watershed restoration planning seem to involve a more active participation of the DMs and require a more important integration of different sources of knowledge coming from the decision-makers, community, experts, scientists, and practitioners involved in the planning activity. Many of the DSSs applied to watershed management focus on sharing information and presenting synthesized and comprehensive information to the users (Allen et al., 1998; Demissie et al, 1999). Other DSSs focus only on one or two problematic issues in the watershed or a few restoration projects (Al-Rashdan, 1999; Crist et al., 2000; Nero et al., 2001; Westphal et al., 2001) rather than incorporating a holistic perspective of watershed management.

Finally, some DSSs depend on a number of different components running together, compared to RESTORE that is an integrated tool (Prato and Fulcher, 1998; Reynolds et al., 1999; Call and Hayes, 2001). To date, significant efforts have been placed on information organization, modeling, and analysis rather than on decision-making issues (Avogadro et al., 1997). The discipline of decision-making requires the development of an integrated watershed restoration DSS that can help DMs through the entire evaluation process (Demissie and Tidrick, 2001).

The conceptual framework that we present here aims to contend with the lack of decision-making tools applied to watershed restoration decision problems. It integrates and makes use of existing decision-making approaches and techniques, GIS technologies, and it exploits wide-ranging models to support a holistic approach to watershed restoration planning.

2.3 CASE STUDY

The participation of stakeholders in identifying relevant data, models, and decision-making criteria is crucial for building a DSS tool that can express their objectives and preferences. For that purpose, we partnered with watershed councils in two watersheds in western Oregon's Willamette Valley: (1) the South Santiam watershed (3400 km^2) and (2) the Long Tom watershed (1050 km^2) (Figure 2.1). These watersheds were selected for (1) their diversity, one being a larger rural watershed and the other, a smaller watershed on an urban fringe, (2) their range of ecological, geomorphic, and socio-economic conditions, and (3) the availability of a number of spatially explicit datasets capable of supporting the types of analyses envisioned in this project. The South Santiam watershed includes the rural service centers of Lebanon, Sweet Home, and Scio. The watershed is the main source

of city drinking water. While substantially modified since the 1850's, the South Santiam is a less-disturbed ecological system. The Long Tom watershed is much more urbanized, adjacent to Oregon's second-largest metropolitan area, Eugene-Springfield. It is more disturbed by agricultural and urban activities and has been the site of a number of conflicts related to land use and resulting ecological impacts.

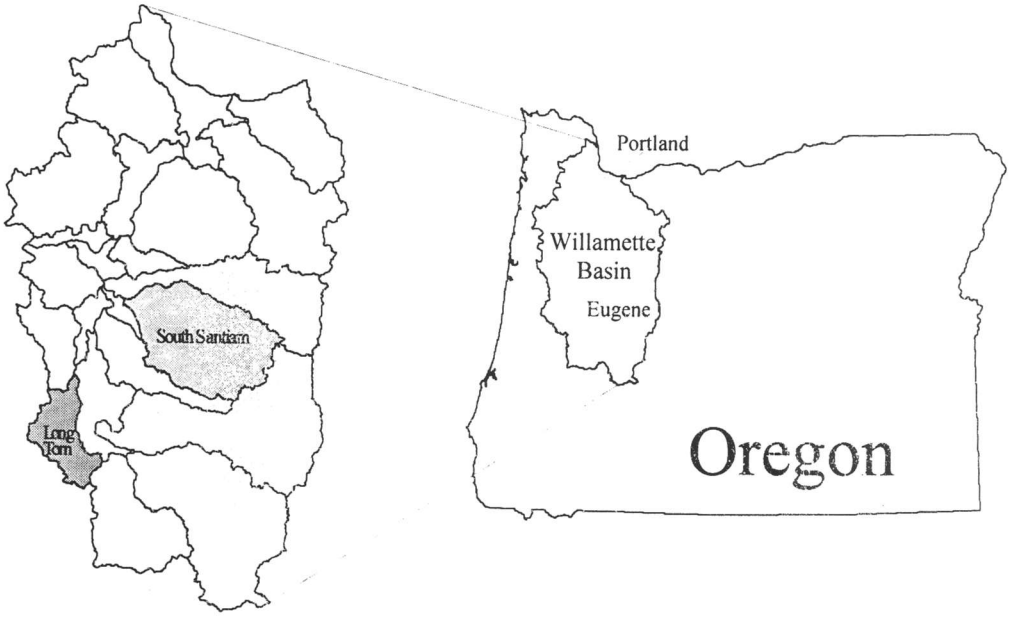

Figure 2.1: Location of Study Areas

2.4 METHODOLOGY

We approach watershed restoration planning as a holistic activity, gathering information from a wide variety of disciplines; synthesizing, exploring, and developing that information based on DMs objectives into a plan to guide in the selection of restoration projects. To assist this process, we developed a decision-making methodology shown in Figure 2.2. The overall objective of this methodology and more specifically of the decision-making tool, RESTORE, is to help the DMs understand, dissect, and structure the decision problem. We hypothesize that this ability will improve the rationality of the

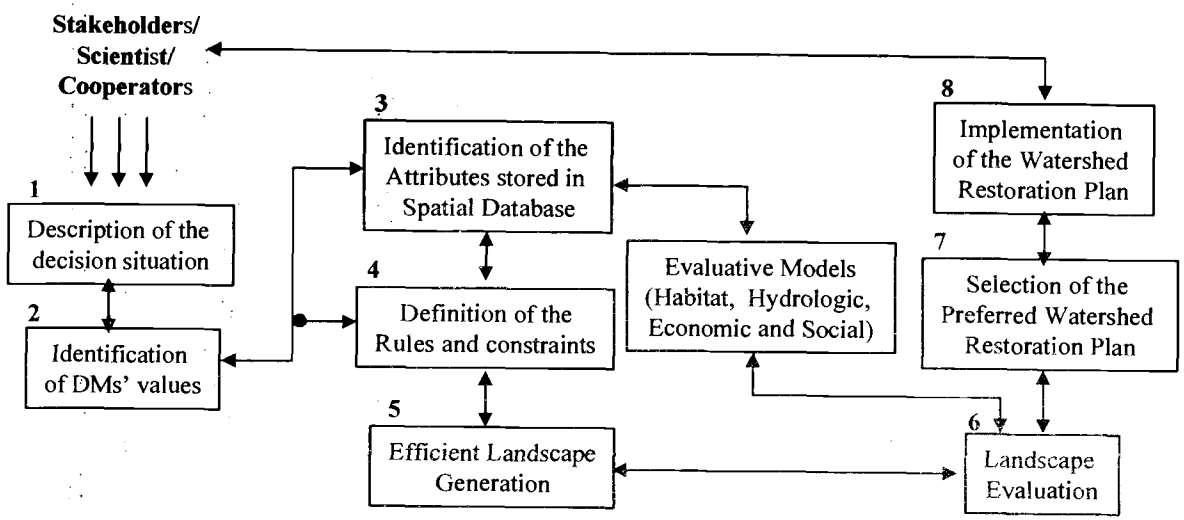

Figure 2.2: Diagram of the decision-making process used in RESTORE

decision-making process and therefore its quality. This approach is based on the availability of accurate information and on the openness of the planning procedure, which should involve DMs early in the decision-making process (Karacapilidis et al., 1997; Moualek, 1997).

RESTORE supports all steps in the decision-making. The role of RESTORE is to provide insight into the decision problem by reducing the cognitive resources the users need to make choices among the restoration options, encouraging the DMs to look at the watershed holistically, and evaluating the restoration options that could be used to address DMs objectives. RESTORE allows the user to specify watershed area(s) of interest, the objectives and subobjectives to be addressed, and the restoration options to be considered in the creation of a watershed restoration plan.

2.4.1 Description of the decision situation

Problems arise from a series of interconnected events, actions, and needs. This first step of the methodology is to clearly define the nature of the system under consideration, and to develop a shared knowledge and perception of the decision problem.

In the Long Tom watershed, a decision problem is concerned about the quality of drinking water, which may be threatened by industrial waste, and urban and agricultural runoff. The context should be described in terms of social, economic, biological, and hydrologic issues. RESTORE allows the user to visualize, through its GIS-based module, the data and information on which the system is based, facilitating the problem definition.

Within RESTORE, a user starts the assessment of the decision situation by selecting the watershed of his or her interest. A cell, ranging from 0.4 ha. to 12 ha., is considered as the smallest spatial land unit on which decision-makers can make a decision. The cells are

built on the assumption that small landscape areas can be aggregated into individual units that are homogeneous with respect to land use, soil, and drainage. In Figure 2.3, the RESTORE user-screen illustrates the study area divided into cells. Each cell is color coded to a specific land use. A cell's properties table portrays the different characteristics of the selected cell (e.g. cell no.: 5371; land use = pasture; area: 1.57 ha).

2.4.2 Identification of a set of objectives and restoration options by the DMs

The watershed council sets the objectives and the restoration options used to develop to preferred watershed restoration plan. A restoration option is a site modification or change in management that addresses one or more stakeholder objectives. Examples include installation of a riparian buffer along a water course or reducing toxicant use on agricultural fields. Options applied at specific sites are used as building blocks for a future watershed restoration plan. Objectives reflect stakeholder goals when considering restoration planning and in RESTORE are defined hierarchically. The intent of the objectives hierarchy is to provide the DMs with a logical framework that structures their priorities and concerns (Clemen, 1996; Al-Rashdan et al., 1999). Explicit presentation of objectives makes DMs conscious of their own and others' perspectives. The main outcome of this second step is an increased understanding of the decision problem for the DMs, the community, the experts or any interested parties (French et al., 1998). Focus group meetings, content analysis of newsletters, meeting minutes, and discussions with watershed council leaders helped in the identification of the five main objectives, the twenty-eight subobjectives, and the twenty restoration options presently used in RESTORE (Figure 2.4).

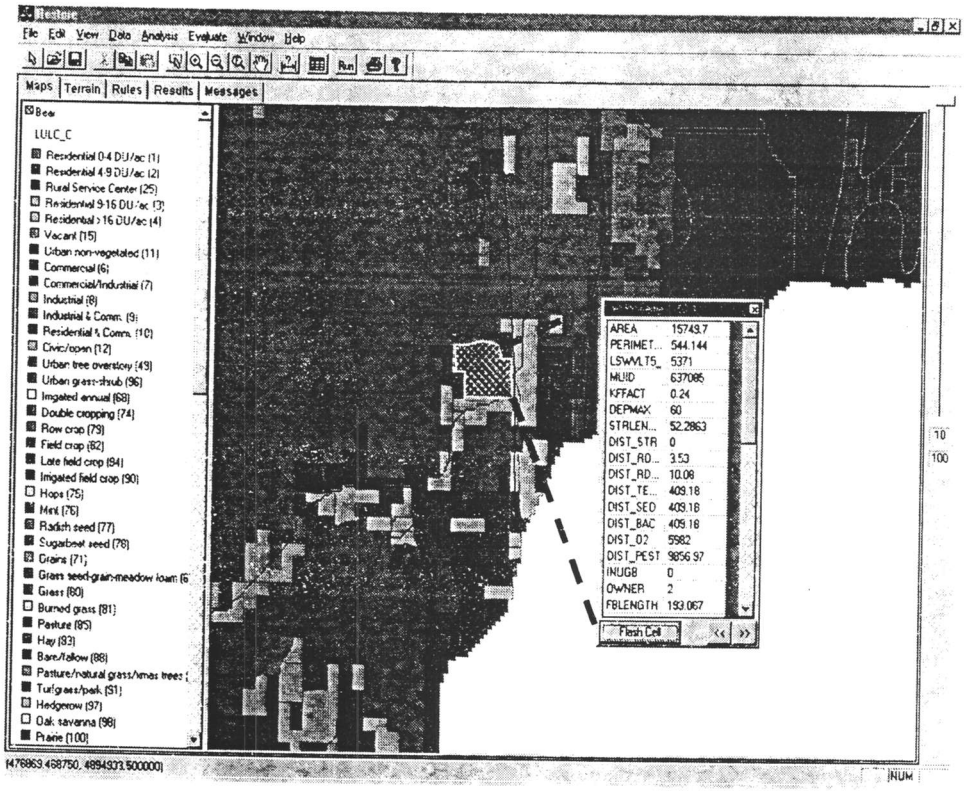

Figure 2.3: RESTORE user-screen illustrating the study area divided into cells and displaying the decision variables (attributes) of the cell. Each cell is shaded with a color that corresponds to a specific land use identified in the legend.

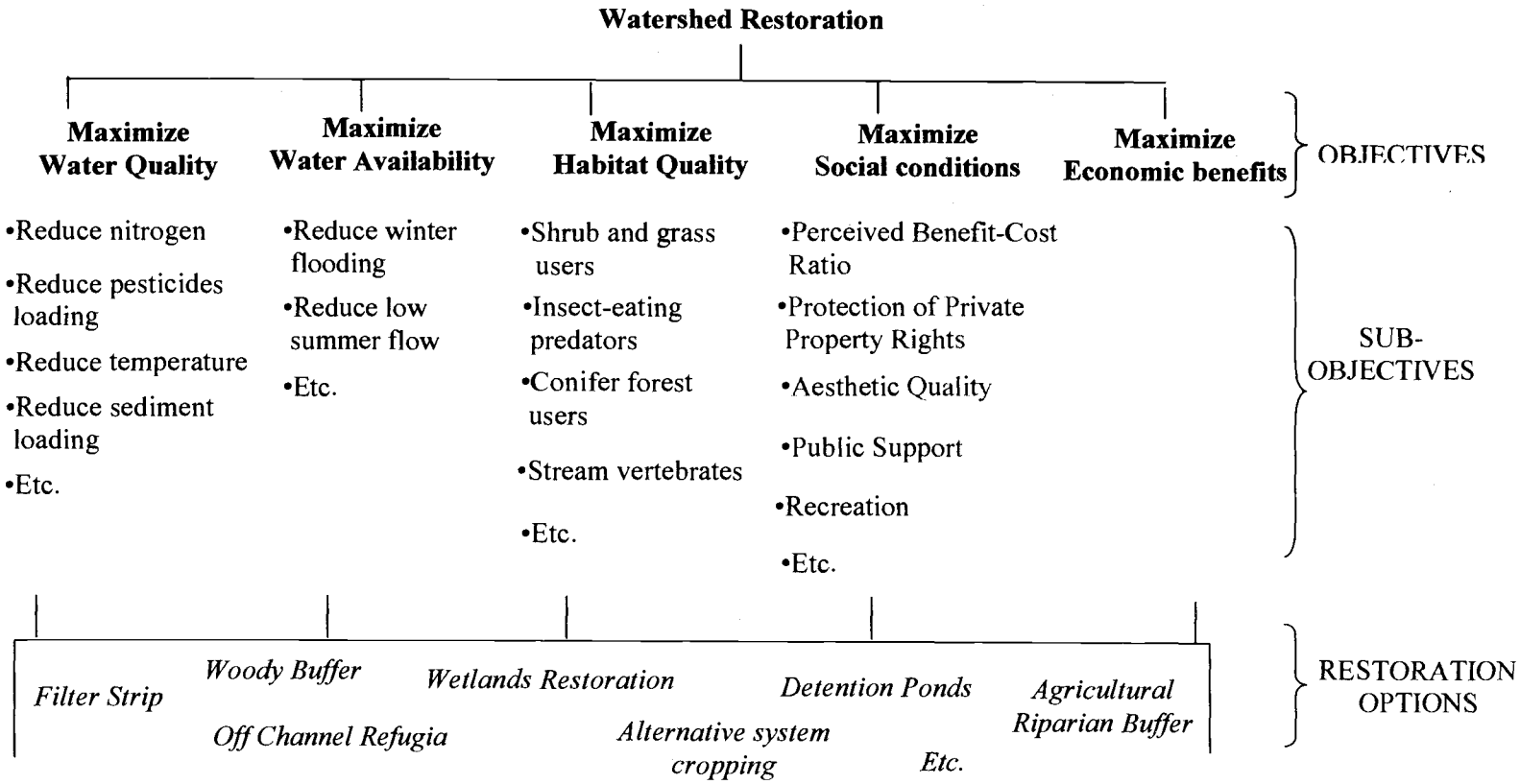

Figure 2.4: Objectives hierarchy that structures the DMs priorities and concerns

The decision-making framework does not limit the DMs to a constrained set of watershed restoration objectives, subobjectives, or options. In RESTORE, the user assigns a weight to each objective to be included in the decision analysis and selects from among the different subobjectives and restoration options those to be considered by the decision framework. Weights are used to resolve tradeoffs between objectives by including the DMs relative preferences for specific objectives (Chankong and Haimes, 1983; Sen and Yang, 1998). In the following example (Figure 2.5), we illustrate one set of priorities and concerns.

Here, water quality and water quantity are primary concerns (objectives), reflecting interest in decreasing water temperature and runoff, conserving water and increasing stream flows, improving nutrient management, and protecting drinking water and wells (subobjectives). These concerns are followed closely by interest in socio-economic issues, including education and outreach, social networking, and building community involvement. Maintaining and enhancing fish and wildlife habitat are a relatively low priority. The weights given to the five different objectives are: Water Quality objective weight: 0.9; Water Quantity objective weight: 0.9; Habitat Objective weight: 0.3; Social objective weight: 0.7, and Economic objective weight: 0.7 (Figure 2.5, right part of RESTORE user-screen). All of the restoration options that are listed in the left part of the user-screen are considered in the analysis (box is checked), as well as the complete set of subobjectives that can be seen in other RESTORE user-screens.

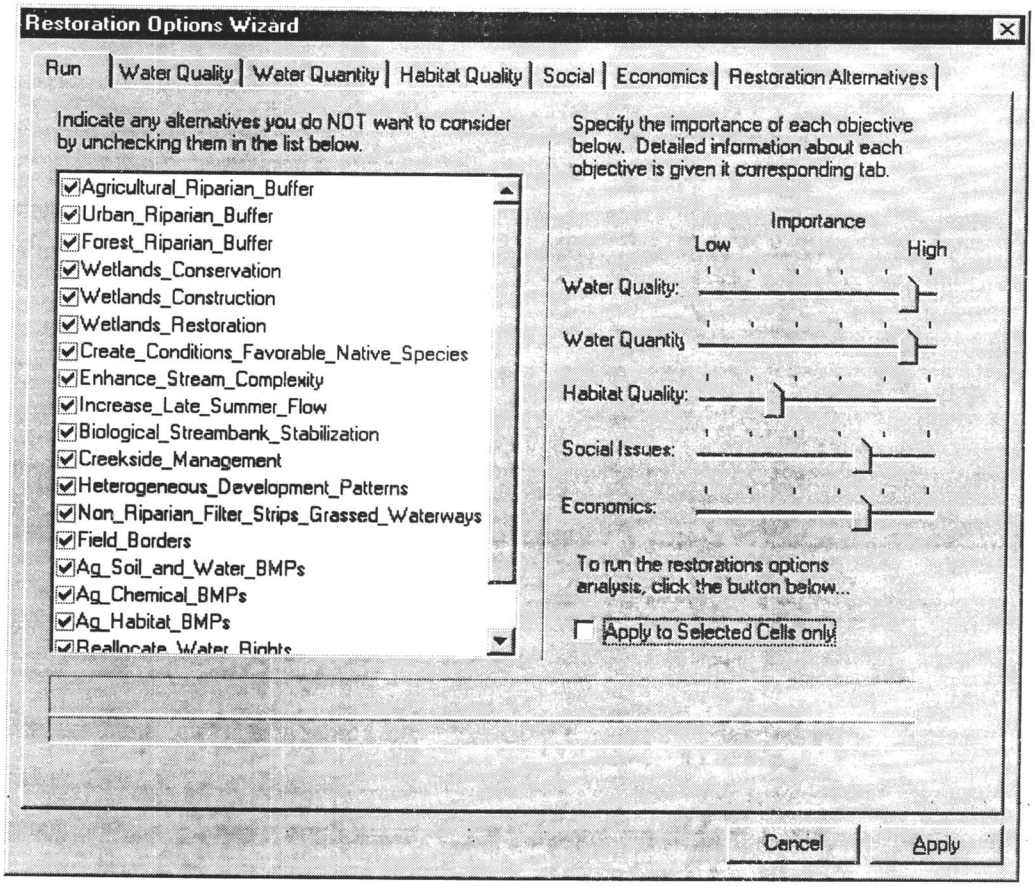

Figure 2.5: RESTORE Dialog Box for identifying weight on each objective, and the restoration options that should be considered by the decision framework

2.4.3 Identification of attributes that relate to each objective

Attributes are site-based decision variables that need to be considered by RESTORE when directing the selection of specific restoration options. These are qualitative or quantitative measures used to characterize a site with respect to its potential to support various restoration options. They may be given by a model, measured directly or assessed subjectively (Mollaghasemi and Pet-Edwards, 1997). Most of the attribute data used in RESTORE are widely available. These data are brought together in a GIS and structured to allow its sharing and evaluation by all those involved in the decision-making process. Examples of attribute data used by the decision-making tool are land use, hydrology, topography, and proximity to landscape features (e.g.: wetlands, roads, streams, urban areas).

2.4.4 Definition of the rules and constraints

Once objectives and attribute data are identified, the next step is to organize important relationships between entities in the system. In RESTORE, rules and constraints embody the knowledge about site and landscape-level guidelines for restoration options. For each cell, the rules and constraints direct a socio-economic and environmental impact assessment of the different restoration options, as a function of the cell's landscape position. Constraints determine if a restoration option should be considered at a site based on the site attributes. If constraints are satisfied, applicable rules score different restoration options based on the options ability to meet each objective. The rules are represented by IF-THEN statements that are an intuitive way to represent knowledge. A collection of rules has the ability to represent different sources of knowledge in a consistent format.

All rules provide a quantitative describing a positive or negative impact of a specific restoration option at addressing an objective. These impacts are (e.g. low = 1; moderate = 2; significant = 3; high = 4; low negative = -1; moderate negative = -2; significant negative = -3, and high negative = -4). For example, the following rule assesses the efficacy of an "agricultural riparian buffer" for meeting the water quality objective.

IF Erosion potential is less than 2 tons/acre

THEN Effectiveness of an "agricultural riparian buffer" at reducing sediment transport into a stream is considered low (1)

RESTORE currently has approximately 350 such rules describing the utility of various restoration options at meeting restoration objectives under various site conditions.

2.4.5 Efficient landscape generation

Watershed councils generally need to focus on solutions that will simultaneously meet multiple objectives. To do so, the SAW method is used to rank, for each cell, the utility of different restoration options by combining single objective scores weighted by the objective preferences described previously. The SAW method uses the following equation to evaluate the efficacy *(V)* of the *x th* alternative:

$$V_x = \sum_{i=1}^{m} w_i v_{ix} \qquad (2.1)$$

In equation (2.1), *(v)* corresponds to the scores resulting from the decision rules' output. It describes the efficacy of a particular restoration option *(x)* at reaching a specific objective *(i=1, ..., m)*. We assume that the objectives are mutually independent, a requirement for the SAW additive structure. The priorities assigned to each objective are denoted as weights *(w)*. The goal of the SAW method is to score the utility of each

restoration option at meeting multiple objectives. RESTORE then uses these scores to rank the restoration options for a site and select the highest scoring option.

RESTORE evaluates 20 restoration options per cell. For a typical watershed, over 15 000 cells are examined, with more than 20^{15000} possible "proposed landscapes" or watershed restoration plans. We hypothesize that the use of the SAW method combined with a rule-based approach can generate a representative subset of efficient "proposed landscapes". In RESTORE, an efficient "proposed landscape" is considered as a feasible watershed restoration plan that cannot be dominated by another plan (Bogetoft and Pruzan, 1991). Based on the set of objectives and weights identified by the DMs, the purpose of step 5 is (1) to select a restoration option (including a "no restoration option") for each cell, leading to the creation of an efficient "proposed landscape" and (2) by varying the weights associated with each objective, to generate a representative subset of efficient "proposed landscapes".

Figure 2.6 shows the results of the analysis on an area of the Bear sub-basin within the Long Tom watershed. The analysis allocates a specific restoration option to a cell only if all applicable constraints are met. For instance, the efficient option that best addresses the concerns identified in Step 2 for the cell 5371 was an "agricultural riparian buffer". This cell is broadly characterized by a pastureland land use and its adjacency to a stream and a road. The "agricultural riparian buffer" option obtained scores of 4, 1, 4, 3.5, and 0 for the "water quality", "water quantity," "habitat quality," "social", and "economic" objectives, respectively. Since the weights given to the objectives were respectively 0.9, 0.9, 0.3, 0.7, 0.7; the composite score after weights normalization equals 2.33 out of 4. These scores

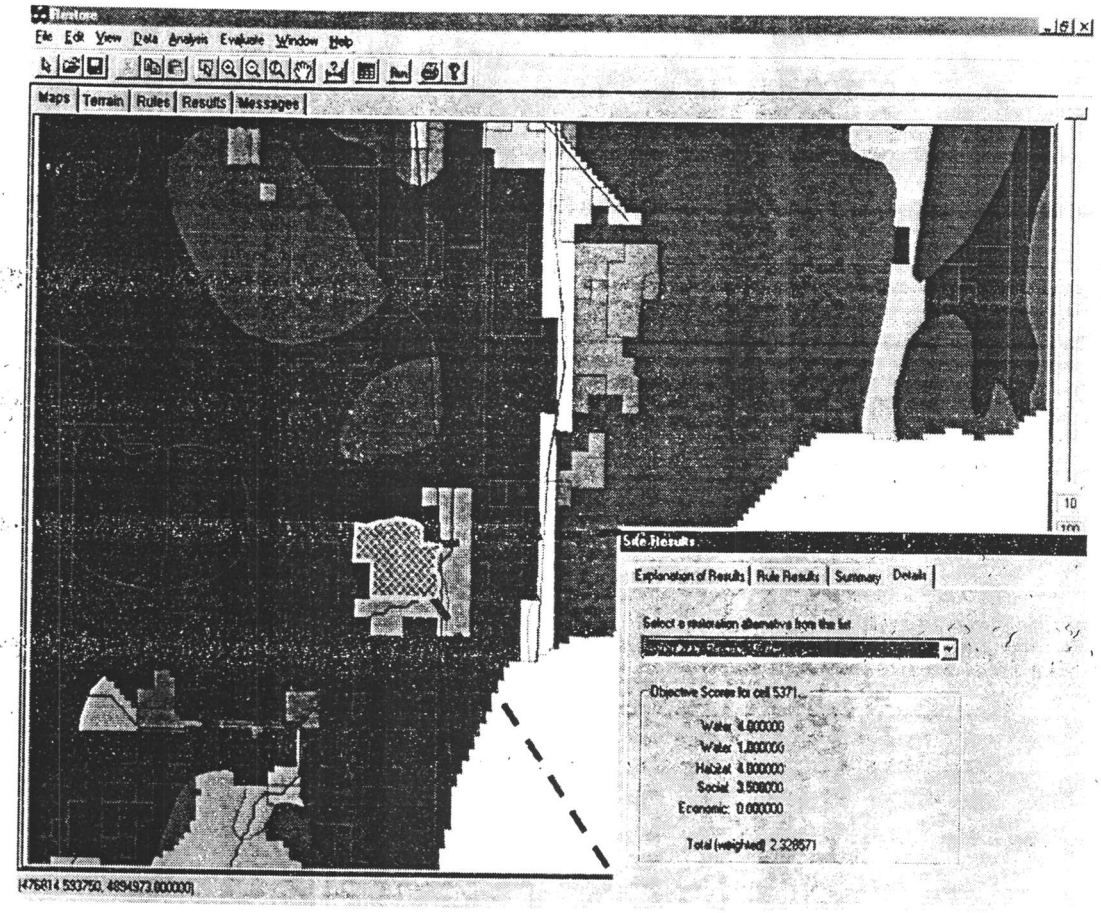

Figure 2.6: RESTORE user-screen displaying the results from the MODM analysis for a specific cell. The results include a composite score and the scores that relate to each objective. Scores describe the efficacy of the restoration option at reaching the DMs objectives.

reflect the combination of applicable rules available to RESTORE. These scores emphasize the fact that an "agricultural riparian buffer" option was selected for the cell 5371 mainly due to its positive impacts on the water quality (e.g. maintain cool water, reduce transport of sediments and other pollutants into the stream) and the creation of social opportunities (e.g. aesthetically pleasing, provide opportunities for recreation).

2.4.6 Landscape evaluation

The final output of RESTORE is a spatially and visually explicit preferred "proposed landscape". A preferred "proposed landscape" should be viewed as the DMs' preferred watershed restoration plan integrating a mix of restoration options that are optimal or near optimal at addressing the various objectives of the DMs. However, the preferred watershed restoration plan cannot be developed in the first run. Rather, it should evolve as a result of the evaluation process of the several efficient "proposed landscapes" created in step 5.

As implemented in RESTORE, DMs can perform a visual evaluation of the "proposed landscapes". They can look at different combinations of information layers and perform multiple-scale analyses of the generated "proposed landscapes". In Figure 2.7, a RESTORE user-screen depicts a Bear sub-basin "proposed landscape". The largest portion of the screen is devoted to the map. Each cell is shaded with a color that corresponds to a specific restoration option in the legend. The histogram illustrates the ratio of the main restoration options that were applied in the "proposed landscape". The "create condition favorable to native species", "forest harvest type scale modification", "agricultural chemical BMPs", "increase late summer flow", "wetlands construction" restoration options were applied to respectively 33%, 30%, 13%, 11%, 10% of the Bear sub-basin's cells.

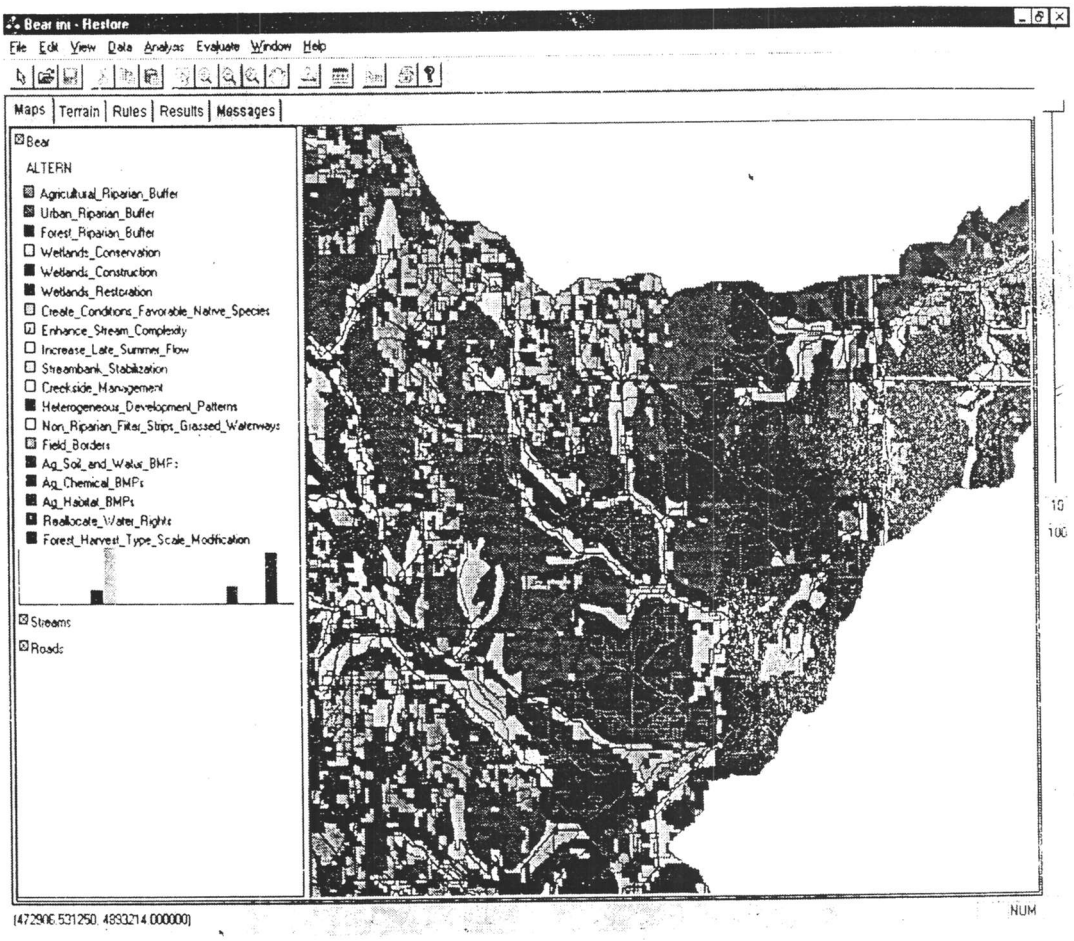

Figure 2.7: RESTORE user-screen displaying a preferred watershed restoration plan that integrates a mix of restoration that are optimal or near optimal at addressing the DMs objectives.

We also use a multiple objective optimization method to evaluate the efficient "proposed landscapes" that satisfy guidelines for meeting watershed level objectives. The multiple objective optimization method being developed uses the SAW method for the same reasons that were expressed previously. The objectives and decision variables that are used at the watershed level are different than the ones used at the cell level, since key issues and observed processes are different for different spatial scales. Therefore, evaluative models were developed to look at the patterns, structure, and functions of the "proposed landscapes". Such models allow the user to explore the effects of landscape characteristics on the fundamental processes observed at the watershed level and to assess how well each of the efficient "proposed landscapes" is at meeting the different objectives.

2.4.7 Selection of the preferred watershed restoration plan

Selecting a preferred watershed restoration plan is an iterative process. It is critical that several solutions are considered simultaneously to keep the DMs aware that there is no claim that any one of these is the preferred watershed restoration plan (French, 1986). The process is completed when the DMs are satisfied with the preferred watershed restoration plan; i.e. when they feel that the analysis is requisite.

2.5 DISCUSSION

The work reported in this paper is on going; it addresses the lack of decision-making tools that can be applied to watershed restoration decision problems. We present the features of a DSS for watershed restoration being implemented and validated in two Oregon watersheds. The questions addressed in this paper are (1) what are the socio-economic and environmental impacts of the different restoration options as a function of landscape position? and (2) what is the preferred watershed restoration plan that responds

to the DMs' objectives at the watershed level? To answer these specific questions, we present a methodology and a decision-making tool that generates a mix of restoration options in the form of a watershed restoration plan that satisfies the objectives specified by the DMs at both the local and the watershed levels.

The approach offers several advantages, including: (1) a learning environment enabling all those involved to develop a more holistic view of watershed restoration planning, (2) the capability of structuring and articulating problems, and (3) the automation of the decision-making process. Our approach also demonstrates a GIS-based approach where rule-based models and other modeling techniques are used rationally to solve a spatially explicit decision problem.

RESTORE is a fully integrated DSS. It does not depend on proprietary software or commercial simulation models that may be difficult for users to understand and it does not require that users are knowledgeable about the different RESTORE components.

RESTORE captures the expert judgment, in the form of rules, to enable DMs to evaluate different restoration options at the cell level, based on quantitative and qualitative attributes. The rule-based approach was selected because it allows flexible knowledge representation and is relatively easy to maintain and modify. A MODM module creates a final ranking of the restoration options resulting in a subset of efficient "proposed landscapes". The RESTORE MODM module utilizes the SAW method. Subsequently, each efficient "proposed landscape" is evaluated at the watershed scale to assess the landscape's impacts on predefined environmental and socio-economic criteria. The "proposed landscape" that best addresses the watershed restoration objectives is selected as the DMs preferred watershed restoration plan. The decision-making framework does not limit the DMs to a constrained set of watershed restoration objectives or options; instead, it

offers a framework for almost limitless possibilities to configure a wide variety of alternative watershed restoration plans that meet selected objectives.

The RESTORE interface supports each step of the methodology. It is broad enough to accommodate a wide variety of decision situations, thus stimulating collaboration between DMs. Maps-based and textual summaries of restoration decision-making are readily available in a friendly format. They are a useful and meaningful way of presenting both attribute information and decision results. They are easily interpreted and understood, facilitating the exploration and evaluation of alternative solutions.

We see our modeling process as iterative and dynamic. We continue to interact with DMs, citizens, and experts to make improvements to the decision-making tool, and to each step of the decision-making methodology. Still, progress remains to be made to improve the RESTORE tool. We continue to improve watershed scale evaluative tools. In addition, continued evaluation of RESTORE by DMs is required if the decisions made with RESTORE are to effectively address watershed restoration needs.

Other improvements to the present structure of RESTORE include modeling of the different sources of uncertainty, which are intrinsically part of human judgments and the landscape characterization. A sensitivity analysis module would allow investigation of the effects of changes in the input data on the suggested solutions and to test the robustness of the decisions made. Finally, since conflicts of interest and negotiations are inevitable in any decision-making environment, future research might consider the addition of group decision-making techniques to stimulate consensus development, decrease the time to make decisions, and improve the quality of the decisions made.

2.6 CONCLUSIONS

The proposed DSS has a number of limitations, but by providing a fertile test-bed for exploration, it raises a variety of ideas and questions for future research in the development of DSS tools that address watershed restoration in a holistic way.

The results obtained so far strongly reinforce the fact that multiple-objective methods provide a valuable tool in the analysis of complex watershed management issues. We hypothesized that, when used properly, our methodology allows DMs to explore a broad range of drivers and consequences. The RESTORE methodology helps to identify and explore possible solutions. It leads to a better understanding of the impacts of decisions. DMs and experts were involved throughout the development process. They have been consulted on the main assumptions underpinning the system and on the different choices embodied in the system. Our experiences tell us that the perspective provided by RESTORE is compatible with the utilization by DMs. However, to confirm or refute this first impression, a complete assessment of the decision-making system must be done to evaluate how useful it is and whether it can promote decision-making in a watershed restoration context.

CHAPTER 3

A FUZZY LOGIC APPROACH TO DECISION-MAKING FOR WATERSHED RESTORATION PLANNING

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3.1 INTRODUCTION

Performance evaluation of restoration options for addressing watershed restoration objectives is a complex task, due to the multiplicity and diversity of management objectives and technological choices (Lamy et al., 2002a). It requires an understanding of ecosystem processes and functions in the context of the landscape patterns and structure and restoration option characteristics. In most watershed management decision-making situations, experts and modelers could utilize multiple-criteria decision-making (MCDM) approaches to assist decision-makers (DMs) to integrate and synthesize the relevant data and information and to holistically address concerns relating to ecological, economic, and sociological issues. Lamy et al. (2002a) asserted that without such approaches and related tools, DMs and community groups would have difficulty in integrating multiple objectives into watershed-level plans for restoration. Additionally, in such context they cannot rationally and realistically assess the potential success of restoration strategies to meet watershed restoration objectives that are often in conflict within a sustainable development paradigm. Relevant objectives may refer to biodiversity, water quality, water storage, habitat quality, social, and economic issues. Although MCDM approaches may support DMs in complex decision-making contexts, most of these approaches use deterministic techniques that do not address the intrinsic uncertainties in real world decision situations (Mower, 2000). Decision-making approaches that include an uncertainty analysis can be seen as more credible, since they recognize that parameters are not precisely known and decision models are abstract views of the world. Uncertainty analysis provides critical information to DMs, allowing them to make more informed decisions. Such information provides them a pragmatic basis to better evaluate the soundness of the conclusions

reached, thus increasing DMs' confidence in the decision model (Byström el al., 2000; Crossetto et al., 2000).

When modeling real phenomena, Zimmermann (2000) identified the following sources of uncertainties: lack of information, abundance of information, conflicting evidence, ambiguity, measurement, and beliefs. In most situations, it is an intricate task to appraise all sources of uncertainty present in a decision-making process. Therefore, proposed methodologies should attempt to focus on sources of uncertainty that have an impact on the decisions that have to be made. A variety of approaches, such as probability theories (de Finetti, 1972), fuzzy set theory (Zadeh, 1965), rough set theory (Pawlak, 1982), and Dempster-Shafer theory (Dempster, 1967; Shafer, 1976) can be used to model uncertainty. Each theory can address only specific types of uncertainty; consequently the choice of the appropriate theory is context dependent (Armacost and Pet-Edwards, 1999).

In a community-based watershed restoration context, the process of evaluating and selecting restoration options is often accomplished based on information expressed in linguistic terms, which are intrinsically subjective and imprecise. This paper thus focuses on the modeling of the ambiguity in expert's knowledge, which we hypothesize could be well captured by fuzzy set theory.

A growing number of publications on MCDM and fuzzy MCDM (FMCDM) applications related to water resource management have been published (Chang et al, 1997; Reynolds et al., 1999; Despic and Simonovic, 2000). However, little research has been done on MCDM and FMCDM applied to holistic watershed restoration decision problems (Lamy et al., 2002a). To address the lack of such decision-making tools, we explore the application of a FMCDM approach at modeling the uncertainty in experts' knowledge in the context of RESTORE, a watershed restoration decision tool. RESTORE (Lamy et al.,

2002a) is a geographical information system-based decision-making tool developed to help watershed councils evaluate and rank restoration activities at the watershed level. It includes a rule-based system that models the experts' perception of restoration options performance at meeting DMs' multiple objectives. A performance evaluation leads to the ranking of the restoration options, which results in a subset of efficient watershed management plans. It is done in terms of the restoration option's impacts on the predefined environmental and socio-economic criteria. RESTORE's performance evaluation module is developed from experts' knowledge and experience. It provides a crisp (no uncertainty) evaluation of the restoration alternatives. The complexity of the various landscape processes and human subjectivity suggest that a robust inference process should involve the modeling of the inherent uncertainties of experts' knowledge.

The aim of this paper is to: (1) characterize the types of uncertainty in experts' knowledge that the approach can address; (2) introduce a novel ranking method for fuzzy performance evaluation, and (3) evaluate the ability of the approach at exploiting the knowledge provided by experts. Section 1 presents an overview of the fuzzy set mathematical framework, section 2 presents the methodology overview, and section 3 illustrates the application of the methodology with an example.

3.2 FUZZY SET THEORY OVERVIEW

In 1965, Lofti Zadeh proposed fuzzy set theory, a mathematical framework that gives experts the ability to convey the fuzziness or the intrinsic vagueness of qualitative concepts. Most qualitative concepts have no precise boundaries or cannot be described precisely, therefore soft boundaries are used to handle the idea of partial truth.

For instance, a characterization of commonly accepted boundaries between what is believed to be moderate soil erosion and excessive soil erosion could never be done because it is highly subjective and context dependent. For a certain community, a 6 t/ha value can be to some extent moderate and to some extent excessive, there is a gradual transition so that there is no single value at which the soil erosion abruptly begins to be excessive (Figure 3.1). In these situations uncertainty mainly originates from linguistic ambiguity, which could be captured by fuzzy set theory. Fuzzy set theory is more compatible with linguistic terms than a two-valued logic or a crisp logic, where a membership function μ_A of a fuzzy set A associates a membership value ($\mu_A(x)$) in the interval [0, 1] with each element x of the universe of discourse U.

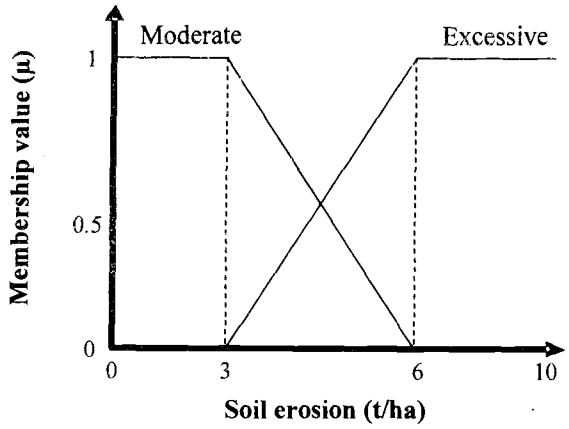

Figure 3.1: Membership functions describing the experts' view of the linguistic terms "moderate" and "excessive" soil erosion

Membership values model degrees of truth of fuzzy propositions, ranging from 0 (incompatibility with the set) to 1 (full compatibility with the set). Degrees of truth or membership values describe how much each given object is compatible with each of the linguistic terms represented by a given fuzzy subset. Linguistic terms (e.g. moderate and excessive) can be seen as subjective categories describing a linguistic variable (e.g. soil

erosion). Fuzzy subsets can be arbitrarily defined using a diverse set of mathematical functions. A detailed description of fuzzy set theory concepts can be found in Zimmermann (1987) and Klir and Yuan (1995).

3.3 METHODOLOGY

There are a number of surveys on FMCDM (Chen and Hwang, 1992; Lai and Hwang, 1994; Ribeiro, 1996). The field of fuzzy set theory matured since its development in 1965 by L.A. Zadeh. Still, Dubois et al. (2000) pointed out that uncertainty analysis and MCDM theory are two fields that have been developed almost completely independently until recently. Applications of FMCDM can be seen in energy production, engineering, resource allocation, transportation, waste management, manufacturing, imaging systems, robot simulation, economics, and other fields.

The FMCDM methodology presented here is applied to holistic watershed management. Its goal is to assist DMs in the selection process of restoration options when creating watershed restoration plans. However, the methodology could be applied to any performance evaluation contexts where multiple criteria and intrinsic uncertainty are involved. The methodology allows DMs to express their experience, intuition or beliefs in vague linguistic terms, which may more realistically reflect real world decision-making problems. It consists of three main steps, which lead to the creation of a feasible watershed restoration plan (Figure 3.2).

3.3.1 Description of the decision situation and identification of objectives

This first step of the methodology is to describe the system being considered and to identify DMs' objectives in this specific decision situation. This step, which helps to

develop a shared comprehension and perception of the decision problem, is critical to guarantee the success of watershed restoration efforts. Successful watershed restoration planning is often characterized as one that ensures water quality, riparian and wetland habitat for fish, wildlife, and native plants while recognizing the importance of people's economic livelihood and quality of life.

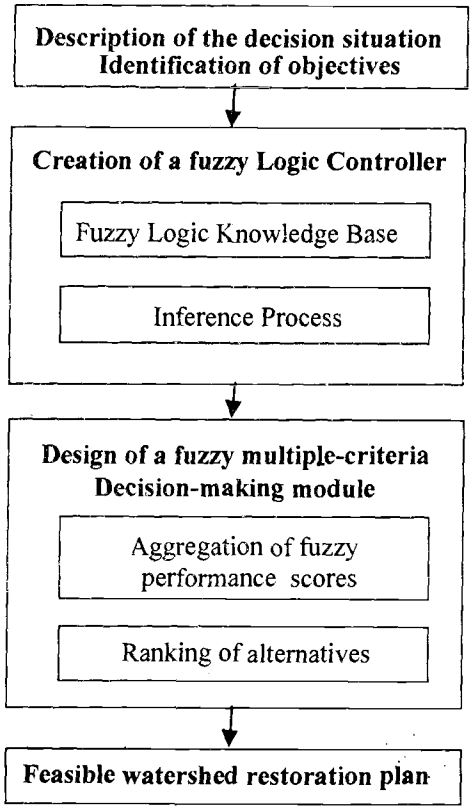

Figure 3.2: Diagram of the FMCDM methodology for the design of feasible watershed restoration plans

Once the decision situation and relevant objectives are characterized, restoration options that may drive the solution toward the design of a feasible watershed restoration plan should now be identified. Restoration options are used as building blocks for a future watershed restoration plan. An objectives hierarchy is used to graphically summarize the

identified priorities and concerns (Clemen, 1996). It helps to understand what is the vision of DMs when restoring their watershed. The main outcome of this step is an increased understanding of the decision problem by the DMs, the community, the experts or any interested parties. Focus group meetings, content analysis of newsletters, and meeting minutes, as well as discussions with watershed council leaders help in the identification of the five main objectives, the twenty-eight subobjectives, and the twenty restoration options used in RESTORE and available to the watershed councils (Figure 3.3).

3.3.2 Creation of a Fuzzy Logic Controller

Once priorities and concerns are identified, the next step is to create a fuzzy logic controller (FLC) that directs a socio-economic and environmental impact assessment. The impact assessment evaluates the performance of the restoration options at meeting each objective individually as a function of the cell's landscape position. A cell is considered the smallest site or land unit on which DMs can make a decision. In the literature, there is no broadly accepted practice for fuzzy control design (Glorennec, 1994; Klir and Yuan, 1995). In general, the design involves the development of a rule base and an inference engine that embodies mechanisms for interpreting these rules and drawing conclusions from them, based on the characteristics specific to the decision problem. Rules are defined using linguistic variables described by fuzzy subsets. Several decisions have to be made when designing a FLC, including the definition of the rules collection, the linguistic variables and linguistic terms in the input and output spaces, the shape of the linguistic terms' membership functions, aggregation operators, and ranking process. For the FLC presented here, the design components are described below.

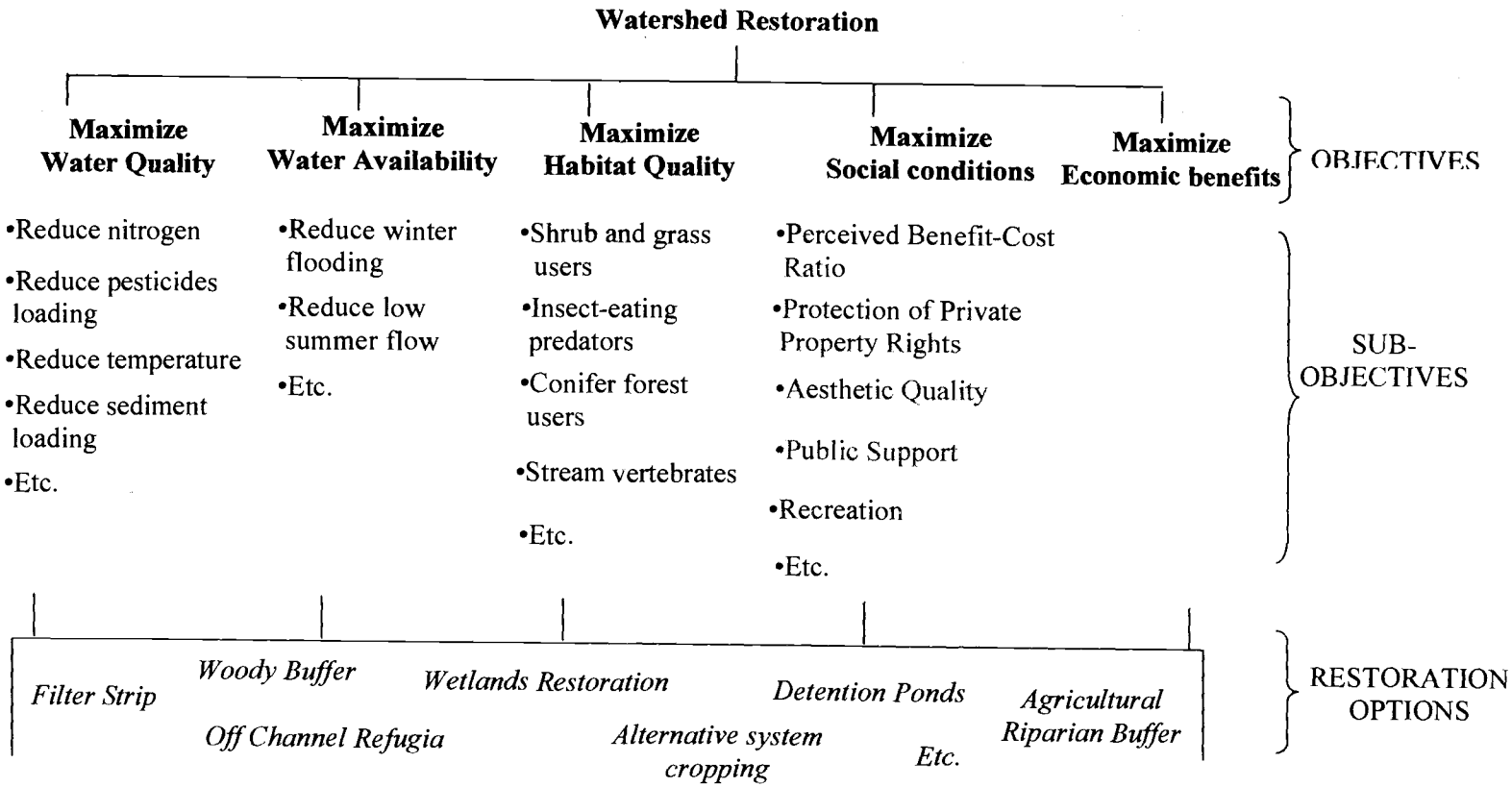

Figure 3.3: Objectives hierarchy that structures the DMs priorities and concerns

Fuzzy Logic Knowledge base

Through a fuzzification process, the fuzzy rule base was built from a subset of RESTORE's 350 crisp rules. Fuzzification is a process that uses membership functions or fuzzy subsets to translate system input and output into linguistic variables. Two distinctive classes of fuzzification methods are proposed in the literature, direct and indirect methods (Klir and Yuan, 1995). In the proposed approach a direct fuzzification method was used. Experts are asked to identify the linguistic terms and associated fuzzy subsets defining each concept present in the rules. The rules in RESTORE embody knowledge about site and landscape-level guidelines for restoration options. Rules use qualitative or quantitative attributes that need to be considered when directing the selection of restoration options. Examples of the main quantitative attributes driving the decision-making process are land use, land cover, hydrology, topography, and proximity to landscape features (e.g.: fish distribution, wetlands, roads, streams, urban areas). All rules provide a conclusion describing a positive or negative impact (e.g. low, moderate, significant, high, low negative, moderate negative, significant negative, and high negative) of a specific restoration option at addressing an objective under specific site conditions. Applicable rules' conclusions are linked by the sentence connective *also*. They are run in parallel to produce an overall conclusion considering the information coming from all the applicable rules (Cox, 1999). In Figure 3.4, rules assess the efficacy of an "agricultural riparian buffer" at meeting the water quality objective.

The linguistic terms "low" and "medium" are defined by fuzzy subsets associated with the linguistic variable "soil erosion". The linguistic terms "moderate" and "significant" are defined by fuzzy subsets associated with the linguistic variable "impact on the water

quality objective". The antecedent (the rule's premise) describes under what conditions the rule contributes to the model solution, while the conclusion (the rule's consequent) assigns a membership function to each of the output variables that is correlated with the truth of the antecedent. Membership functions can take an infinite number of forms. However, most FLCs use only fairly simple linear equations. In the approach used here; DMs can choose between linear, triangular, or trapezoidal shapes, which could be bounded or not.

IF	erosion potential is "low" ***or*** erosion potential is "moderate"	*(antecedent)*
THEN	effectiveness of an "agricultural riparian buffer" at reducing sediment transport into a stream is considered as "moderate"	*(conclusion)*
also		
IF	a stream listed for fecal coliform is "near" the site ***and*** a stream is present on the site	*(antecedent)*
THEN	effectiveness of an "agricultural riparian buffer" at reducing sediment transport into a stream is considered as "significant"	*(conclusion)*

Figure 3.4: Rules assessing the efficacy of an "agricultural riparian buffer" at meeting the water quality

Inference process

A fuzzy inference process defines the mapping from a given input space to an output space. It evaluates the truthfulness of the fuzzy rules, selects the rules that contribute to the conclusion, aggregates these rule conclusions, and infers a fuzzy conclusion. An inference process should be context dependent, limit the loss of information and aim to model DM's behavior when making a decision. A few operators have a major impact on the inference process: fuzzy implication operator, sentence connectives *"and"* and *"or"*, and the sentence connective *"also"*.

Fuzzy implication operator

Fuzzy implication could be defined as a mechanism that defines the degree of truth of a rule. Numerous fuzzy implication operators are available including t-norm, strong implication, residual implication, and quantic implication. Research concerning the applicability of implications operators for different applications has been conducted by various authors (Kiszka et al., 1985; Cao and Kandel, 1989; Cárdenas et al., 1994; Cordón et al., 1997). These researchers generally concluded that each operator generated good results in a specific context and that t-norm minimum (MIN) operator frequently performed well. The MIN implication operator was selected in our methodology. In the approach used here, the sentence connective *"and"* is modeled by the MIN operator, because experts point out that two facts linked by the sentence connective *"and"* must be both true to a certain extent for the rule to be considered in the evaluation process. The rule's impact on the fuzzy conclusion is negligible when at least one of the two facts is not true. The sentence connective *"or"* is modeled by the MAX operator, because experts are said to believe in the rules' conclusion at least to an extent equivalent to the condition having the highest degree of truth.

Sentence connective "also"

Under the composition step, all of the rules' conclusions are combined together, with the sentence connective *"also"*, to form a single fuzzy subset associated to the output space. This step is seen as the one of aggregating experts' opinions (Portilla et al., 2000).

In a decision situation, aggregating experts' opinion can be modeled by using disjunctive, conjunctive, or compromise operators. Zimmermann and Zysno (1980) stated that most decisions involving a performance evaluation needed to allow compensation

between different degrees of performance achievements. Compensation assumes that good performance by one rule is perceived to partially compensate for lower performance by another. In the case of a community-based decision problem, a compensatory approach that trades off opinions about potential impacts can allow consideration of different opinions or conflicting evidence. The inference process used here uses a compensatory parameterized function (equation 3.1) to model the sentence connective *"also"* that combines multiple rule conclusions. This function is a weighted combination of the non-compensatory *"and"* and the fully compensatory *"or"* that is used to model the performance ($\mu_{predicate}$) of a restoration option at meeting each objective individually. A weighting factor (X) represents the degree of optimism of DMs. It models the balance that DMs want to reach, toward the minimum or maximum fuzzy conclusion (Cox, 1999).

$$\mu_{predicate} = (1 - X)\min(\mu_a[x], \mu_b[x]) + X\max(\mu_a[x], \mu_b[x]) \quad \text{with } 0 \leq X \leq 1 \qquad (3.1)$$

This method was selected because it is intuitive, the degree of compensation can be controlled, and it takes into account the full range of performance achievements.

3.3.3 Design of a fuzzy multiple-criteria decision-making module

The design of the FMCDM module consists of two steps. The first step is the aggregation of the performance scores, computed by the FLC, with respect to all the objectives for each decision alternative. The second step is the ranking of the decision alternatives to the aggregated scores. Both steps aim to make use of techniques that preserve knowledge and experiences provided by experts during the design of the *Fuzzy*

Logic Knowledge base, and keeping this information ensures a more complete and comprehensive analysis of the decision alternatives' performance (Islei et al., 1999).

Aggregation of the fuzzy performance scores

The main challenge, when aggregating fuzzy performance scores, is to choose an aggregation function that properly models the concerns of experts and DMs. In the approach used here, the FMCDM problem is defined as a finite set of (n) decision alternatives, which are evaluated with respect to (m) objectives (V_i). The priorities assigned to each objective are represented as weights (w_i). The result of the aggregation is a composite objective function (D) represented by a fuzzy subset. As mentioned previously, as in fuzzy control, the aggregation of subjective categories in the context of real world MCDM situations generally shows some degree of compensation (Shih and Lee, 2000; Despic and Simonovic, 2000). In the approach used here, the decision-making problem is said to be compensating because good performance on one objective is perceived to partially compensate for lower performance on another.

Fuzzy set theory provides a large number of different compensatory aggregation connectives for combining membership functions. Frequently used compensatory aggregation connectives in FMCDM are the arithmetic mean and the geometric mean. With these methods, however, the degree of compensation cannot be controlled to reflect the specific DM's behavior. To express the DMs' subjective attitude toward the comparison of different fuzzy subsets, the generalized mean aggregation function (Dyckhoff and Pedrycz, 1984) (equation 3.2) was selected.

$$Dn = \left\{ \frac{\sum_{i=1}^{m} w_i V_i^{\gamma}}{m} \right\}^{1/\gamma} \tag{3.2}$$

where γ is a DM's attitude control parameter. According to the method, the grade of compensation can cover the entire interval between the MIN ($\gamma = -\infty$) and the MAX ($\gamma = \infty$). In the approach used here, the weights are determined by direct estimation. DMs are asked to represent the importance of each objective with a value between zero (unimportant objective) and one (critical objective). The output of the aggregation of the fuzzy performance scores step produces a fuzzy subset that represents the overall performance of each decision alternatives at simultaneously addressing the different objectives.

Ranking of the decision alternatives

Ranking decision alternatives represented by fuzzy subsets is an important issue of fuzzy decision-making unlike crisp sets which form a natural linear order. Many approaches for ranking fuzzy subsets have been proposed in the literature. There exists an assortment of methods classified by Chen and Hwang (1992) as: (1) preference relation, (2) fuzzy mean and spread, (3) fuzzy scoring, and (4) linguistic method. In spite of the existence of a variety of methods, no single method can rank fuzzy subsets satisfactorily in all cases and situations. Most of them suffer from drawbacks, including difficulty of implementation, counter-intuitive behavior, lack of discrimination, and failure to include all information. Others make assumptions about the DM's behavior and fuzzy subset shape

(Bortolan and Degani, 1985; Wang and Kerre, 2001). These factors have made selection of a ranking method subjective and specific to each decision context.

The need for further study focusing on the development of customizable and intuitive ranking methods that account for the information richness of fuzzy subsets is manifest. Consequently, a novel approach for ranking fuzzy solutions based on a *grade of merit index* (GMI) is presented.

The proposed GMI method can be broadly characterized as a method using a FMCDM model and uncertainty-based information to analyze the information content of the fuzzy subset coming from the overall performance evaluation of each decision alternative. Generalized information theory deals with the broad concept of uncertainty-based information, which is defined in terms of uncertainty reduction (Klir, 1999). In fuzzy set theory, two different types of uncertainty-based information exist, which are fuzziness and nonspecificity (Klir, 1987). The GMI method aims to address the abovementioned drawbacks of the existing ranking methods by considering more information in the ranking process and emulating the way experts think about a specific problem. A decision alternative with the highest GMI score is the one that best meets experts' and DMs' expectations in terms of what should be considered as a good solution. Expectations could be the one of a risk-taking, a risk-averse, or a risk-neutral DM. The GMI ranking method offers (1) flexibility at modeling the expert behavior when making decisions; (2) inclusion of different forms of information that are manifested in the fuzzy solution, and (3) ability of ranking arbitrary fuzzy qualifier shapes.

The GMI ranking method integrates information about both the expected performance of the decision alternative at meeting DMs' objectives and the uncertainty of the evidence supporting the performance itself. To capture the properties of the fuzzy solutions, the GMI involves four criteria: (1) expected performance of the restoration option at meeting DMs'

objectives, (2) vagueness of the expected performance, (3) ambiguity of the expected performance, and (4) accumulation of evidence. Each criterion is represented by fuzzy subsets. The GMI uses (1) a FLC, similar to the one employed for evaluating the performance of each restoration option, to evaluate each decision alternative in terms of the four criteria and their associated attributes and (2) a simple additive weighted method (Chen and Hwang, 1992) is used to rank the decision alternatives by combining single criterion scores coming from the FLC into a composite criteria score.

Weights could be assigned to each criterion, allowing experts to identify compensation between the expected performance and the uncertainty related to it. More weights given to the performance criterion could be seen as a risk-taking DM. Conversely more weights given to the uncertainty related criteria could be seen as a risk-adverse DM. For instance, in some situations, a high score on the performance criterion might not be appropriate, due to possible uncertainty or risk related to proposed watershed restoration plans. In some cases, DMs might want to select a solution whose uncertainty is minimal or whose range of impacts simultaneously belongs only to a few neighboring fuzzy subsets.

Figure 3.5 presents a hierarchy of the information used by the GMI ranking method. The upper level of the hierarchy presents the four aforementioned criteria based on which the decision alternatives are ranked and the lowest-level of the hierarchy are the seven attributes that measured the criteria. DMs and experts could easily include in the analysis any other criteria to better model their values and perspective.

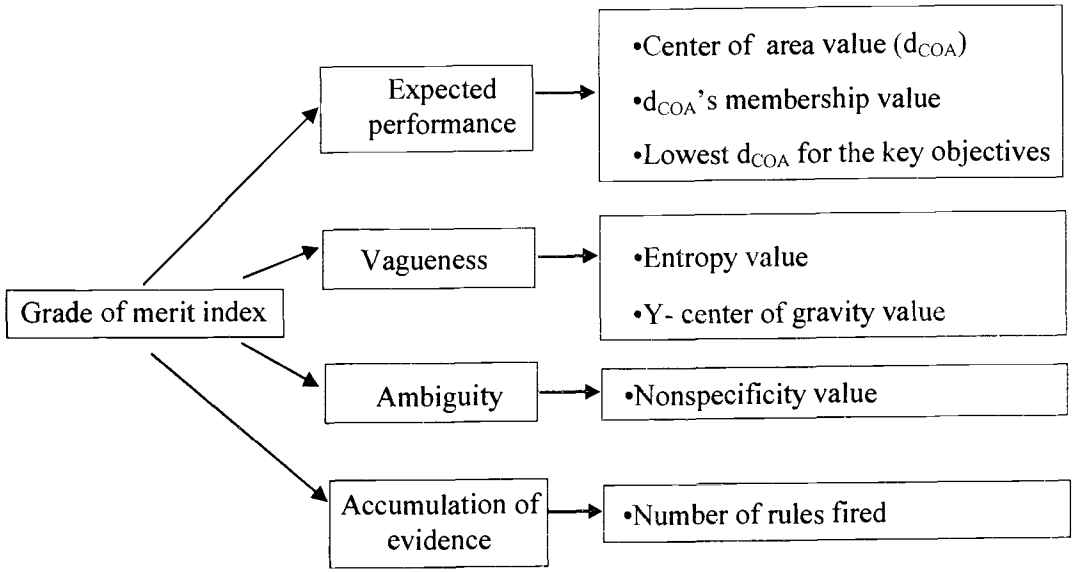

Figure 3.5: Hierarchy of the information used in the ranking process

Criterion 1: Expected performance

In the literature, one of the most commonly used practices to evaluate the expected performance of fuzzy alternatives makes use of a defuzzification method. The alternative with the greatest defuzzified value is selected as the one that best meets the overall DMs' objectives. The most widely used defuzzification method is the center of area method (COA) (Mamdani and Assilian, 1975). The GMI uses the COA as a defuzzification method. It was selected over other defuzzification methods for its simplicity and the fact that it combines evidence from all rules (Cox, 1999). However, this method has serious drawbacks. For instance, if output membership functions lie on the same single vertical axis, their COA value (d_{COA}) remains constant independently of whether the rule fired strongly or weakly. COA is not able to discriminate between the three fuzzy subsets shown in Figure 3.6, where the fuzzy subset *B* is intuitively preferable to fuzzy subset *A* and *C*.

Therefore, simple COA is not suitable for computing decision alternatives expected performance.

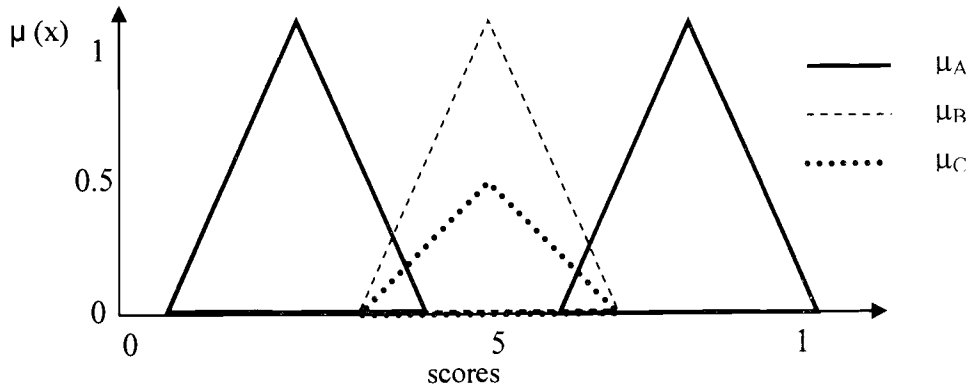

Figure 3.6. COA value and COA truth-value for three different fuzzy subsets.
$COA\mu_A = COA\mu_B = COA\mu_C$;
COA truth-value $\mu_A = 0$, COA truth-value $\mu_B = 1$, COA truth-value $\mu_C = 0.5$.

In order to overcome COA drawbacks, the GMI uses the d_{COA} in combination with two other attributes to compute the expected performance criterion of each decision alternative. These are the membership value of the d_{COA} and the lowest d_{COA} obtained for the key objectives. A good expected performance value is one that maximizes each of the three attribute values.

(1) Center of area value (d_{COA})

The COA (also known as the center of gravity method) converts each fuzzy subset conclusion (A) obtained from equation (3.2) to a single real number. It could be seen as a mean value representing the overall performance of the restoration at meeting simultaneously the DMs' objectives. The d_{COA} is computed as:

$$d_{COA}(A) = \frac{\int_{-a}^{a} A(y)y\,dy}{\int_{-a}^{a} A(y)dy} \tag{3.3}$$

(2) Truth value of the center of area value

The d_{COA} is a single crisp value representing the total range of the fuzzy subset solution. However, it may not locally represent the fuzzy subset and thus, the d_{COA}'s membership value in the fuzzy subset conclusion is computed. For instance, the three different fuzzy subsets, shown in Figure 3.6, result in an identical d_{COA} of 5, though the membership values are different. This attribute allows experts to assert that the higher the d_{COA}'s membership value, the more representative or reliable the d_{COA} might be of the expected performance.

(3) Lowest COA value among the key objectives

When defining the objectives hierarchy in step 1, DMs identify their values in terms of objectives and associated weights to be considered when selecting a restoration option for a particular site. GMI allows experts to limit the expected performance of a decision alternative by the lowest d_{COA} obtained by one of the objectives or by a subset of objectives (e.g. objectives having received a weight higher than 0.6 on a scale of 0 to 1). Considering the lowest d_{COA}, as an attribute, means that conservative experts could say that a very low performance on one important objective might cancel any favorable performance on other objectives or in other words might reduce the credibility of the expected performance score.

Criterion 2: Fuzziness

Fuzziness results from the imprecise boundaries of fuzzy subsets representing the experts' point of view about corresponding linguistic terms (Klir and Yuan, 1995). In the context of the GMI, a measure of fuzziness characterizes to what extent the decision alternative performance applies to each linguistic term describing impacts. Therefore, it is necessary to have a criterion to measure the fuzziness of fuzzy subsets. The following two attributes are used to evaluate the fuzziness criterion. A good score on the fuzziness criterion could be one that minimizes the entropy value and maximizes the y-centroid value.

(1) Entropy value

An entropy measure can be seen as uncertainty-based information, measuring the fuzziness or vagueness of a fuzzy subset. DeLuca and Termini (1972) proposed a measure of entropy based on the classical Shannon entropy function. Kaufmann (1975) proposed that the fuzziness of a fuzzy subset can be measured through the distance between the fuzzy subset and its nearest non-fuzzy subset. Yager (1979) introduced a measure that is considered as a holistic idea of the measurement of fuzziness, which is expressed by the distance between the fuzzy subset and its complement. The GMI uses the Yager's method (equation 3.4), because it is intuitive and easy to model (Higashi and Klir, 1982).

$$F_p(A) = 1 - \frac{D_p(A, CA)}{\| Supp(A) \|} \tag{3.4}$$

$$D_p(A, CA) = \left[\sum_{i=1}^{n} \left| \mu_A(x_i) - \mu_{CA}(x_i) \right|^p \right]^{1/p} \quad p = 1, 2, 3 \ldots \tag{3.5}$$

Let

$$S = Supp(A) : D_p(S, CS) = \|S\|^{1/p} \tag{3.6}$$

CA = complement of the fuzzy subset A

p = scaling factor

$\|S\|$ = relative cardinality of A

Entropy is considered as minimum F_p (A) = 0, when the fuzzy solution could be seen as a crisp set, in other words when the mapping between the linguistic variables and the quantitative values is either 0 or 1. A maximum fuzziness is obtained when the degree of membership is 0.5.

(2) The Y -center of area

Identical entropy value can be obtained for two fuzzy subsets that have different centroid value ($\bar{y}$) in the y axis (Figure 3.7), however intuitively between these two fuzziness values experts might prefer the fuzzy subset with the highest center of gravity in the y-axis. Therefore, to differentiate fuzzy subsets having the same fuzziness, the y-center of area (equation 3.7) is used.

$$\bar{y} = \frac{1}{2A} \int_{x=a}^{x=b} f(x)^2 dx \tag{3.7}$$

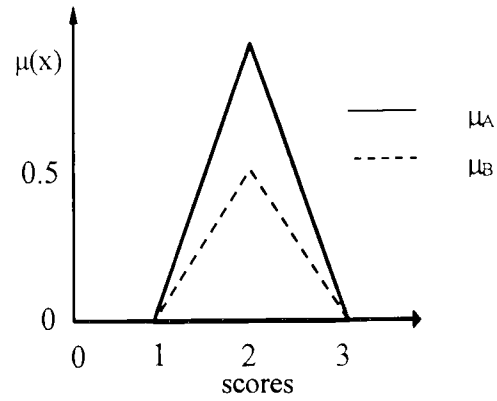

Figure 3.7: Entropy values for two different subsets
$F_p\mu_A = F_p\mu_A = 1$

Criterion 3: Ambiguity

A fuzzy subset describing the expected performance of a decision alternative might be related to various linguistic variables. For instance, the solution might simultaneously have to some extent low-negative, moderate, and high-positive impacts on the different objectives. The ambiguity in a set is connected with the size of the subsets. In our case, subsets designate linguistic variables describing the restoration options' impacts on the different objectives. The larger the subsets, the less specific is the characterization. The following decision variable is used to model the ambiguity of the fuzzy solution.

(1) Nonspecificity

The nonspecificity variable is another uncertainty-based information measure that is connected with the size (cardinalities) of fuzzy solutions or subsets. Nonspecificity can be thought of as a way of assessing the consistency of the different solutions. For instance, if all the impacts are described by the same linguistic variable, then the ambiguity regarding the impact is low. This is the most straightforward situation to deal with from an expert's

perspective. Nonspecificity provides an indication of the dispersion of the characterization. Thus a high value of nonspecificity indicates that the solution belongs to several different descriptive categories and this information could be used in risk-based management decision-making.

To compute the nonspecificity of any nonempty set A defined on a finite universal set X, we use the U-uncertainty function (equation 3.8), a generalization of the Hartley function (Higashi and Klir, 1983).

$$U(A) = \frac{1}{h(A)} \int_0^{h(A)} \log_2 \left| {}^{\alpha}A \right| d\alpha \tag{3.8}$$

where $\left| {}^{\alpha}A \right|$ represents the cardinality of the α-cut of A and h(A) is the height of A. The α-cut of a fuzzy subset A is the crisp set ${}^{\alpha}A$ that contains all the elements of the universal X whose membership grades in A are greater than or equal the specified value of α.

High specificity is obtained when a solution belongs to a single set. The meaning of a wide fuzzy subset is more ambiguous compared to a narrow one which meaning is more definite. For instance, a number of experts could prefer a solution defined by a narrow fuzzy subset, because impacts are constrained to only one category of impacts. In other circumstances, a solution with a wide output would be preferred for its versatility since it pertains simultaneously to different categories of impacts.

Criterion 4: Accumulation of evidence

(1) Number of rules

Intuitively, the reliability of a fuzzy solution could be seen as proportional to the number of rules fired, because more extensive knowledge is accumulated.

3.4 WATERSHED RESTORATION PLANNING EXAMPLE

The proposed approach was applied using RESTORE, a DSS for watershed restoration planning. RESTORE selects the most desirable restoration options under specific land use characteristics and creates a watershed restoration plan. The Upper Amazon sub-basin, part of the Long Tom watershed of Oregon's Willamette River Basin, was studied. The Upper Amazon sub-basin is substantially urbanized and is in to Oregon's second-largest metropolitan area, Eugene. The sub-basin has been significantly disturbed by agricultural and urban activities, resulting in a number of conflicts related to land use and consequent ecological impacts.

For this study, RESTORE MCDM algorithm (Lamy et al., 2002a) was modified to use a FMCDM when selecting a preferred restoration option. RESTORE evaluates, compares, and ranks restoration options subject to stakeholders' objectives. In the following example, we illustrate one set of stakeholders' priorities and concerns. DMs were considered risk-neutral. Water quality and water quantity were among five primary objectives, reflecting subobjectives of decreasing water temperature and runoff, increasing stream flows and improving nutrient management. These objectives were followed closely by socio-economic issues, including aesthetic quality, public support, and education and outreach. Maintaining and enhancing fish and wildlife habitat had a relatively low priority. The normalized weights given to the five objectives are: water quality 1; water quantity 1; habitat 0.33; social 0.78, and economic 0.78.

The RESTORE framework evaluates more than 20 restoration options per cell. For the Upper Amazon sub-basin, 12 200 cells are examined, with more than 2012200 possible landscapes or watershed restoration plans. Cells are built on the assumption that small

landscape areas can be aggregated into an area that is reasonably homogeneous with respect to land use, soil, and drainage. The example presented here focuses on a small riparian area of the watershed, where five restoration options were considered for each cell. These restoration options were: (1) riparian agricultural buffer, (2) increase late summer flow, (3) riparian forest buffer, (4) create condition favorable for native species, and (5) wetlands construction (Figure 3.8). Detailed results for a specific site (#3424) are presented in Table 3.1. This site can be broadly characterized as agricultural land adjacent to a stream and road.

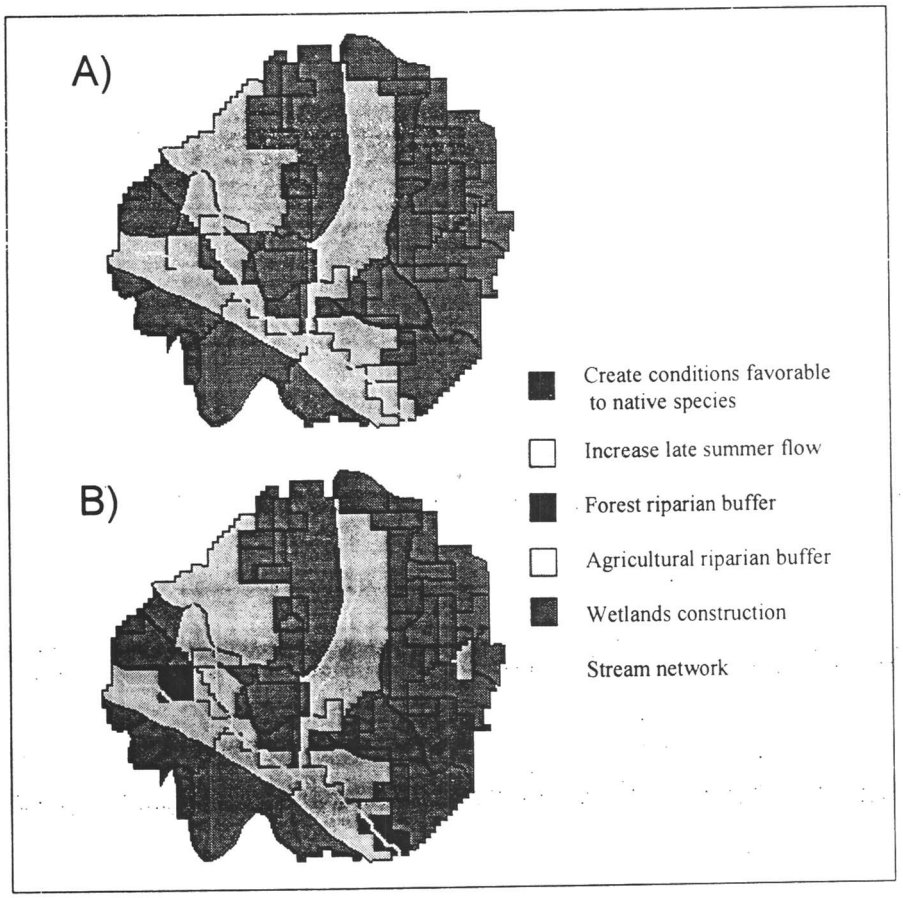

Figure 3.8: Proposed restoration plans resulting from the analysis performed by (A) MCDM RESTORE model and (B) FMCDM RESTORE model, on the study area. The MCDM analysis allocated to each site the restoration option with the highest score and the FMCDM analysis allocated to each site the restoration option with the highest GMI

As shown in Table 3.1, both the crisp and the fuzzy approaches rejected from the evaluation process "the forest riparian buffer" and the "wetlands construction" restoration options, because the agricultural site under study has not met the constraints of these two restoration options. No significant differences can be seen in the ranking results coming from the two approaches. The RESTORE framework ranks decision alternatives based on one attribute, which is the performance of the alternatives at simultaneously meeting the multiple objectives. In contrast the FMCDM approach ranks decision alternatives based on four criteria and seven attributes. One of the criteria relates to the expected performance of the alternative at simultaneously meeting the multiple objectives and the three other criteria relate to the uncertainty or the risk related to the expected performance itself. Both approaches (Table 3.1) concluded that the "late-summer flow control" restoration option was the best among the other alternatives at meeting the performance criterion. Therefore, the RESTORE MCDM framework applied the "late-summer flow control" restoration option on cell #3424 with a score of 2.69 out of 4. However, the RESTORE FMCDM approach, which modeled a risk-neutral DM, selected the "agricultural riparian buffer" restoration option over the "late-summer flow control" restoration option with a score of 5.84 out of 10 (in fuzzy terms, it is described by both moderate and a significant impacts). It was assumed that high scores on the uncertainty criteria compensated for the lower score obtained on the expected performance criterion.

The RESTORE MCDM algorithm assumes that variables can be represented by single discrete numbers, ignoring their continuous and wide-ranging nature. Such an approach entails certainty about the existing knowledge and averages the overall performance of each decision alternative at simultaneously addressing the different objectives. During this averaging process, diversity and uncertainty inherent in original information is lost.

Table 3.1: Detailed results of the FMCDM approach for a specific site

Restoration option	Ambiguity criterion	Expected performance criterion	Accumulation of evidence criterion	Vagueness criterion	GMI Score	RESTORE score
Agricultural riparian buffer	6.34	5.22	8.42	3.38	5.84	2.07
Late-summer flow control	4.68	6.84	4.68	3.94	5.03	2.69
Create condition favorable for native species	3.33	3.95	3.84	3.33	3.61	1.04
Forest riparian buffer	6.68	6.31	6.33	3.32	0	0
Wetlands construction	4.68	4.14	6.94	3.53	0	0

In contrast, the RESTORE FMCDM approach enables experts to express their knowledge and experiences with linguistic terms represented by fuzzy subsets (which can be seen as uncertainty intervals) rather than discrete values. Such approach widens the range of the solution space by adding tolerance and flexibility in the analysis of the alternatives. Fuzzy rules use fuzzy subsets that allows a membership in more than one category, which makes the model more robust in front of uncertainty in expert knowledge or when adding new information. For instance, an alternative is not excluded from the evaluation process simply because it exceeds a constraint (e.g. stream proximity should be less than 20 meters) by a small amount (e.g. 1 meter).

The output of the FMCDM evaluation process is a fuzzy subset, which is rich in information-content. Information-content may refer to local characteristics (e.g. extent to which an option has met or not met the rules' conditions, and extent to which an option is

characterized by one linguistic term) or global characteristics (e.g. center of area, uncertainty-based information) of the fuzzy subset. This information can be used in the ranking process, as it is done by the GMI. In addition, having this information allows a DMs and experts to reevaluate in some cases the benefits of a restoration apparently not suitable in the first place. When more information is included in the ranking process, the decision alternatives are better understood by DMs. A GMI score provides an indication of the quality of the evidence showing the value of the different alternatives, being either included or rejected from the evaluation process. The GMI extends the existing ranking methods by providing a more complete analysis of the fuzzy subset being ranked and by better supporting the accumulated information. More specifically, it does so by (1) making use of a FMCDM technique that considers four criteria and seven attributes characterizing the different facets of fuzzy subsets (most existing methods use only one attribute to rank fuzzy subsets) and allows experts to specify weights on each criterion, (2) including uncertainty-based information as attributes for measuring the uncertainty of the fuzzy subsets, (3) not making any assumptions about the shape of the fuzzy subsets to be ranked, and (4) making use of fuzzy rules to evaluate each criterion, which brings transparency and flexibility to the ranking process and allows DMs to express their values and perspective about what should be considered a good alternative in a specific decision context.

The evaluation and selection process of alternatives in a community-based watershed restoration planning context is often accomplished with information expressed in linguistic terms which are intrinsically subjective and imprecise. A FMCDM approach is more realistic than a traditional MCDM approach because it gives experts' the flexibility to take into account the uncertainty involved in the decision-making process.

3.5 CONCLUSIONS

A FMCDM approach was proposed and applied to the context of RESTORE, a decision tool for holistic watershed restoration planning. The approach involves three basic steps: (1) expert values are first captured and serve as a starting point to additional analysis steps, (2) a FLC is built, which contains (a) a knowledge base, (b) an inference process enabling DMs to evaluate the performance of the restoration options at meeting the different objectives separately, and then (3) a FMCDM module is developed, which (a) aggregates fuzzy subsets to calculate a composite objective function for each option and finally (b) integrates a novel ranking method to create a final ranking of the restoration options, resulting in an efficient watershed management plan.

The results obtained so far strongly indicate that our FMCDM approach provides a valuable tool in the analysis of complex watershed management issues because it properly addresses the inherent ambiguity in experts' knowledge. The approach presents a novel fuzzy ranking method, GMI. The GMI is a flexible and intuitive ranking method that uses a FMCDM technique, includes uncertainty-based information, does not make assumptions about the shape of the fuzzy subsets to be ranked, and allows DMs and experts to express their values and perspective about what should be considered as a good alternative in a specific decision context.

Community-based decision-making is a collaborative process, where negotiations among participants and conflicts of interest are almost inevitable. DMs need tools to support consensus and compromise building. A future version of RESTORE should include methods providing a systematic means for developing effective group decision making, where the inclusion of conflicting opinions may alter the shape of the fuzzy criteria and the ranking of decision alternatives.

Other improvements to the present structure of RESTORE include the modeling of other sources of uncertainty. This paper was concerned with the linguistic uncertainty in expert knowledge which does not include the uncertainty related to the occurrence of an event. In some situations, a DM might not be 100% sure about the shape of a fuzzy subset or the truthfulness of a rule, which could be translated as uncertainty due to a lack of knowledge or ignorance about a situation. There is an opportunity to combine fuzzy set theory with another uncertainty theory that would specifically address this type of uncertainty.

CHAPTER 4

DEVELOPMENT AND EVALUATION OF THREE UNCERTAINTY APPROACHES IN RESTORE, DECISION-MAKING TOOL FOR COMMUNITY-BASED WATERSHED RESTORATION

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4.1 INTRODUCTION

Watershed restoration decisions involve interactions between socio-economic and environmental systems, which are both complex and not fully understood. Typically, a decision-making process involves several distinct and iterative steps, including decision problem description, identification of decision-makers (DMs)' values, creation of a knowledge base, and generation and evaluation of feasible solutions (Lamy et al., 2002a). Spatially explicit decision support systems (DSSs) show potential for assisting in the production of watershed restoration plans. These plans typically involve multiple DMs' interests and must balance a variety of often conflicting objectives. DSSs have been defined as computer-based systems that support the decision-making process by enhancing problem comprehension and by providing data, analytical tools, and methods to characterize uncertainty (Mowrer, 2000). However, only a few DSSs recognize and implement uncertainty assessment (Heuvelink, 1998; Crosetto et al. 2000, Mowrer, 2000).

Several theories to model uncertainty in expert knowledge have been proposed, including Bayesian theory (de Finetti, 1972), possibility theory (Zadeh, 1978), Dempster-Shafer theory (Dempster, 1967; Shafer, 1976), fuzzy set theory (Zadeh, 1965), and certainty factor model (Buchanan and Shortliffe, 1984). Even though each of them can only be applied to specific decision-making contexts, modelers have a tendency to favor one theory and apply it to all cases. Additionally, few studies have compared the suitability of different theories to specific decision problems. The selection of appropriate methods for modeling uncertainty is decision context dependent (Zimmermann, 2000).

To date, no study has compared the applicability of different uncertainty theories to watershed restoration. Here, we explore the utility of three uncertainty theories, including certainty factor model, Dempster-Shafer theory, and fuzzy set theory; at modeling the

uncertainty in experts' knowledge using RESTORE. RESTORE (Lamy et al., 2002a) is a geographical information system-based decision-making tool developed to help watershed councils evaluate and rank restoration activities at the watershed level. It includes a rule-based system that models the experts' perception of restoration alternatives performance at meeting DMs' multiple objectives. Objectives considered include water quality, water storage, habitat quality, social concerns and economics that often conflict. A multiple criteria decision-making (MCDM) performance evaluation leads to the ranking of restoration alternatives, which are used as building blocks for future restoration plans. Rankings reflect alternatives' impacts on the objectives described above, which are determined through the application of a set of rules, developed from experts' knowledge. A rule describes a restoration alternative's performance at achieving a specific objective for given site conditions.

The complexity of the various landscape processes and human subjectivity suggest that a robust performance evaluation module would involve the modeling of uncertainties inherent to experts' knowledge. This information can be critical from a DM's point of view and can allow a DM to make more informed decisions (Crosetto et al., 2000; Hoffman et al., 1999). In RESTORE, evaluation of alternatives is carried out using a crisp (no estimate of uncertainty) rule base that contains heuristic knowledge, which utilizes spatial data (e.g. soil type, slope, distance to stream) stored in a geographic information system (GIS) database. Heuristic knowledge is generated from experts' experiences, beliefs, and judgments (Yen, 1999) and takes the form of rules that embody the experts' knowledge about site and landscape level guidelines for restoration alternatives.

Knowledge representation is crucial to the ability of RESTORE and similar systems to capture important decision processes. Methods dealing exclusively with precise statements often cannot fully capture the richness and complexity of experts' knowledge (Baroni et

al., 2001). For example, assessing the ability of a wetlands restoration project at improving the aesthetic quality of an area is a difficult task because (1) the assessment is qualitative and often based on the experience, judgment, and beliefs of experts in the field, (2) experts might not have all the information available to make an unequivocal assessment, and (3) the experts' natural language used to describe an impact (e.g. low or significant impact on the aesthetic quality objective) is inherently vague. Due to these difficulties, uncertainty exists in the estimated value of a restoration alternatives' ability to address DMs' objectives.

Various methods have been proposed to quantitatively represent experts' knowledge and related uncertainty in DSSs. In this paper, certainty factors model, Dempster-Shafer theory, and fuzzy set theory approaches are investigated using RESTORE's rule base. In the following sections, we will (1) explore the basic mechanisms for reasoning under uncertainty advocated by each approach, (2) identify criteria that should help modelers assess whether or not an uncertainty method is appropriate for a specific MCDM context, (3) characterize each theory in terms of the identified criteria using RESTORE, and (4) apply each theory using RESTORE.

4.2 METHODS OF UNCERTAINTY

In this paper, the notion of uncertainty refers to Zimmermann's (2000) interpretation: "Uncertainty implies that in a certain situation a person does not dispose information which quantitatively and qualitatively is appropriate to describe, prescribe, or predict deterministically and numerically a system, its behavior or other characteristics". In other words, a statement is considered as uncertain if an expert, based on the available information, cannot evaluate its truth or falsity in a dichotomous way. In heuristic

modeling approaches such as RESTORE, uncertainty in experts' knowledge originates from (1) beliefs (e.g. partial beliefs, conflicting beliefs, disagreement among experts about potential impacts), (2) linguistic imprecision (ambiguity of the terms or linguistic variables used in the knowledge base), and (3) ignorance about the true state of nature (Cleaves, 1995).

A classical method for addressing model's uncertainty is the Bayesian probabilistic approach (de Finetti, 1972). However, this approach is not well suited to experts systems, such as RESTORE, since it requires the evaluation of a priori probability distributions for all facts in the rules, while these probabilities are generally not available (Beynon et al., 2000; Kozine and Filimonov, 2000). Furthermore, Bayesian theory is inadequate to model ignorance. For these reasons, other approximate reasoning theories have been developed; among these are (1) fuzzy set theory, (2) certainty factor model, and (3) Dempster-Shafer theory; all of which were used in this study. These theories can either model beliefs, ambiguity, and/or ignorance in experts' knowledge.

Here, we relate uncertainty theory and generalized information theory (Klir and Smith, 1999). The aim of the generalized information theory is to characterize uncertainty-based information within any feasible mathematical framework (Klir and Yuan, 1995). In this theory, the term information is given a mathematical meaning as a numerically measurable quantity. Three types of uncertainty-based information are recognized: fuzziness, nonspecificity, and conflict (Klir and Yuan, 1995). However, in this study, we considered ignorance as another facet of uncertainty-based information. Ignorance in evidence represents the inability of the experts to completely assign their belief to one or more subsets of the universal set X. Nonspecificity in evidence is related to the size of the subsets that characterize a solution; the larger the subset, the less specific (or more ambiguous) the characterization. Dissonance is present whenever there is inconsistency or

disagreement in evidence. It is exhibited when there is more than one disjoint subset describing a solution. Finally, fuzziness results from the imprecise boundaries of fuzzy subsets. The shape of a fuzzy subset presents a measure of the fuzziness of the corresponding linguistic term in the mind of the experts. Specific characterizations of uncertainty reflect the mathematical theory used; therefore any uncertainty theory is capable of capturing only certain types of uncertainty-based information.

Uncertainty-based information allows DMs to evaluate the quality of the evidence supporting a decision alternative. In the event of poor evidence quality (e.g. high nonspecificity, fuzziness, conflict, and/or ignorance), DMs might decide to reject an alternative or look for new information to reduce the uncertainty. The amount of uncertainty and the amount of information are intimately connected (Klir and Yuan, 1995).

Following is a brief description of the certainty factor model, Dempster-Shafer theory, and fuzzy set theory. Special attention is given to the theoretical concepts, inference process, and uncertainty-based information.

4.2.1 Certainty factors model

The certainty factor model (CFM) was created in the mid 1970's by Bruce Buchanan and Edward Shortliffe (1984) for the rule-based medical expert system Mycin. The model has been applied primarily in the medical field, with additional applications in other domains, e.g. mineral exploration (Yardick et al., 1986) and housing discrimination (Anandanpillai and Barta, 1999). In this model, each proposition is assigned a measure of certainty, called a certainty factor (CF: [-1, 1]) that combines degree of belief (MB: [0, 1]) and disbelief (MD: [0, 1]) into a single number (equation 4.1).

$$CF\ [h, e] = MB[h,e] - MD[h, e] \quad (4.1)$$

where MB[h,e] = the measure of increased belief in the hypothesis h, based on evidence e and MD[h, e] = the measure of increased disbelief in the hypothesis h, based on evidence e. A CF of -1, 0, and 1 means respectively that the proposition is known with certainty to be false, no evidence support its truthfulness or falsity, and known with certainty to be true.

In RESTORE, a CF assigned to a rule (or hypothesis) is equal to MB since, in RESTORE, experts do not express disbelief. A CF is an experts' subjective belief, often seen as subjective probability, that describes the strength of their confidence in the conclusion of a rule, assuming the rule's premise is true (Figure 4.1). A CF is applied to every rule; these are then combined to compute the CF of a conclusion. For instance, having a first rule which takes the following form: IF *A* then *B*, with a measure of belief (CF=0.8) in conclusion *B*. Giving another rule IF *C* then *D* with a CF=0.5 in conclusion *D*, the combined CF ($CF_{revised}$) of two rules is defined as: $CF_{revised} = CF_{old} + CF_{new}\ (1\text{-}CF_{old})$. In the preceding example, $CF_{revised} = 0.8 + 0.5\ (1\text{-}0.8) = 0.9$. This approach accumulates certainty to a result as more evidence supporting that result is considered. Rules may contain multiple antecedents. For conjunctive antecedents of a rule, the combined CF is equal to the minimum of the antecedents' CFs. For disjunctive antecedents, the combined CF is equal to the maximum of the antecedents. In spite of its simplicity, the CFM performed well when judged against human domain experts in Mycin (Horvitz et al., 1988).

The output of the traditional CFM is a single number, which does not allow the representation of the different types of uncertainty-based information that are recognized here, i.e. fuzziness, nonspecificity, conflict, and ignorance.

RESTORE crisp rules

rule1
IF soil erosion is < 2 {tons/acre}
THEN the Agricultural Riparian buffer's impact on the water quality objective is 1/4

rule2
IF Erosion_Potential >= 2 {tons/acre} and Erosion_Potential < 5 {tons/acre}
THEN the Agricultural Riparian buffer's impact on the water quality objective is 2/4

rule3
IF Distance_to_Pesticide_listed_Stream >= 1000 {meters}
THEN the Agricultural Riparian buffer's impact on the water quality objective is 1/4

RESTORE certainty factor rules

IF soil erosion is < 2 {tons/acre} *with certainty of (1)*
THEN the Agricultural Riparian buffer's impact on the water quality objective is 1/4 *with a certainty of (0.8)*

IF Erosion_Potential >= 2 {tons/acre} and Erosion_Potential < 5 {tons/acre} *with certainty of (1)*
THEN the Agricultural Riparian buffer's impact on the water quality objective is 2/4 *with a certainty of (0.8)*

IF Distance_to_Pesticide_listed_Stream >= 1000 {meters } *with certainty of (1)*
THEN the Agricultural Riparian buffer's impact on the water quality objective is 1/4 *with a certainty of (0.8)*

RESTORE Dempster-Shafer rules

IF soil erosion is < 2 {tons/acre}
THEN the Agricultural Riparian buffer's impact on the water quality objective is *(1)* low *with a belief of (0.8) and (2) unknown with a belief of 0.2*

IF Erosion_Potential >= 2 {tons/acre} and Erosion_Potential < 5 {tons/acre}
THEN the Agricultural Riparian buffer's impact on the water quality objective is *(1)* moderate *with a belief of (0.8) and (2) unknown with a belief of 0.2*

IF Distance_to_Pesticide_listed_Stream >= 1000 { meters }
THEN the Agricultural Riparian buffer's impact on the water quality objective is *(1)* low *with a belief of (0.8) and (2) unknown with a belief of 0.2*

RESTORE fuzzy rules

IF soil erosion is low
THEN the Agricultural Riparian buffer's impact on the water quality objective is low

IF Erosion_Potential is moderate
THEN the Agricultural Riparian buffer's impact on the water quality objective is moderate

IF Distance_to_Pesticide_listed_Stream is far
THEN the Agricultural Riparian buffer's impact on the water quality objective is low

Figure 4.1: Examples of RESTORE's crisp rules translated into the scheme of certainty factor model, Dempster-Shafer theory, and fuzzy set theory.

4.2.2 Dempster-Shafer theory

The Dempster-Shafer theory (DST) (Dempster, 1967; Shafer, 1976) provides a method for representing and reasoning with degrees of belief. DST uses a number between 0 and 1 to indicate a subjective assessment of the degree of support that a body of evidence provides for a proposition (Yager, 1983). Unlike probabilistic approaches, DST theory does not require a complete set of prior and conditional probabilities. In addition, DST provides an explicit way for representing a lack of knowledge or ignorance about a specific state of nature. DST is more suitable for decision problems that involve a hierarchical structure, because it allows experts to assign degrees of belief to a collection of hypotheses and a single hypothesis. Such a feature facilitates the aggregation of evidence gathered at varying levels of detail. RESTORE's decision domain has a natural hierarchical structure.

In Figure 4.2, an illustration of a RESTORE value tree objective is presented. The main objective is "Watershed Restoration", which consists of five key objectives, each characterized by subobjectives, then attributes are added under the subobjectives. Attributes are site-based decision variables that are considered by RESTORE when evaluating the impacts of alternatives on DMs' objectives. The lowest part of the hierarchy is composed of decision alternatives that are connected to the attributes.

Few researches have investigated the use of a DST-based MCDM approach (Beynon et al., 2000; Yang, 2001; Beynon, 2002). Furthermore, to the knowledge of the authors, no research has been conducted on the application of a DST-based MCDM approach to watershed management issues in general and more specifically to watershed restoration. DST has been applied to topics such as safety analysis (Wang et al., 1995), engineering (Yang and Sen, 1997, Sönmez et al., 2001), word recognition (Bowles and Damper, 1989),

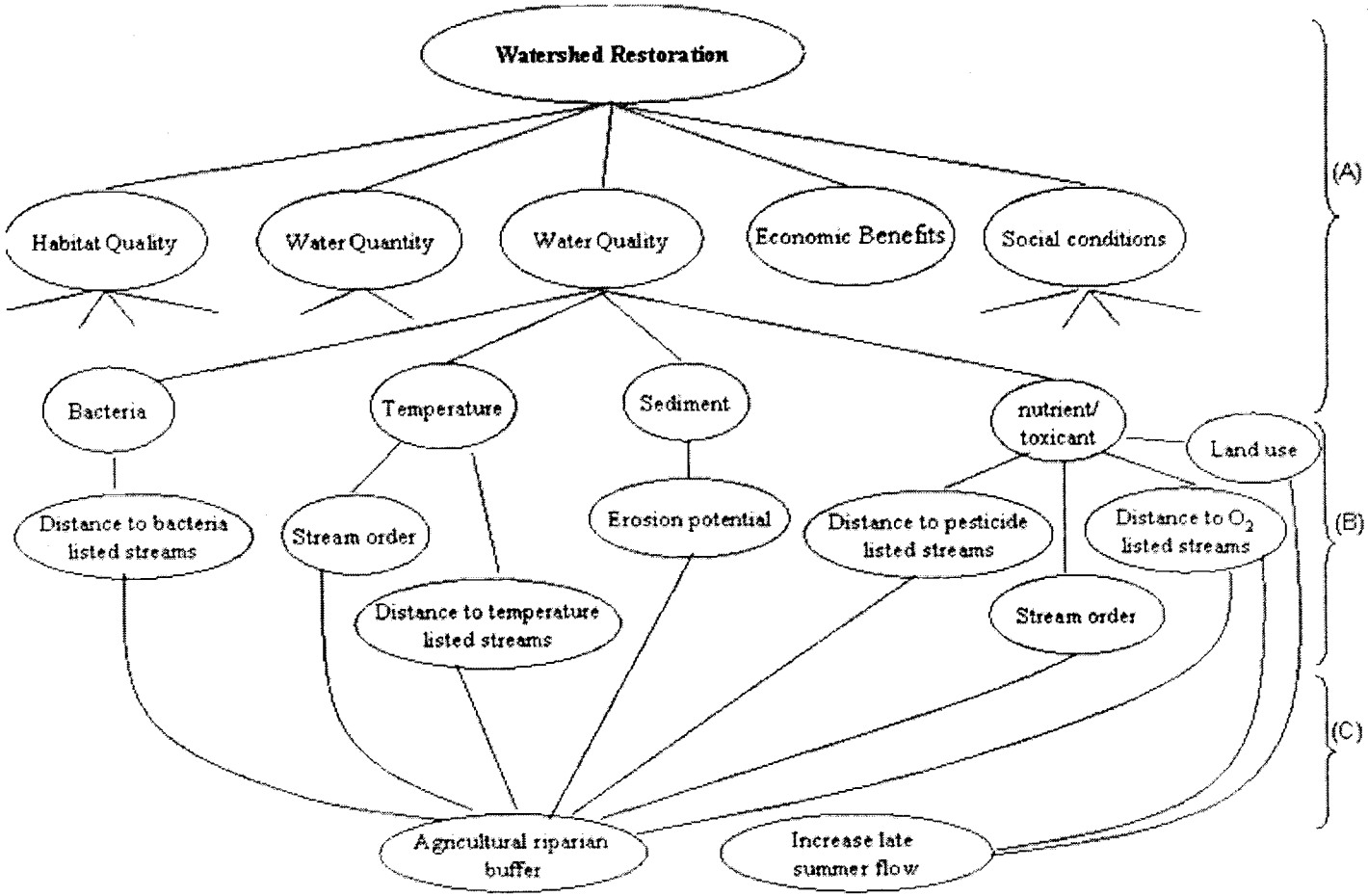

Figure 4.2: RESTORE's value tree for the water quality objective; (A), (B), and (C) correspond respectively to objectives, attributes, and decision alternatives.

and remote sensing (Le Hégarat-Mascle, et al., 1997; Bendjebbour et al., 2001). Yet the vast potential of DST has remained unexploited (Hajek, 1994).

DST assumes a frame of discernment denoted by θ, which is a finite, nonempty set of the possible hypotheses assumed to be mutually exclusive. In RESTORE, these hypotheses can be the set of grades defining an impact (e.g. low, moderate, significant, and high). Each hypothesis in θ corresponds to a single subset (singleton). DST uses a basic probability assignment (bpa) that allocates a degree of belief (m) of 0 to the empty set m(Φ) and a value in the range of [0,1] to each subset of all possible subsets of θ, which is denoted by the power set 2^{θ}. A subset for which (m) > 0 is called a focal element. The total degree of belief assigned must sum up to 1. The quantity of m(θ) is a measure of that portion of the total degree of belief that experts were unable to assign to any particular subset of θ. It is seen as experts' ignorance about possible outcomes.

For a given bpa allocated to a subset A of θ, Bel(A) is a belief measure that corresponds to the total amount of belief that supports the subset A. A plausibility measure is the total amount of belief that A is compatible with the available evidence. The interval [Bel(A), Pl(A)] can be considered to be a measure of ignorance about A. Evidence in θ is combined using Dempster's rule of combination (2). The bpas assigned to rule 1 (m_1) and rule 2 (m_2), being respectively X and Y are combined by summing all products (equation 4.2), such operation focuses on the intersection X∩Y, as shown in Table 4.1. Then the resulting bpa $m_{12}(C)$ is combined with a third rule; all rules are combined using this technique.

$$m_{12}(C) = \sum_{X \cap Y = C} \frac{m_1(X) m_2(Y)}{1 - K} \tag{4.2}$$

$$K = \sum_{X \cap Y = \Phi} m_1(X) m_2(Y) \tag{4.3}$$

where $m_1(X)$ and m2(Y) are beliefs that run over all hypotheses of θ.

K is a normalizing factor, which measures how much m_1 and m_2 are conflicting. It normalizes the new belief distribution by re-assigning any bpa which is assigned to the empty set, Φ, by the combination. Table 4.1 presents an example of Dempster's rule of combination using the rules 1 and 3 from the *RESTORE Dempster-Shafer rules* presented in Figure 4.1. In this example, experts estimated that for a specific site, based on available information and evidence, an agricultural riparian buffer's ability to address the water quality objective was low with a confidence of 0.8. The remaining 0.2 was the unassigned degree of belief ($m(\theta)$), which may have been due to a lack of knowledge or information about the impact of the alternative on the water quality objective.

The uncertainty-based information that can be measured in DST is nonspecificity and conflict. Nonspecificity measures the inability to distinguish which of several possible alternatives is the true one in a particular situation. Nonspecificity occurs when beliefs are assigned to overlapping subsets. Conflict measures the inconsistency or disagreement present in the evidence. Conflict occurs when one piece of evidence points in one direction and a second piece points in another direction. The degree of conflict is proportional to the strength of the disagreeing pieces of evidence.

A measure of nonspecificity was first proposed for possibility and necessity measures by Higashi and Klir (1983). It was later generalized by Dubois and Prade (1985) for belief functions. The measure of *nonspecificity* is defined as:

$$N(m) = \sum_{A \in F} m(A) \log_2 |A| \tag{4.4}$$

where |A| is the cardinality of the focal element A and F signifies the set of all focal elements. All focal elements are weighed by their basic bpas. The measure of nonspecificity is a weighed average of the Hartley function (1928), which was conceived in terms of classical set theory. It measures the uncertainty associated with sets of alternatives.

Table 4.1: Example of the Dempster's rule of combination. The results of the combination of the rules 1 and 3 from Figure 4.1 are shown in the *normalized combined basic probability assignment*. L, M, S, H, and θ representing respectively low, moderate, significant, high, and unknown impact on specified objective.

Evaluation grades	**L**	**M**	**S**	**H**	**θ**	**Φ**
Rules/assessment						
Rule 1	*0.8*	*0*	*0*	*0*	*0.2*	
Rule 3						
L *0*	0	0	0	0	0	
M *0.8*	Φ (0.64)	0	0	0	M (0.16)	
S *0*	0	0	0	0	0	
H *0*	0	0	0	0	0	
θ *0.2*	L(0.16)	0	0	0	θ (0.04)	
Combined bpas	0.16	0.16	0	0	0.04	0.64
Normalized Combined bpas	**0.44**	**0.44**			**0.11**	

Various methods have been presented for measuring conflict (Höhle, 1982; Klir and Ramer, 1990). The method preferred in this study is Yager's (1983) method. It uses the function E, called the *measure of dissonance*, defined by:

$$Em = -\sum_{A \in F} m(A) \log_2 Pl(A) \tag{4.5}$$

4.2.3 Fuzzy Set Theory

In 1965, Lofti Zadeh proposed fuzzy set theory, a mathematical framework that gives experts the ability to convey the fuzziness or the intrinsic vagueness of qualitative concepts. Most qualitative concepts have no precise boundaries or cannot be described precisely; therefore, soft boundaries are used to handle the idea of partial truth. Fuzzy logic models the intrinsic fuzziness or vagueness of natural language. Fuzziness relates to the degree to which an event occurred, rather than to the likelihood of its occurrence. Fuzzy set theory is more compatible with linguistic terms than a two-valued logic or a crisp logic, where a membership function μ_A of a fuzzy set A associates a membership value ($\mu_A(x)$) in the interval [0, 1] with each element x of the universe of discourse U.

A usual fuzzy inference process includes the following major steps: (1) fuzzification, (2) implication, (3) aggregation, and (4) defuzzification (Cox, 1999). These steps, shown in Figure 4.3, are described below:

1. *Fuzzification.* A variety of fuzzy subsets is defined for each input and output variable. For instance, in Figure 4.3, the fuzzy set (linguistic variable) soil erosion is defined in terms of the fuzzy subsets (linguistic terms): low, moderate, and significant.

2. *Implication.* A mechanism that defines the degree of truth of a rule. The truth-value for the premise of each rule is computed and applied to the rule's conclusion. In Figure 4.3, the minimum implication function (MIN) is applied, truncating the output membership function by the rule premise's minimum degree of truth.

3. *Aggregation.* Fuzzy subsets assigned to output variables are combined together to form a single fuzzy subset. In Figure 4.3, the maximum function is used, taking the pointwise maximum over all of the combined fuzzy subsets.

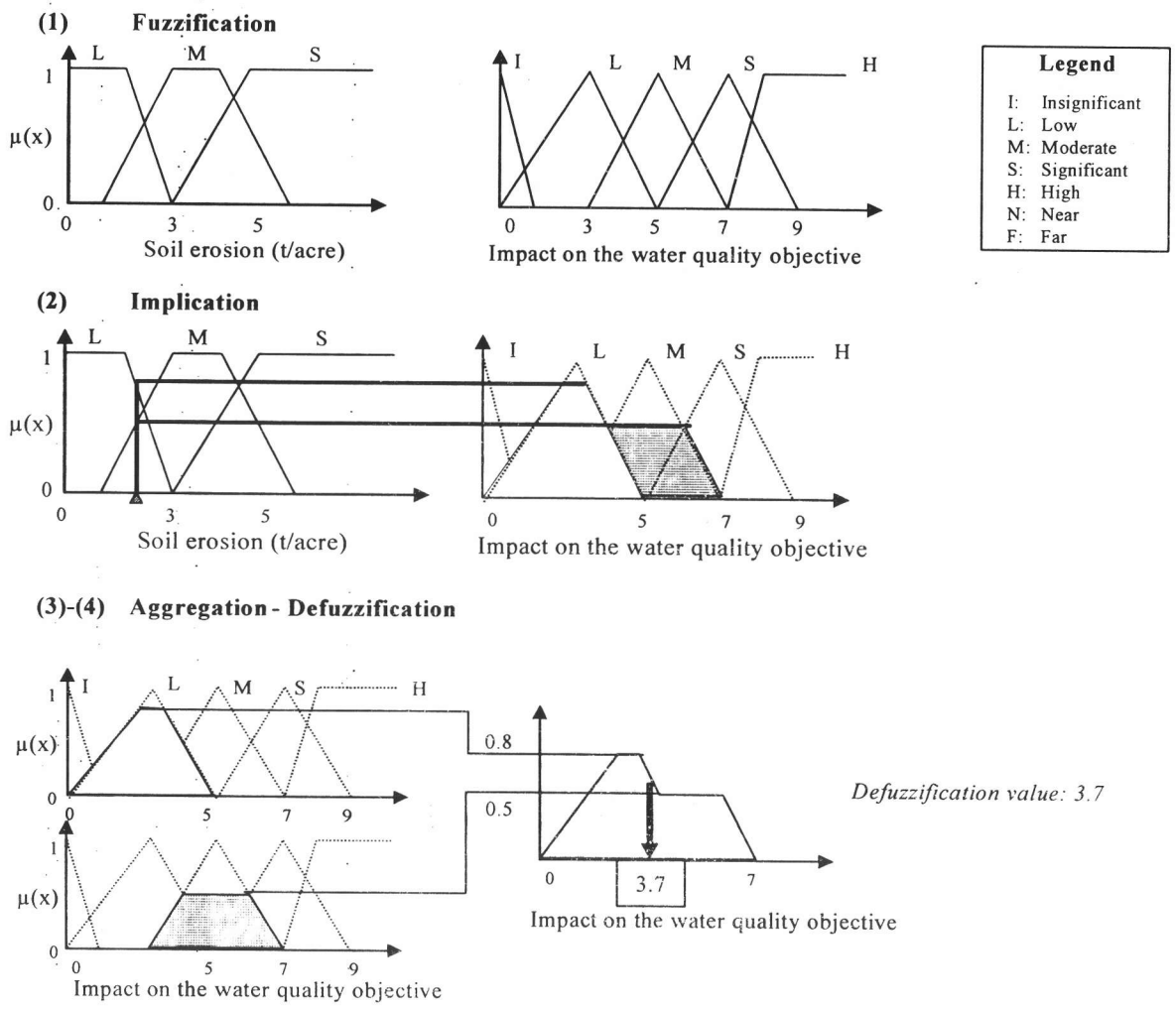

Figure 4.3: Fuzzy inference process using rules 1 and 2 from Figure 4.1. Site's soil erosion = 2.4 t/acre.

4. *Defuzzification*. A fuzzy subset is converted to a crisp number. There are many defuzzification methods available in the literature; the most often used is the center of area method (Mamdani and Assilian, 1975) (equation 4.6). This method weights the area under the fuzzy subset (A) with the truth-value A(y).

$$d_{COA}(A) = \frac{\int_{-a}^{a} A(y)y\,dy}{\int_{-a}^{a} A(y)dy} \tag{4.6}$$

Fuzzy set theory allows the measurement of two types of uncertainty-based information, fuzziness and nonspecificity. Fuzziness results from the imprecise boundaries of fuzzy subsets representing the experts' definition of corresponding linguistic terms (Klir and Yuan, 1995). Entropy measures are used to quantitatively evaluate the fuzziness of a fuzzy subset. DeLuca and Termini (1972) proposed a measure of entropy based on the classical Shannon entropy function. Kaufmann (1975) proposed that the fuzziness of a fuzzy subset can be measured through the distance between the fuzzy subset and its nearest non-fuzzy subset. Yager (1979) introduced a measure of fuzziness (F_p), expressed as the distance (D_p) between the fuzzy subset (A) and its complement (CA). Yager's method (equation 4.7) is intuitive and easy to model (Higashi and Klir, 1982).

$$F_p(A) = 1 - \frac{D_p(A, CA)}{\| Supp(A) \|} \tag{4.7}$$

$$D_p(A, CA) = \left[\sum_{i=1}^{n} |\mu_A(x_i) - \mu_{CA}(x_i)|^p \right]^{1/p} \quad p = 1, 2, \ldots \tag{4.8}$$

$$S = Supp(A) = \|S\|^{1/p} \tag{4.9}$$

where $\mu_A(x)$ is a membership value of value x in the fuzzy subset A, and $\mu_{CA}(x)$ being its complement; p is a factor allowing the distance specification (p=1, p=2 and p=∞, represent

respectively the Hamming, Euclidean, and Sup metrics), and $\|S\|$ is the relative cardinality of A.

Nonspecificity measures the size (cardinalities) of a fuzzy subset. Nonspecificity provides an indication of the dispersion of the characterization. In RESTORE, a low nonspecificity means that an impact assessment is well represented by the evidence gathered; thus, there is a low risk and ambiguity about the likely impacts of a solution on the prioritized objectives. To compute the nonspecificity of a fuzzy subset C, the U-uncertainty function, a generalization of the Hartley function (Hartley, 1928; Higashi and Klir, 1983), is used.

$$U(A) = \frac{1}{h(A)} \int_0^{h(A)} \log_2 \left| {}^{\alpha}A \right| d\alpha \tag{4.10}$$

where $\left| {}^{\alpha}A \right|$ represents the cardinality of the α-cut of the fuzzy subset A, h(A) is a normalizing factor corresponding to the maximum truth value of the fuzzy subset A. An α-cut of a fuzzy subset A is the crisp set ${}^{\alpha}A$ that contains all the elements of the universal X whose membership grades in A are greater than or equal the specified value of α.

4.3 ANALYSIS CRITERIA

To date, no research has compared uncertainty theories using MCDM applied to watershed management. Since no single method is able to model all types of uncertainty and to address all DMs' and experts' practical requirements, the examination of various uncertainty theories is a critical step in any given application. Each theory is proficient at modeling at least one kind of uncertainty present in experts' knowledge, related either to experts' beliefs, linguistic imprecision, and/or ignorance about the true state of nature. Ideally, the selected method should be able to maximize the use of the information

provided by experts and to provide unambiguous results from a DMs' standpoint. To help modelers in the selection process, we identified a list of criteria that can be used to characterize uncertainty theories. To date, most research has focused on the theoretical issues of uncertainty; their practical application has received less attention (Walley, 1996). The theoretical foundations of each of the three theories have been extensively investigated. This paper proposes an application-oriented list of criteria. Ultimately, the objective of such criteria is to find a match between the profile of a decision situation and the profile of one or more uncertainty theories. These criteria are described below.

1. Interpretation

The chosen theory should provide a clear interpretation of the uncertainty that is being addressed. When modeling uncertainty, a modeler should identify the sources of uncertainty specific to the context under study. An unambiguous interpretation is important from a modeler's point of view because it allows the identification of sources of uncertainty that can be modeled by the uncertainty theory and the successful design of an inference process. Each theory uses an inference process most suitable for the corresponding interpretation. From a DM's point of view, an unambiguous interpretation allows a clear understanding of the conclusions coming from the inference process.

In RESTORE, an uncertainty theory should be able to at least model uncertainty related to experts' beliefs, linguistic imprecision, and/or ignorance.

2. Information required from the experts

Each uncertainty theory requires specific information from experts. Before selecting a theory, it is critical to assess if the theory can exploit the information richness provided by

the experts and if the experts are able to provide the information required by the theory. In RESTORE, the experts provide information in terms of rules, using crisp variables.

3. Output information required by DMs

In every decision-making context, DMs may request specific types of information to make comprehensive decisions. DMs' requirements for this information may include that it (1) is understandable, (2) is provided in a suitable format, i.e. numerical, intervals or linguistically (Zimmermann, 2000), (3) allows the measurement of uncertainty-based information (e.g. nonspecificity, fuzziness, ignorance, etc.), and (4) allows an unequivocal ranking order. It should be noted that the complexity of the ranking procedure is generally proportional to the amount of information present in the output solution.

4. Inference process

When selecting an uncertainty theory it is important to be familiar with the different options made available by the theory's inference process and to evaluate if these options match the decision problem. The inference process encompasses methods by which knowledge is interpreted and used to emulate DM's decision-making behavior.

5. Compatibility with the MCDM paradigm

Not all uncertainty methods are applicable to MCDM. It is important to identify if a theory provides methods for aggregating multiple criteria. If such methods are not already available, modelers should assess if the uncertainty theory could easily be adapted to a MCDM context.

6. Implementation

The ease of implementation can be an important criterion. Tools that support particular uncertainty analysis approaches and that can integrate well with MCDM methods used to address specific applications are desirable.

4.4 CHARACTERIZATION OF THE THREE UNCERTAINTY THEORIES

In this section, each uncertainty theory is characterized using the list of criteria proposed above, followed by a discussion of utility of these characteristics in RESTORE.

4.4.1 Certainty Factors Model

1. Interpretation

In the literature, many have presented a CF associated with a rule as a subjective probability (Buchanan and Shortliffe, 1984; Horvitz et al., 1988; Herrmann, 1997; Lucas, 2001), which can be interpreted as the certainty that the conclusion of a rule will be true given the certainty of the rule' antecedents. Buchanan and Shorliffe (1984) emphasized that rule independence is necessary for a combination to be consistent with probability theory. The CFM allows the modeling of one source of uncertainty, which is belief that can take an infinite number of degrees of belief, representing various shades of uncertainty. For instance CF=1, CF=0.5, and CF=0 respectively represent full certainty, partial belief, and no support of an impact score value.

2. Information required from the experts

One of the strengths of the CFM is its simplicity. Providing CFs is generally an easy step. Experts are often hesitant to give probability values and usually prefer to provide rough estimates of certainty. The CFM was specifically developed to be applied to rule-

based approaches. Consequently, the model can easily be applied to RESTORE without major changes in the way experts' knowledge is captured. Usually, preference is given to relative CFs' values rather than absolute values; thus consistency across the rule base was considered more important than precision when developing CFs for RESTORE.

3. Format of the output information

The CFM provides a single crisp number, as output. In RESTORE, such a number gives information about experts' confidence on the impact score of a decision alternative. This representation has proven to be easy to understand from a DM's point of view (Buchanan and Shortliffe, 1984). However, a crisp number does not allow the measure of uncertainty-based information, such as fuzziness, nonspecificity, conflict, and ignorance. In the CFM framework, a ranking procedure could include both restoration alternatives' impacts assessment on DMs' objectives and its related experts' confidence. The assessment of alternatives' impacts on DMs' objectives comes from the RESTORE MCDM performance evaluation module (Lamy et al., 2002a).

4. Inference process

Few choices can be made in the traditional CFM inference process when combining evidence in rule's antecedent. The CFM uses the standard minimum operator to model conjunctions and the standard maximum operator to model disjunctions. In the case of RESTORE, these two operators were believed to be appropriate (Lamy et al., 2002b). However, in other decision contexts, these operators may be considered improper because they do not allow modelers to differentially weigh evidence (Yeung and Tsang, 1997). To combine evidence coming from two or more rules, the traditional CFM offers one

combination method. Other methods have been proposed (Tsadiras and Margaritis, 1998; De Baets and Fodor, 1999), but these have not been broadly investigated.

The decision-making performance of the CFM has received little attention. For instance, in Mycin, the diagnosis with the highest CF was the one selected as the most probable disease. To our knowledge, no research has been done in a context like RESTORE, where a CF is associated with an impact score value and where a decision must be made taking into account these two numerical pieces of information. Ranking methods including these two numbers have to be developed.

5. Compatibility with the MCDM paradigm

We are not aware of any formal research on the use of a CFM-based MCDM approach. To be applied to RESTORE, multicriteria aggregation procedures have to be developed. In RESTORE, a CF is assigned to each alternative's negative or positive impact at achieving a specific objective. A multiple criteria aggregation method should be identified for combining the CFs assigned to each impact on each objective into a meaningful CF describing the experts' confidence in the multiple criteria performance evaluation of an alternative.

6. Implementation

Since the CFM was developed to be used in a rule-based framework, it is easy to implement using RESTORE. In a MCDM context, the traditional minimum operator was used to aggregate criteria.

4.4.2 Dempster-Shafer Theory

1. Interpretation

Belief, as in DST, is a crisp number that can be seen as the subjective probability that describes the evidence supporting a proposition. DST uses a number between 0 and 1 to specify the degree of support a body of evidence provides for a proposition (Yager, 1983). A lack of belief does not imply disbelief as in Bayesian theory. Rather, lack of belief in any particular hypothesis implies belief in the set of all hypotheses, which is referred to as the state of ignorance.

In RESTORE, m(A) measures the portion of belief that is confined to A. For instance m(A)=1, m(A)=0.5, and m(A)=0 represent respectively total evidence (certainty), partial evidence, and no evidence that an alternative address one or more objectives. DST can represent a scale of partial belief, from no evidence and ignorance to total evidence. However, as with CFM, it does not address the ambiguity or linguistic imprecision intrinsic in natural language.

2. Information required from the experts

DST is well suited for hierarchically structured decision problems. MCDM problems are hierarchical by nature. In CFM, only one number, a CF, is required for each rule from the experts. In contrast, when using DST, experts assign a belief value to every hypothesis of the frame of discernment, a time consuming task (Table 4.1). As with CFM, in RESTORE, relative beliefs are more important than absolute beliefs.

3. Format of the output information

DST theory provides a complete set of beliefs for all subsets of the frame of discernment including the unassigned belief subset. The raw output is a vector of beliefs, rather than a discrete number as with CFM.

Some authors have associated beliefs with utility intervals to better describe the impact of missing information on decision analysis. In DST, beliefs (m(A)) are associated with each hypothesis of the frame of discernment θ, each of which may correspond to a utility value (u(A)) (e.g. in RESTORE, θ include grades such as low, moderate, significant, and high impact, which are associated with utility values being respectively 1, 2, 3, and 4). Combining beliefs and utilities (equations 4.11-4.13) allows experts to quantitatively represent uncertainty in their knowledge in a confidence interval. Savage (1954) was the first to introduce this concept that is part of the subjective expected utility theory. In RESTORE, a confidence interval takes values between the minimum expected utility (lower belief function) and the maximum expected utility (an optimistic assessment that the evidence supports a proposition) (Yang, 2002). This interval of beliefs also helps prioritize where more information is needed to reduce uncertainty.

$$\text{Minimum expected utility value} = \sum_{A \in F} m(A) \times u(A) \tag{4.11}$$

Maximum expected utility =

Minimum expected utility value + m(θ)*maximum utility value (4.12)

Average expected utility =

(Maximum expected utility – Minimum expected utility)/2 (4.13)

In RESTORE, DST allows the measurement of three types of uncertainty-based information: nonspecificity, conflict, and ignorance (see Section 2). Nonspecificity was considered as negligible since beliefs in RESTORE are not nested among subsets. The ranking procedure in the DST is not obvious, since one can consider beliefs alone, the maximum, minimum or average expected utility scores, and/or the uncertainty-based information.

4. Inference process

DST traditionally offers one method to combine evidence. Dempster' rule of combination is the classical function to aggregate two bodies of evidence. Some researchers have praised (Haenni, 2002) and others (Lefevre et al., 2002) have criticized Dempster's combination function for its unintuitive results. Alternative functions have been proposed (Lefevre et al., 2002); however, none of them enjoy unanimity.

When coupled with utility theory, DST's ranking method is based on the expected utility of the decision alternative. To model a risk-averse DM, preferred decision alternatives can be the ones maximizing minimum utility score values. In contrast, when modeling a risk-seeker DM, preferred decision alternatives can be the ones maximizing average or maximum utility values. In the literature reviewed, no effective ranking methods have been proposed. Efficient ranking methods should maximize the use of the solutions' information content. A first step in this direction is the integration of uncertainty-based information in the ranking process. Using this information can provide a good indication of the quality of the evidence. For instance, when a DM wants to avoid risk or conflicting evidence related to the potential impacts of his (her) decisions, uncertainty-based information can be integrated into the ranking process.

5. Compatibility with the MCDM paradigm

DST is compatible with a MCDM paradigm; however, only a few studies investigated the use of DST-based MCDM applications. Yang and Xu (2002) proposed an evidential reasoning approach and Beynon (2002) used the Analytic Hierarchy Process (Saaty, 1980) MCDM method in combination with DST. This area of research is still immature; research should address the use of DST in combination with other MCDM methods.

6. Implementation

One of the major drawbacks of DST relates to the high computational intricacy of its combination rule. The Intelligent Decision System (IDS) supporting the evidential reasoning approach is currently the only software capable of handling uncertainty modeled with the DST in a MCDM context (Yang and Xu, 2002). In RESTORE, a typical watershed assessment implies the evaluation of more than twenty restoration alternatives for each of typically 15, 000 sites. Such assessment is impracticable even when using the IDS package. More efficient algorithms need to be developed to effectively and easily apply DST in a watershed management context.

4.4.3 Fuzzy Set Theory

1. Interpretation

Zadeh (1965) defines fuzzy set theory as a theory modeling the degree of membership of an element in a specific set. The theory does not model the uncertainty related to the occurrence of an event, but the extent to which an event occurred. For example, the impact

of an agricultural riparian buffer on the water quality objective may be highly positive to some extent and moderately positive to another extent. The inclusion of more information will not reduce the uncertainty in experts' knowledge. The use of fuzzy subsets to describe a variable allows a gradual transition between sets, so experts are not required to provide exact numbers (Temponi et al., 1999).

2. Information required from the experts

The use of fuzzy rules requires that the evidence and hypothesis be expressed as linguistic terms, each represented by a given fuzzy subset. Experts often are more comfortable at providing a range of values (membership functions) than exact numbers to describe a particular value. Fuzzy methods allow these values to be part of multiple sets.

3. Format of the output information

In order to use a fuzzy subset for decision-making, two approaches can be taken. One is to keep the solution fuzzy and the other is to transform it to a crisp score through a defuzzification process. Keeping a solution fuzzy requires that experts identify suitable criteria to characterize such solution and make it meaningful from a DM's perspective. For instance, uncertainty-based information could be seen as such criteria. To transform a fuzzy solution to a crisp score, a defuzzification method should be used. Many defuzzification methods exist, the most often used are center of area, center of sums, and mean of maxima (Zimmermann, 1987).

4. Inference process

One strength of fuzzy set theory is that it supports several operators and methods for combining evidence and ranking solutions. Modelers have flexibility in determining inference characteristics to better model DMs' behavior in a specific application. A critical issue in the fuzzy inference process is the ranking step. Methods range from horizontal and vertical evaluation of fuzzy subsets to comparative methods. However, one of the main drawbacks of these methods is that they only base their ranking on portions of the fuzzy subset solution, thus, information is irreversibly lost (Bortolan and Degani, 1985).

5. Compatibility with the MCDM paradigm

The literature contain many references on the use of fuzzy MCDM (FMCDM) approaches in the context of watershed management, but few related to watershed restoration. Lamy et al. (2002b) proposed a comprehensive FMCDM approach to watershed restoration. Chen and Hwang (1992) and Lai and Hwang (1994) provide a thorough review of the different FMCDM that have been developed and used in different decision contexts.

6. Implementation

Many expert systems shells implementing fuzzy inference are available, e.g. *FuzzyCLIPS* (National Research Council Canada, 1994) and *StarFLIP++* (Institute of Information Systems, 1997). Here, we implemented a custom fuzzy inference process procedure.

4.5 CASE STUDY – RESTORE

In this case study, a MCDM approach was developed for each of the three theories, namely CFM, DST, and fuzzy set theory. These CFM-based MCDM, DST-based MCDM, and FMCDM approaches were applied to RESTORE. Each approach was designed to capture experts' knowledge, evaluate, and rank restoration alternative subject to DMs' objectives. The three theories differ in the way they perform these phases of the decision-making process. CFM-based MCDM and DST-based MCDM are comparable because they model the same types of uncertainty stemming from experts' belief. The FMCDM approach addresses uncertainty related to linguistic imprecision, which cannot be modeled by the two other approaches.

Most research to date has focused on knowledge representation instead of studying the analytical behavior of decision issues (Dubois et al., 2000). Available ranking methods for all three theories are not proficient at considering the richness of the information available in the output solutions. In light of this, a novel ranking method was introduced for each approach to fully exploit this information. The ranking methods allow a modeler to make a distinction between the best decision approach for a risk-seeker, risk-neutral, and risk-averse DM. When selecting a decision alternative, a DM displays a risk-aversion behavior if he (she) does not tolerate any risk about an expected impact. A DM is said to be risk-seeker if he (she) prefers a risky decision alternative with a higher expected utility over a no-risk decision alternative with a lower expected utility.

Following are the three ranking methods proposed for each uncertainty approach.

Certainty factor model ranking method

We introduced a novel CFM ranking method that is based on subjective expected utility (SEU) theory. SEU coupled with CFM, allows DMs to express attitude toward risks (e.g. risk aversion, risk neutral, risk seeking). Savage (1954) was the first to introduce the concept of SEU. Here, we combine a CF and its related impact score, which gives a SEU describing the expected impact of a decision alternative on the prioritized objectives. The combination takes the following form:

$$SEU = V \times CF + ((1 - CF) \times (u)) \tag{4.14}$$

where (V) is the impact score value coming from the crisp RESTORE MCDM algorithm (equation 2.1). To model partial ignorance, we assume that (1-CF) is the unassigned belief that could be assigned to any utility value (u) (e.g. -4 to 4 in RESTORE). This approach for representing partial ignorance (1-CF) and partial belief (CF) allows the characterization of an interval of subjective probabilities for a proposition A, similar to DST where this interval is bounded by a lower belief (Bel (A)) and its upper belief (Pl(A)). Additionally, using this approach, uncertainty-based information is quantified in terms of an ignorance measure. In the traditional CFM, (1-CF) was not defined as experts' ignorance. In this case study, u was assigned to the 0 utility value, assuming a risk-averse DM. The preferred decision alternative is the one that maximizes the SEU value, which values, in RESTORE, range from [-4, 4].

Dempster-Shafer Theory ranking method

The ranking method for DST uses a MCDM approach to combine three criteria that are assumed to effectively encompass the solution's features. The three criteria were (1) impact criterion, defined by the minimum utility attribute, (2) ignorance criterion, defined by the unassigned belief attribute, and (3) conflict criterion, defined by the dissonance attribute. These criteria were combined using Dempster's combination function. A good score is one that maximizes the minimum utility and minimizes both the dissonance value and the belief allocated to the unassigned subset. The output of the ranking method is a crisp score value ranging from −1 to 1. The decision alternative with the highest score value is the one selected as the preferred alternative.

Fuzzy set theory ranking method

We believe that ranking decision alternatives based only on the result of a defuzzification method is not a convincing ranking measure because it combines all impacts into a single value, losing information about the fuzziness of the result in the process. New methods that take advantage of the richness of information contained in the output fuzzy subset should be considered. Lamy et al. (2002b) accomplished a first step in this direction with the development of the grade of merit index (GMI) ranking method that uses a fuzzy rule-based approach to score different restoration alternatives based on their ability at meeting each criteria. A FMCDM ranking method combines four criteria defined by seven attributes. The output of the ranking method is a crisp score ranging from -10 to 10. To facilitate the comparison of the results coming from the three uncertainty approaches, the FMCDM ranking method used here is a simplified version of the GMI method. It includes two criteria: (1) impact criteria, defined by the center of area of the

fuzzy subset and (2) nonspecificity criteria, defined by the nonspecificity measure. A DM was believed to prefer a solution with a high center of area value and a low nonspecificity value.

Numerical example

In the following example, we illustrate one set of DMs' priorities and concerns. DMs were considered risk-averse. Water quality and water quantity were among five primary objectives, reflecting subobjectives of decreasing water temperature and runoff, increasing stream flows, and improving nutrient management. These objectives were followed closely by socioeconomic issues, including education and outreach, social networking, and greater community involvement. Maintaining and enhancing fish and wildlife habitat had a relatively low priority. The normalized weights given to the five objectives were: water quality, 1; water quantity, 1; habitat, 0.33; social, 0.78; and economic, 0.78. When using the CFM-based MCDM and DST-based MCDM approaches, we assumed that the amount of uncertainty associated with each rule was constant across methods. Experts were assumed to support each rule with a belief of 0.8, and the remaining 0.2 was assigned to the unassigned subset. For the fuzzy set approach, a range of approximately 0.2 was used to transform a crisp value into a membership function.

Each approach selected the most desirable restoration alternatives under specific site characteristics to create a watershed restoration plan for a small area of the Upper Amazon sub-basin. This sub-basin is part of the Long Tom watershed of Oregon's Willamette River Basin. The Long Tom watershed is substantially urbanized and is adjacent to Oregon's second-largest metropolitan area, Eugene. Agricultural and urban activities have generated a number of conflicts related to land use and its ecological impacts. The example presented

here focuses on a small riparian area of the watershed, where four restoration alternatives were considered for each site. These restoration alternatives were: (1) agricultural buffer, (2) increase of late summer flow, (3) forest riparian buffer, and (4) create condition favorable to native species. Detailed results for a specific site (#3424) are presented in Table 4.2. This site can be broadly characterized as agricultural land adjacent to a stream and a road. Table 4.2 shows that when modeling a risk-averse DM, the ranking of restoration alternatives for all sites remains the same for the three uncertainty approaches and the crisp RESTORE approach. Relatively similar differences between score values are obtained, as seen from the results for site #3424.

Similar ranking was expected for two main reasons. First, the knowledge and the amount of uncertainty associated to the decision context were preserved when moving from one approach to another. For the CFM-based MCDM and DST-based MCDM approaches, the same assumptions were made about the structure of the experts' beliefs. Both proposed ranking methods allowed the assignment of the ignorance belief to any utility value. In this case study, when modeling a risk-averse DM, the ignorance belief was assigned to a utility value of 0. Secondly, the three proposed ranking methods based their ranking on similar information, including impact, nonspecificity, and ignorance criteria. Similarity in the results suggests that the four methods are consistent and are capable of generating credible results.

Table 4.2: Scoring results (site #3424) for the RESTORE' crisp MCDM, CFM-based MCDM, DST-based MCDM, and FMCDM approaches.

CRISP RESTORE				
Restoration alternative	*RESTORE impact score*			
Late-summer flow control	2.69			
Agricultural riparian buffer	2.07			
Create conditions favorable for native species	1.04			
Forest riparian buffer	0			
CERTAINTY FACTOR MODEL APPROACH (CFM)				
Restoration alternative	*RESTORE impact score*	*Certainty factor*	*Ignorance*	*Subjective expected utility*
Late-summer flow control	2.69	0.80	0.20	2.15
Agricultural riparian buffer	2.07	0.80	0.20	1.66
Create conditions favorable for native species	1.04	0.80	0.20	0.83
Forest riparian buffer	0	0	0	0
DEMPSTER-SHAFER THEORY APPROACH (DST)				
Restoration alternative	*Impact Criteria*	*Dissonance criteria*	*Ignorance criteria*	*Ranking Score*
Late-summer flow control	0.47	0.54	0.63	0.51
Agricultural riparian buffer	0.26	0.54	0.63	0.34
Create conditions favorable for native species	0.09	0.61	0.56	0.30
Forest riparian buffer	0	0	0	0
FUZZY SET APPROACH				
Restoration alternative	*Impact Criteria*	*Nonspecificity Criteria*	*Ranking Score*	
Late-summer flow control	7.95	3.42	4.83	
Agricultural riparian buffer	2.07	6.34	4.12	
Create conditions favorable for native species	1.04	2.33	2.02	
Forest riparian buffer	0	0	0	

4.6 DISCUSSION

The purpose of this study was to describe the potential offered by three uncertainty theories, namely CFM, DST, and fuzzy set theory, at modeling uncertainty in experts' knowledge and to evaluate if they can be applied in a MCDM approach to watershed restoration. The selection of a specific uncertainty theory should be derived from an evaluation of the decision application as well as DMs' and experts' preferences. To facilitate the evaluation of the suitability of these three uncertainty theories, we identified a set of criteria against which they were assessed. Then, a MCDM approach was proposed for each uncertainty theory, i.e. CFM-based MCDM, DST-based MCDM, and FMCDM approaches and applied using RESTORE. Results show that the CFM, DST, and fuzzy set theory and their related MCDM approaches, all appear to be suited to the RESTORE decision problem.

Fuzzy set theory differs significantly from the CFM and DST in its inference reasoning process. It models uncertainty resulting from linguistic imprecision while CFM and DST model uncertainty related to experts' beliefs and ignorance about restoration alternatives' impacts on prioritized objectives. With fuzzy logic, information is complete; i.e. no more information can be gathered to reduce uncertainty. Under the CFM and DST approaches, information is incomplete; thus, information can be gathered to reduce the uncertainty or the risk related to an impact. For this reason, the FMCDM approach cannot directly be compared with the two other approaches.

The CFM-based MCDM approach was more straightforward to implement than the DST-based MCDM method, since CFs can be easily applied in a rule-based framework. The development of a DST-based MCDM approach was a time-consuming task. Its use of a frame of discernment requires that modelers modify the way knowledge is captured and experts need to provide their knowledge in a more complete form. DST allows a more

complete description of the experts' knowledge and its related uncertainty and carries, throughout the inference process, beliefs that are assigned to each element of the frame of discernment. Using RESTORE, such as fuzzy set theory, DST allows the modeling of two different kinds of uncertainty-based information: dissonance and ignorance. In contrast, CFM can model only ignorance. There is a tradeoff between model completeness and simplicity of implementation.

In comparison to the other two theories, fuzzy set theory supports a greater number of widely used operators, combination rules and ranking methods. A FMCDM approach uses fuzzy subsets to model linguistic imprecision, which allows the use of elastic constraints that relax the need for exact numbers when defining rules' antecedents and consequents. The implementation of a fuzzy approach in RESTORE was time-consuming since each variable needed to be translated into fuzzy subsets.

In the literature, the problem of ranking decision alternatives has not received much attention. To address this gap, we looked at the ranking procedures available for the three uncertainty theories and proposed original ranking methods for each uncertainty theory. The three proposed MCDM approaches are not necessarily suited for each decision context; yet they introduce novel ideas that could be further developed. We have shown that MCDM techniques are well suited to incorporate ranking because they allow experts to include more than one criterion when evaluating alternatives. Additionally, we have shown that the integration of uncertainty-based information can be readily incorporated into a MCDM. Many expert systems, including RESTORE, tend to assume strong consensus in the evaluation process. They generally perform best only when there is strong evidence supporting a single conclusion. To address this deficiency, we proposed the use

of uncertainty-based information to quantitatively assess the quality of the evidence supporting the decision alternatives' impacts on DMs' objectives.

As mentioned in Nakamori and Sawaragi (2000), the results coming from a DSS can never be formally proven to have been the best possible decision alternatives. The major justification of the utility of a DSS is acceptable quality and the value of information the system provides to the users. Through the practical example presented in the case study, we showed that the uncertainty approaches were able to generate good decisions under a limited set of conditions, but more robust testing is needed to verify these results in a more comprehensive setting.

Overall, we conclude that the inclusion of uncertainty analysis in expert-systems (1) reduced the need for precise experts' judgments and (2) increases the value of the system since it provides more information to DMs, enhances their comprehension of the issues that may affect the outcome of their decisions, and/or broadens their perspective when selecting restoration alternatives. In a specific context, domain experts might have different opinions and even not be representative of the whole domain experts' community; therefore the inclusion of uncertainty makes the system more robust to small changes in knowledge and does not imply that impacts are known with complete confidence.

4.7 CONCLUSIONS

The main objectives of this paper were to (1) describe the potential offered by the DST, CFM, and fuzzy logic in a MCDM watershed restoration decision-making application and (2) apply each theory using RESTORE. To this end, we (1) identified a list of criteria to evaluate the potential offered by different uncertainty theories in MCDM, (2) applied CFM, DST, and fuzzy set theory in a MCDM DSS watershed restoration context, and (3) developed an MCDM approach for each uncertainty theory, including an original

ranking method considering criteria related to uncertainty-based information resulting from each theory. Proposed ranking methods showed that instead of selecting a restoration alternative based only on impact score values, additional parameters can be introduced to better represent DM's behavior when selecting decision alternatives.

The choice of a specific uncertainty method is dependant on application-specific needs. Each theory can model only specific types of uncertainty, either related to experts' beliefs and ignorance or experts' linguistic imprecision. The results obtained showed that each uncertainty theory can be utilized in a MCDM context such as RESTORE. The inclusion of an uncertainty analysis in RESTORE can be seen as an improvement of the DSS because it provides DMs with meaningful information on the quality of the evidence that supports the impact of a decision alternative at addressing objectives

CHAPTER 5

GENERAL CONCLUSIONS

DSSs have been defined as computer-based systems that should support the decision-making process by enhancing problem comprehension and by providing data, analytical tools, and methods to characterize uncertainty (Mowrer, 2000). While this definition is broadly accepted, very few decision tools support all the abovementioned capabilities. This project was motivated by the lack of existing decision-making tools that integrate MCDM approaches, uncertainty analysis, GIS technologies, and that exploit wide-ranging models to support a holistic watershed restoration planning approach.

This study was successful in illustrating a comprehensive decision-making methodology and its related decision tool RESTORE, which supported each step of the decision process, including description of the decision situation, identification of DMs' values, identification of attributes that relate to each objective, definition of the rules and constraints, efficient landscape generation, landscape evaluation and selection of the prefereed watershed restoration plan. Important questions being addressed by the methodology included (1) what are the socio-economic and environmental impacts of the different restoration options as a function of landscape position and (2) what is the mix of restoration options (watershed restoration plan) that is a most preferred solution in terms of its suitability in responding to DMs' objectives at both the site and watershed levels. The RESTORE methodology helped DMs to identify and explore possible solutions leading to a better understanding of the impacts of their decisions.

The complexity of the various landscape processes and human subjectivity suggest that a robust performance evaluation module would involve the modeling of uncertainties inherent to experts' knowledge. There is a need for expert systems that better emulate DMs' behavior and exploit information-content of proposed solutions when making decisions.

To address these issues, we explored the use of uncertainty assessments in the RESTORE decision-making process. We first proposed a RESTORE FMCDM approach. The approach involves three basic steps: (1) expert values were first captured and served as a starting point to additional analysis steps, (2) a FLC was built, which contained (a) a knowledge base, (b) an inference process that enabling DMs to evaluate the performance of restoration options at meeting different objectives, and (3) a FMCDM module was developed, which (a) aggregated fuzzy subsets to calculate a composite objective function for each option and (b) integrated a novel ranking method to create a final ranking of the restoration options, resulting in an efficient watershed management plan. The approach presented a novel fuzzy ranking method, GMI. The GMI is a flexible and intuitive ranking method that uses a FMCDM technique, includes uncertainty-based information, does not make assumptions about the shape of the fuzzy subsets to be ranked and allows DMs to express their values and perspective about what should be considered as a good alternative in a specific decision context.

While several theories are proficient at modeling uncertainty in experts' knowledge, no one can address all sources of uncertainty. We also studied the utility of three uncertainty theories at modeling the uncertainty in experts' knowledge (e.g. conflict in evidence, partial belief, ignorance, and/or ambiguity). To describe the potential offered by the DST, CFM, and fuzzy set theory in the context of MCDM watershed restoration context, we identified seven-fold criteria against which each uncertainty theory was evaluated. To apply the three uncertainty theories using RESTORE and easily compare their results, an inference approach was proposed for each of them. These approaches introduced ideas that thus far, to the best knowledge of the authors, have not been investigated in decision science. Among them are (1) the application of DST in the context of a MCDM DSS applied to watershed restoration, (2) the application of CFM in any

MCDM context, (3) the association of the CFM with the SEU, and (4) original ranking methods for each of the three approaches. Ranking methods' main characteristic includes the use of a MCDM method including criteria such as uncertainty-based information (e.g. nonspecificity, ambiguity, dissonance, and/or ignorance). These ranking methods aim at translating the decision alternatives' performance evaluation and its related uncertainty into a meaningful index that could be used to unambiguously generate an ordering of the decision alternatives.

In general it can be said that the inclusion of uncertainty analysis in RESTORE highlighted the value of considering uncertainty as another facet of information. From a DM's point of view, the proposed decision alternatives are more attractive than traditional ones, when including uncertainty estimation, because they result in more information from which decisions can be made. Uncertainty assessments provide DMs with information on the quality of the evidence that supports the impact of a decision alternative and on the risks that could jeopardize the expected impacts of an alternative on DMs' objectives. From an expert's point of view, including uncertainty analysis (1) relaxes the need for exact assessment and (2) allows them to express partial belief, conflicting evidence, and/or ignorance, all of which provide experts with better means to express their knowledge in a more comprehensive and complete form. Such inclusion provides more credible and robust approaches.

Future research

Community-based decision-making is a collaborative process, where negotiations among participants and conflicts of interest are almost inevitable. DMs need tools to support consensus and compromise building. A future version of RESTORE should

include methods that would provide a systematic means for developing efficient group decision making, where the inclusion of conflicting opinions may alter the shape of the fuzzy criteria and the ranking of decision alternatives.

In some situations, a DM might not be entirely certain about the shape of a fuzzy subset or the truthfulness of a rule, which could be translated as uncertainty due to lack of knowledge or ignorance about a situation. There is an opportunity to combine fuzzy set theory with other uncertainty theories (e.g. CFM and DST) that would address specifically this type of uncertainty.

The different approaches presented in this work could be applied to other contexts, where expert systems are used to support a decision-making process. Therefore, we would like to apply the novel ideas proposed in this work in a broader range of scientific and practical applications.

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