Jul 1st, 12:00 AM

Uncertainty Management, Spatial and Temporal Reasoning, and Validation of Intelligent Environmental Decision Support Systems

Miquel Sànchez-Marrè

Karina Gibert

Rick Sojda

Jean-Philippe Steyer

Peter Struss

See next page for additional authors

Presenter/Author Information
Miquel Sànchez-Marrè, Karina Gibert, Rick Sojda, Jean-Philippe Steyer, Peter Struss, and Ignasi Rodríguez-Roda

Uncertainty Management, Spatial and Temporal Reasoning, and Validation of Intelligent Environmental Decision Support Systems

M. Sànchez-Marrè[a] and K. Gibert [a] and R. S. Sojda[b] and J. P. Steyer[c] and P. Struss[d] and I. Rodríguez-Roda[e]

[a] *Knowledge Engineering & Machine Learning Group (KEMLG), Technical University of Catalonia, Catalonia (miquel@lsi.upc.edu, karina.gibert@upc.edu)*

[b] *Northern Rocky Mountain Science Center, United States Department of the Interior - Geological Survey, Ecology Department, Montana State University, Bozeman, Montana, USA (sojda@usgs.gov)*

[c] *Process Engineering And Control Engineering (PEACE) group, Environmental Biotechnology Laboratory - INRA, France (steyer@ensam.inra.fr)*

[d] *Computer Science Department, Technical University of Munich, Germany (struss@tum.de)*

[e] *Chemical and Environmental Engineering Laboratory (LEQUIA), University of Girona, Catalonia (ignasi@lequia.udg.es)*

Abstract: There are inherent open problems arising when developing and running Intelligent Environmental Decision Support Systems (IEDSS). During daily operation of IEDSS several open challenge problems appear. The *uncertainty of data* being processed is intrinsic to the environmental system, which is being monitored by several on-line sensors and off-line data. Thus, anomalous data values at *data gathering* level or even uncertain reasoning process at later levels such as in diagnosis or decision support or planning can lead the environmental process to unsafe critical operation states. At *diagnosis level* or even at *decision support level* or planning level, spatial reasoning or temporal reasoning or both aspects can influence the reasoning processes undertaken by the IEDSS. Most of Environmental systems must take into account the *spatial relationships* between the environmental goal area and the nearby environmental areas and the *temporal relationships* between the current state and the past states of the environmental system to state accurate and reliable assertions to be used within the diagnosis process or decision support process or planning process. Finally, a related issue is a crucial point: are really *reliable* and *safe* the decisions proposed by the IEDSS? Are we sure about the goodness and performance of proposed solutions? How can we ensure a *correct evaluation* of the IEDSS? Main goal of this paper is to analyse these four issues, review some possible approaches and techniques to cope with them, and study new trends for future research within the IEDSS field.

Keywords: Intelligent Environmental Decision Support Systems (IEDSS); Uncertainty Management in IEDSS; Spatial and Temporal Reasoning in IEDSS; Validation and verification of IEDSS.

1. INTRODUCTION

1.1 Complexity of Environmental Systems

The increasing rhythm of industrialisation, urbanisation and population growth that our planet has faced for the last few hundred years has forced society to consider whether human beings are changing the very conditions that are essential to life on Earth. Environmental pollution, habitat destruction/fragmentation affects negatively the quality of water, air, and soil, and hence plant, animal and human life (Sydow *et al.* 1998), (El-Swaify and Yakowitz, 1998).

Whenever we attempt to tackle these issues, we are immediately confronted with complexity. There are at least three important reasons for this:

- *Inherent complexity of environmental systems*. Environmental processes involve a huge amount of knowledge containing complex interactions between physical–chemical, biological, ecological, social and economical processes. Also, they are stochastic, and, very often, are spatial and temporal dependent processes.

- *Uncertainty, or approximate knowledge*. Some of the sources of this uncertainty can be tamed with additional data or further investigation. Such is the case of uncertainty arising from random processes or from deficiencies in knowledge (lack of data, unsuitable datasets, etc.). But in other cases uncertainty is insurmountable. This is the case for chaotic behaviour, or for self-organisation processes. It is also typical of socio-ecological systems, which involve numerous players, each with their own goals.

- *Multiplicity of scales*. Environmental problems have been associated traditionally with distinct *spatial* scales (i.e., local, national, global), each associated with specific *timescales*. However, interactions among these scales are becoming increasingly clear. Therefore, advocating a single perspective that encompasses everything in a system is becoming increasingly difficult —plus ineffective.

The consensus is developing that, in order to account for these caveats, environmental issues must be considered in terms of complex systems. But not all environmental systems present the same level of complexity in terms of both the degree of uncertainty and the risk associated with decisions. If the degree of complexity is represented as a function of uncertainty, on one hand, and the magnitude or importance of the decision, on the other hand, then we might distinguish three levels of complexity (Funtowicz and Ravetz, 1993, 1999):

- The first level of complexity would correspond to simple, low uncertainty systems where the issue at hand has limited scope. A single perspective and simple models would suffice to provide satisfactory descriptions of the system. With regard to water issues, this level corresponds, for example, to the evolution of oxygen in a pristine stream after a pulse input of assimilable organic matter. In the context of industrial processes, an example is the design of a single treatment operation where the input is perfectly defined. In these cases, the information arising from analysis may be used for more wide-reaching purposes beyond the scope of the particular researcher.

- The second level would correspond to systems with a higher uncertainty degree, which will cause that simple models can no longer provide satisfactory descriptions. Acquired experience becomes then more and more important, and the need to involve experts in problem solving becomes advisable. In the case of water issues, this level would correspond to a general model of water quality, where the need arises to establish which factors are the most important. In the case of an industrial process, this level would correspond to the installation of a wastewater treatment plant, where goals for the quality of the output are well established but these can be reached through different schemes, and it is the responsibility of the designer to choose the most appropriate configuration.

- The third level would correspond to truly complex systems, where much epistemological or ethical uncertainty exists, where uncertainty is not necessarily associated with a higher number of elements or relationships within the system, and where the issues at stake reflect conflicting goals. It is then crucial to consider the need to account for a plurality of views or perspectives. In the case of water issues, an example would be the problem of water quality in a stream catchment. Here, a variety of factors (economical, technical, ecological, etc.) are at play, and associated with each factor is a different set of goals. Thus, different kinds of expertise need to be taken into account. In the case of a industrial process, this level of complexity is associated, for instance, with the environmental aspects of wastewater treatments, which are discussed at the level of the company's policy. Thus the problem is not the design of end of pipe installations for the treatment of specific outputs, but a more global view on the problem that would contemplate, for example, the installation of cleaner technologies in the production process itself.

In this sense, it is important to realise that environmental problems are characterized by dynamics and interactions that do not allow for an easy division between social and biogeophysical phenomena. Much ecological theory has been developed in systems where humans were absent or in systems where humans were considered an exogenous, simple, and detrimental disturbance. The intricate ways in which humans interact with ecological systems have been rarely considered (Kinzig, 2001). Embracing a socio-economical perspective implies accepting that all decisions related to environmental management are characterised by multiple, usually conflicting objectives, and by multiple criteria (Ostrom, 1991). Thus, in addition to the role of experts, it becomes increasingly important to consider the role of wide public participation in the decision making processes. Experts are consulted by policy makers, the media, and the public at large to explain and advise on numerous issues. Nonetheless, many recent cases have shown, rather paradoxically, that while expertise is increasingly sought after, it is also increasingly contested (Ludwig, 2001).

In our opinion, most environmental systems belonging to the second and third level cannot be only tackled with the traditional tools of mathematical modelling. To confront this complexity, a new paradigm is needed. Adopting it will require that we deal with new intellectual challenges.

1.2 New Tools for a New Paradigm

In the last decades, mathematical/statistical models, numerical algorithms and computer simulations have been used as the appropriate means to gain insight into environmental management problems and provide useful information to decision makers. To this end, a wide set of scientific techniques have been applied to environmental management problems for a long time and with good results.

But most of these efforts were focused on problems that we could assign to the first level of complexity. Consequently, many complex environmental problems have not been effectively addressed by the scientific community. However, the effort to integrate new tools to deal with more complex systems has led to the development of the so-called Environmental Decision Support Systems (EDSSs) (Guariso and Werthner, 1989), (Rizzoli and Young, 1997).

EDSSs have generated high expectations as a tool to tackle problems belonging to the second and third levels of complexity. Thus in a recent review of the relevant literature in the topic, more than 600 references were found (including journal articles, conference papers, and technical reports) during the 90s, with only 10 references in 1992 and more than 150 references per year towards the end of the decade (Cortés *et al.*, 2002). The range of environmental problems to which EDSSs have been applied is wide and varied, with water management at the top (25% of references), followed by aspects of risk assessment (11.5%) and forest management (11.0%). Equally varied are the tasks to which EDSSs have been applied, ranging from monitoring and data storage to prediction, decision analysis, control planning, remediation, management, and communication with society. It is not surprising then that three of the top ten most downloaded articles published in *Environmental Modelling and Software* in January-December 2001 deal with EDSSs.

2. INTELLIGENT ENVIRONMENTAL DECISION SUPPORT SYSTEMS (IEDSS)

Environmental issues belong to a set of critical domains where wrong management decisions may have disastrous social, economic and ecological consequences. Decision-making performed by IEDSSs should be collaborative, not adversarial, and decision makers must inform and involve those who must live with the decisions. What an IEDSS contributes is not only an efficient mechanism to find an optimal or sub-optimal solution, given any set of whimsical preferences, but also a mechanism to make the entire process more open and transparent. In this context, IEDSSs can play a key role in the interaction of humans and ecosystems, as they are tools designed to cope with the multidisciplinary nature and high complexity of environmental problems.
From a functional point of view, and taking into account the kind of problem that the IEDSS solves, two kinds of IEDSS could be distinguished (and of course, most of the systems are in between these two categories):

- Those which are controlling/supervising a process in real-time (or almost real-time), facing similar situations in a regular basis. They must guarantee robustness against noise, missing data, typos and any combination of input data. In general the end-user is responsible to accept/refine/reject system solutions. This responsibility can decrease (thus, increasing IEDSS confidence) over the time as far as the system is facing situations that were successfully solved in the past (real validation).

- Those that give punctual support to decision-making. Mainly used to justify multi-criteria decisions of policy-makers (transparency) more than to make real decisions in a day-to-day basis. It is interesting for the end-user to play with what-if scenarios, to explore the response surface and the stability of the solution (how sensitive our decision is to small variations of the given weight and the value of the relevant variables), etc. The role of socio-cultural and economical issues limits the use of standard databases. Confidence can not be increased according to the results when facing similar situations, because these IEDSS are very specific and sometimes are only built to take (justify) one decision.

According with Fox and Das (2000), a decision support system is a computer system that assists decision makers in choosing between alternative beliefs or actions by applying knowledge about the decision domain to arrive at recommendations for the various options. It incorporates an explicit decision procedure based on a set of theoretical principles that justify the “rationality” of this procedure.

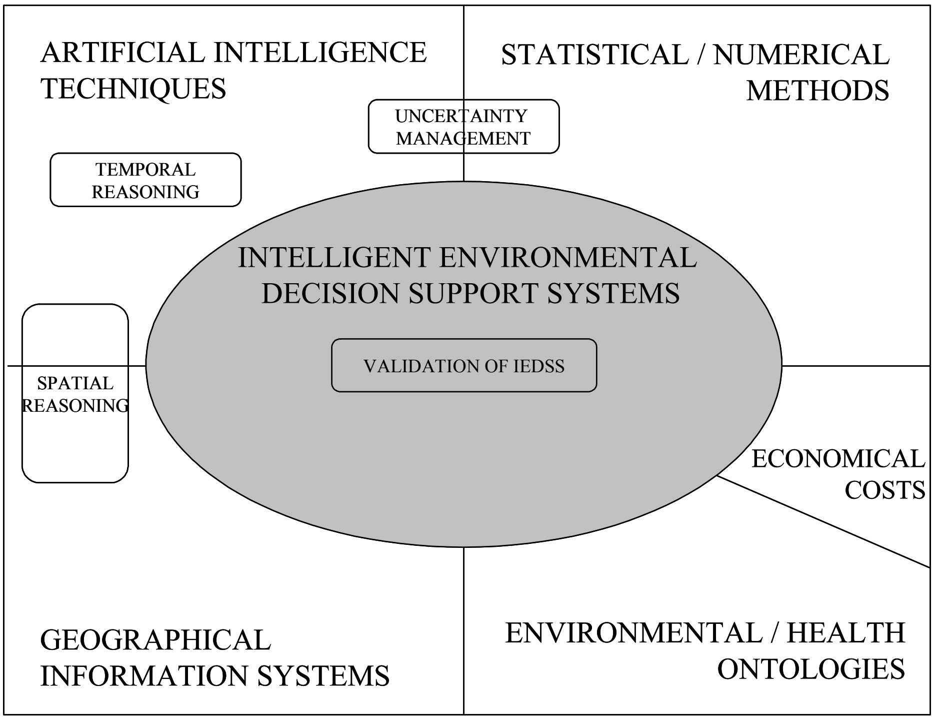

Figure 1. IEDSS conceptual components

Thus, an IEDSS could be defined as:

- R. Sojda (Sojda, 2002) defines the as systems using a combination of models, analytical techniques, and information retrieval to help develop and evaluate appropriate alternatives (Adelman 1992; Sprague and Carlson 1982); and such systems focus on strategic decisions and not operational ones. More specifically, decision support systems should contribute to reducing the uncertainty faced by managers when they need to make decisions regarding future options (Graham and Jones 1988). Distributed decision making suits problems where the complexity prevents an individual decision maker from conceptualizing, or otherwise dealing with the entire problem (Boland et al. 1992; Brehmer 1991).

- An intelligent information system that reduces the time in which decisions are made in an environmental domain, and improves the consistency and quality of those decisions (Haagsma and Johanns, 1994), (Cortés *et al.*, 2001).
- Others definitions could be found in (D'Erchia et al, 2001).

Decisions are made when a deviation from an expected, desired state of a system is observed or predicted. This implies a problem awareness that in turn must be based on information, experience and knowledge about the process. Those systems are built by integrating several artificial intelligence methods, geographical information system components, mathematical or statistical techniques, and environmental/health ontologies, and some minor economical components (see figure 1).

This progression in complexity of the methods, and in the *intensive use of knowledge* usually required to develop an IEDSS corresponds to an *increase in data* required to support the models. See the Fig. 2, adapted from (Witakker, 1993).

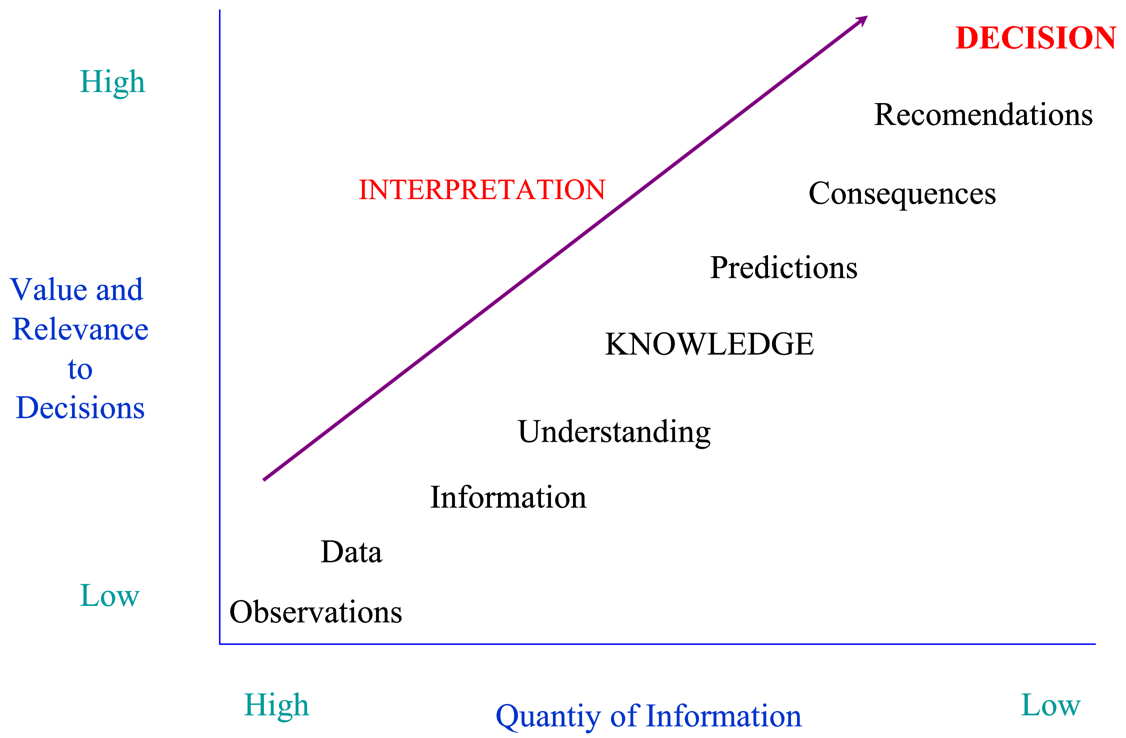

Figure 2. Information and decision, knowledge and data

2.1 IEDSS Development

How a particular IEDSS is constructed will vary depending on the type of environmental problem and the type of information and knowledge that can be acquired. With these constraints in mind, and after an analysis of the available information, a set of tools can be selected. This applies not only to numerical models, but also to artificial intelligence (AI) methodologies, such as knowledge management tools. The use of AI tools and models provides direct access to expertise, and their flexibility makes them capable of supporting learning and decision making processes. Their integration with numerical and/or statistical models in a single system provides higher accuracy, reliability and utility (Cortés *et al.*, 2000).

This confers IEDSSs the ability to confront complex problems, in which the experience of experts provide valuable help for finding a solution to the problem. It also provides ways to accelerate identification of the problem and to focus the attention of decision-makers on its evaluation. Once implemented, an IEDSS, like any knowledge-based system, has to be evaluated for what it knows, for how it uses what it knows, for how fast it can learn something new, and, last but not least, for its overall performance. Figure 3 schematically shows this methodology.

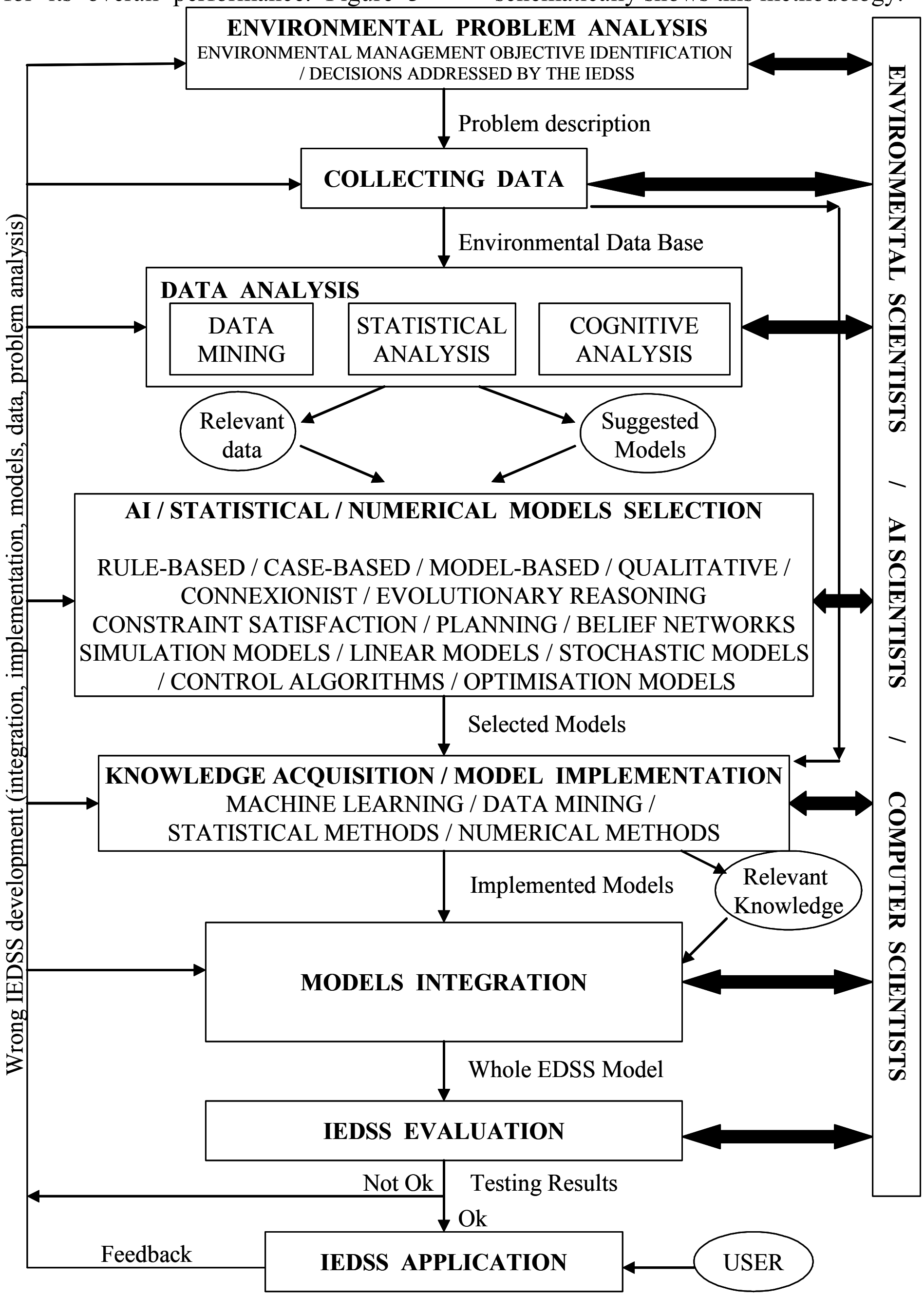

Figure 3. Flow diagram for development of an IEDSS

Both the proposed IEDSS development procedure and the IEDSS architecture are general enough to be intended to cope with any kind of IEDSS deployment.

Cortés *et al*. (2000) proposed an IEDSS architecture based on five steps (Figure 4):

- The first step of the IEDSS (*data interpretation*) encompasses the tasks involved in data gathering and registration into databases. Original raw data are often defective, requiring a number of pre-processing procedures before they can be registered in an understandable and interpretable way. Missing data and uncertainty must be also considered in this level. Also, the knowledge discovery step including data mining techniques are included here providing the IEDSS with the environmental process knowledge.
- The second step, *diagnosis level*, includes the reasoning models that are used to

infer the state of the process so that a reasonable proposal of actuation can be reached. This is accomplished with the help of statistical, numerical and artificial intelligence models, which will use the knowledge previously acquired.

- The third step, *decision support level*, establishes a supervisory task that entails gathering and merging the conclusions derived from AI knowledge models and numerical models. This level also raises the interaction of the users with the computer system through an interactive and graphical user-machine interface. When a clear and single conclusion can not be reached, a set of decisions ordered by their probability or certainty degree should be presented to the user.
- In the fourth level, plans are formulated and presented to managers as a list of general actions or strategies suggested to solve a specific problem.
- The set of actions to be performed to solve problems in the domain considered are the fifth and last step. The system recommends not only the action, or a sequence of actions (a plan), but a value that has to be accepted by the decision maker. This is the final step in the architecture that closes the loop.

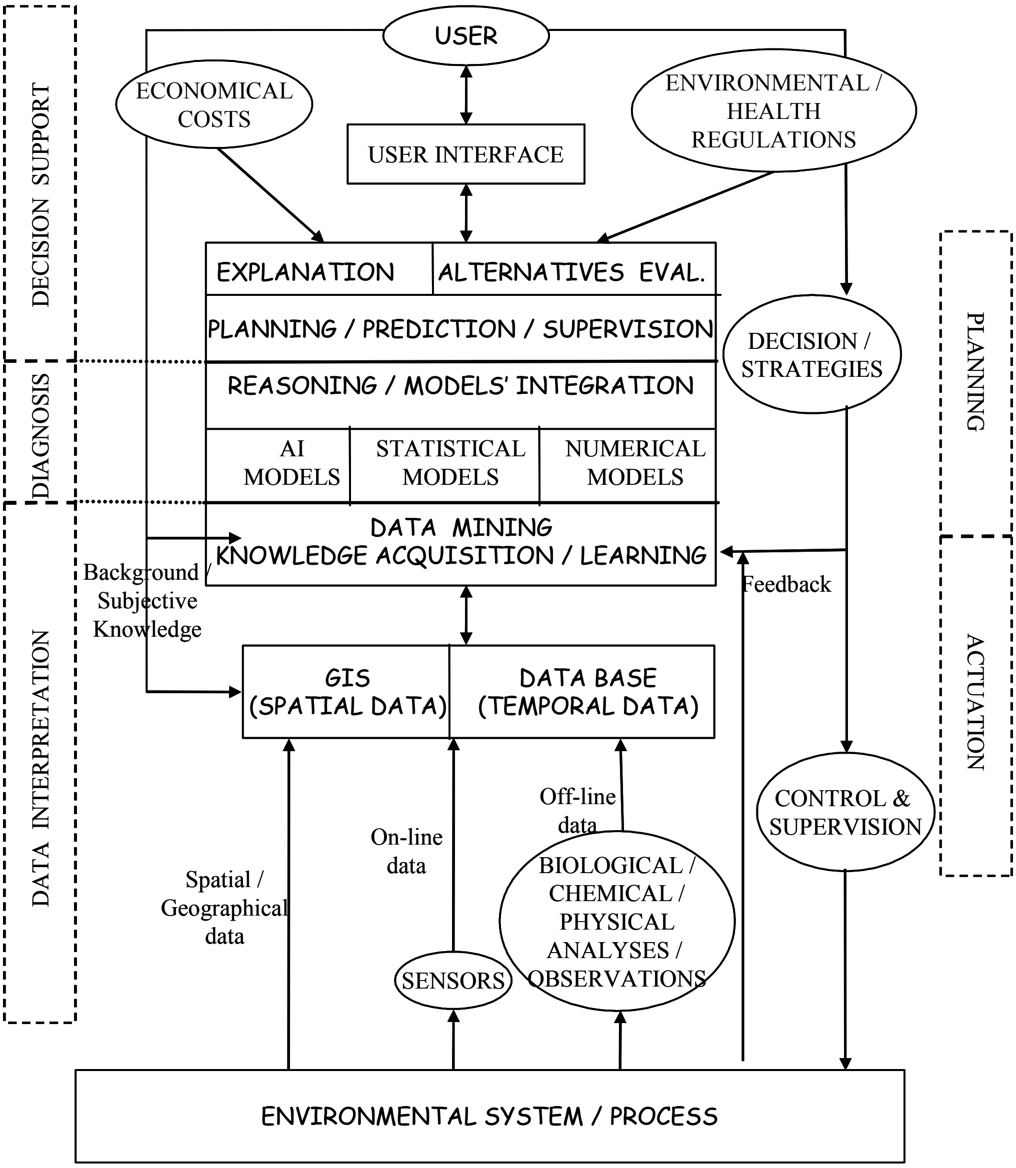

Figure 4. IEDSS Architecture

Although this IEDSS architecture is very nice there are inherent open problems arising when running such systems. During daily operation of IEDSS several open challenge problems appear. The *uncertainty of data* being processed is intrinsic to the environmental system, which is being monitored by several on-line sensors and off-line data. Thus, anomalous data values at *data gathering step* or even uncertain reasoning process at later levels such as in diagnosis or decision support or planning can lead the environmental process to unsafe critical operation states. At *diagnosis step* or even at *decision support step* or *planning step*, *spatial reasoning* or *temporal reasoning* or both aspects can influence the reasoning processes undertaken by the IEDSS. Most of Environmental systems must take into account the *spatial relationships* between the environmental goal area and the nearby environmental areas and the *temporal relationships* between the current state and the past states of the environmental system to state accurate and reliable assertions to be used within the diagnosis process or decision support process or planning process. Finally, a related issue is a crucial point: are really reliable and safe the decisions proposed by the IEDSS? Are we sure about the goodness and performance of proposed solutions? How can we ensure a correct evaluation of the IEDSS?

Main goal of this paper is to analyse these four issues mentioned above, which are depicted in figure 1. Each one of the next sections is devoted to each one of these open challenges.

3. ABOUT UNCERTAINTY MANAGEMENT

No matter the field of application being closed-loop process control, diagnosis or more generally decision support systems; one has to deal with uncertainty. As soon as a real-life system is studied and analysed, uncertainty is indeed inherently present: information sources are not perfect (e.g., fouling of on-line sensors) and sometimes subjective (e.g., human judgement), unknown disturbances can affect the process dynamics, but also knowledge on a system is always partial and incomplete due to system complexity. Lack of information but also abundance of information leads to uncertainty (van Asselt and Rotmans, 2002). As a matter of fact, when dealing with environmental system, lack of information has been for a long time recognised as the main source of uncertainty but due to recent technical advances (in particular sensors development), there are now many situations where "the more we know, the more we don't know". M.B. Beck defines this paradigm for wastewater management as going from a "data poor, information rich" (*i.e.,* few data available but they are well analysed) to a "data rich, information poor" situation (*i.e.,* many data available, in fact too many and their interactions are not carefully analysed and/or understood – Beck, 1987). Moreover, environmental models are also wrong and known to be wrong (Morton, 1993). As a consequence, as stated in the early ages by the philosopher Socrates, "wisdom is to know that you don't know" and uncertainty management is surely of great importance when developing IEDSS.

A general definition of uncertainty can be "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system' (Walker *et al*,. 2003). Other definitions exist to deal with incompleteness, vagueness, validity and inconsistency, the main sources of uncertainty (see for example Zimmermann, 2000) but the above definition has the advantage that it leads to clear different dimensions of uncertainty and for example for model-based decision support systems, the authors have defined:

- The *location* of uncertainty – where the uncertainty manifests itself within the model complexity;
- The *level* of uncertainty – where the uncertainty manifests itself along the spectrum between deterministic knowledge and total ignorance;
- The *nature* of uncertainty – whether the uncertainty is due to the imperfection of our knowledge or is due to the inherent variability of the phenomena being described.

Uncertainty has also several levels ranging from determinism and total ignorance: from determinism, statistical uncertainty is followed by scenario uncertainty, then recognised ignorance and total ignorance, the frontier between these two last items being defined as indeterminacy (Walker *et al.,* 2003).

Even though uncertainty is inherent, one does not have to reject it since there exist several ways to represent it and to integrate it into the reasoning process of an IEDSS. One idea is for example to attribute a confidence index to the source of information, but many other approaches exist in the literature among which the Bayesian theory, the Evidence Theory and the Possibility Theory. See for example some of the seminal papers about fuzzy sets and its application like (Zadeh,1965; Dubois and Prade, 1996), about Bayesian and evidence theory like (Dempster 1967; Shafer, 1976).

Main used approaches to represent and a manage uncertainty are Bayesian Belief networks, Causal networks, certainty factors derived from MYCN expert system, influence diagrams, and fuzzy logic.

Representing uncertainty in a specific context leads to several questions, as pointed out in (Walley, 1996):

- What are the interpretation, calculus and consistency of the uncertainty representation in each of the theories?
- How to evaluate, combine and adapt the measures of uncertainty?
- How to assess the consistency of the uncertain information?
- How to use this measure in the decision taking process?

Comparison of these approaches can be found in several papers and books among which (Klir and Folger, 1988; Smithson, 1989; Sheridan 1991; Krause and Clark, 1993) can be mentioned. In fact, the four theories differ in the calculus they use for defining, updating and combining measures of uncertainty, especially the rules they use to define conditional probabilities and expectations and how they model judgements of independence (Walley, 1996).

When used with environmental issues, uncertainty management is clearly a main issue. A deep review of these aspects of out of the scope of the present paper but as an illustration of the increasing interest, figure 5 presents the number of papers published per year for the last 15 years with "environment" "decision" and "uncertainty" in the title, abstract and/or keywords. One can notice a well pronounced increasing tendency with currently about 65 ISI papers published per year and this tendency should continue in the future.

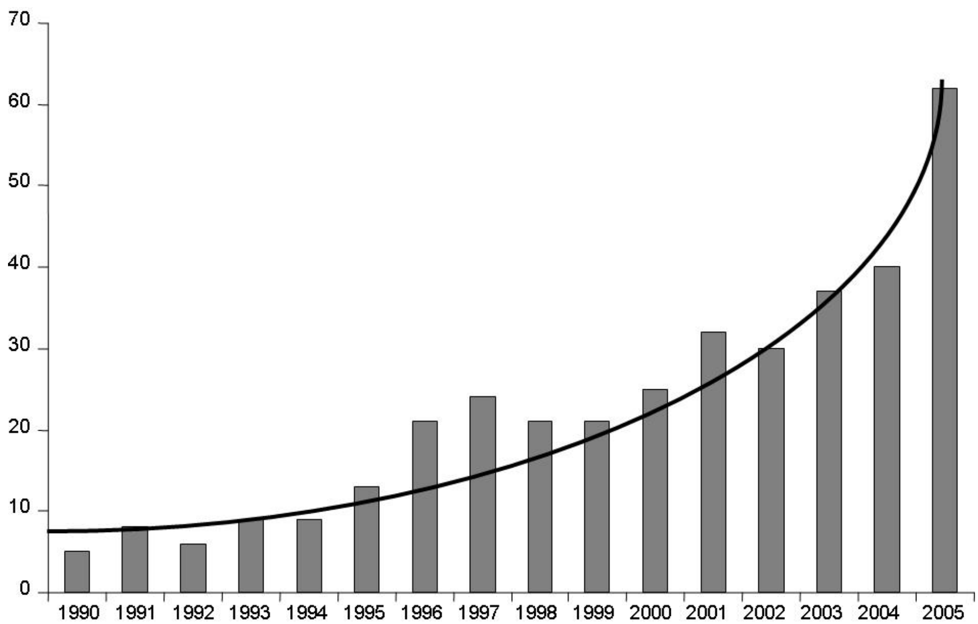

Figure 5. Number of scientific ISI publications dealing with "uncertainty", "environment" and "decision" in the title, abstract and/or keywords over the last 15 years

4. TEMPORAL REASONING

The interest in the area of temporal reasoning, and also spatial reasoning is growing within the artificial intelligence field, as well as within the geographical information systems area. Probably this could be due to many application domains where temporal information, spatial information or both must be managed (Renz and Guesguen, 2004). Most common domains related to artificial intelligence application are *environmental systems* and *medicine/health-care applications*.

Some typical examples within the *environmental systems* field are the monitoring and on-line control of dynamic processes such as power stations control, wastewater treatment plants control, and the forecasting of some meteorological or seismic phenomena. Some applications in the *medical domain* are the monitoring of patients in an intensive care unit, or the diagnosis and/or the prognosis and cure of some medical diseases. Nevertheless, dealing with time and space it is not restricted to artificial intelligence or geographical information systems. Some tasks such as mobile networks, distributed systems, planning, database theory, archaeology, genetics, the design of hardware circuits, the analysis of concurrent programming, scheduling, jet plane control and autonomous robot navigation are also instances of temporal/space domains.

In environmental domains the temporal features are very important. *Temporal relationships* between the current state and the past states of the environmental system constitute fundamental information to state accurate and reliable assertions to be used within the diagnosis process or decision support process or planning process. If these relationships are not taken into account, decisions proposed by an IEDSS would be not very reliable, and the environment could be damaged. Thus, temporal reasoning is a necessary component within IEDSSs.

Within computer science, there are many techniques or formalisms which have been developed to deal with temporal reasoning including non-monotonic logics, modal logics, circumscription methods, chronological minimization methods, relation algebras and applications of constraint-based reasoning, but a generalised understanding across different domains of time/space does not exist. No formal general purpose methodology has been developed and proved to be useful for different spatio-temporal calculi methods (Renz and Guesguen, 2004). In fact, each one of the methodologies is commonly oriented to slightly different features of the time/space problem. This is why temporal reasoning within IEDSS is an open challenge to be deeply studied in the future.

4.1 Relevant Work

From a logical point of view, temporal features in automated reasoning have been widely studied within the field of Artificial Intelligence. For instance, the logic of time work by (van Benthem, 1983); the work by Allen (Allen and Ferguson, 1994; Allen 1984; Allen, 1983) about the temporal interval logic; or the work of temporal logic by (Ma and Knight 2001;Ma and Knight, 1994) and by (Shoham 1987); or the circumscriptive event calculus by (Shanahan, 1995). All these approaches model reasoning processes under temporal constraints, which can modify the truth of logic assertions.

4.2 Approaches to Temporal Reasoning

Formalisms developed to handle temporal reasoning share two main issues (Ligozat *et al*., 2004):

- The development of suitable *representation languages* or *frameworks* for temporal knowledge. Using these tools, the domain knowledge could be constructed.
- The proposal of *techniques and methods for managing and reasoning* about that knowledge. In particular, the management and query answering of the domain knowledge.

Formalisms developed to manage temporal reasoning could be grouped as follows:

- Theoretical-oriented models, which are basically, inspired by certain kind of logics or relation algebras. Outstanding models are the temporal interval logic by Allen (Allen, 1983), generalised intervals by (Balbiani *et al*., 2000), cyclic intervals (Balbiani and Osmani, 2000), partially ordered time model (Anger et al., 2000) or the INDU calculus (Pujari and Sattar, 1999). They are highly concerned with the logical characterization of the models of a given calculus and especially worried about the *consistency* and *computational cost* of basic operations over the domain knowledge.
- Practical-oriented models, which are more inspired by the application domains, and by the practical use of the models, such as in time series models and other mathematical models within statistics and in case-based reasoning (Sànchez-Marrè *et al*., 2005, Ma and Knight, 2003; Jaere *et al*., 2002). They are more concerned by the *efficiency* and *accuracy* of the queries to the domain knowledge.

4.3 Featuring the Problem

Continuous or dynamic or time-dependent or temporal domains commonly involve a set of features, which make them really difficult to work with, such as:

- A large amount of new valuable experiences are continuously generated
- The current state or situation of the domain depends on previous temporal states or situations of the domain
- States have multiple diagnoses.

Taking into account its major characteristics, temporal domains could be defined as those domains where the truth of the logic assertions ($a_{k,ti}$) at a given instant time t_i depends both on the truth of logic assertions at current instant time t_i, and on the truth of logic assertions ($a_{k,ti-\Delta ti}$) at a past time t_i-Δt_i. This is illustrated by figure 6.

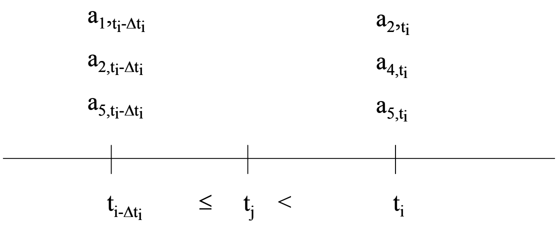

Figure 6. True assertions along the time line in a temporal domain

More formally, the domain could be considered as time dependent iff:

$$\underset{0 \le k \le la_{t_i}}{truth(a_{k,t_i})} = f(\underset{0 \le h \le la_{t_j}}{truth(a_{h,t_j})}, \underset{\substack{0 \le h1 \le la_{t_i} \\ h1 \ne h}}{truth(a_{h1,t_i})}) \qquad (1)$$

The huge complexity of environmental systems makes difficult modelling them with a theoretical-oriented model, because many logic assertions should be stated and demonstrated before some reasoning mechanisms could be applied. On the contrary, practical-oriented models are mainly concerned by allowing effective and accurate reasoning capabilities, in order to make the appropriate decisions at the environmental system. This is the reason why practical-oriented models seem to be more adequate than theoretical-oriented models to cope with environmental systems..

Last years, Case-Based Reasoning (CBR) (Kolodner, 1993) has been started to use, as a promising framework to deal with temporal domains. Main reason is that CBR itself operates retrieving similar solutions within the past experiences (past time actions) to solve a new unseen problem. Thus, it could be easier to incorporate the temporal component to this kind of systems. For this reason, in the next section a new approach based on the concepts of temporal episodes is outlined.

4.4 Case-Base Reasoning for Temporal Reasoning

In CBR systems, this temporal reasoning in continuous or dynamical domains was not studied until recently. Ma & Knight (Ma and Knight 2003) propose a theoretical framework to support historical CBR, based on relative temporal knowledge model. Similarity evaluation is based on two components: non-temporal similarity, based on elemental cases, and temporal similarity, based on graphical representations of temporal references. Most related publications, such as those of (Jaczynski, 1997; Nakhaeizadeh, 1994) use temporal models with absolute references. (Jaere *et al*., 2002) use a qualitative model derived from the temporal interval logic from Allen. In (Likhachev et al., 2002; Rosenstein and Cohen, 1999; Ram and Santamaria, 1997), several approaches are proposed in the field of mobile robots, emphasising the problem of the continuity of data stream in these domains. However, none of these give an answer for temporal episodes. In addition, they focused more on predicting numerical values, which can be described as time series, rather than on using the correlation among cases forming an episode. In (Sànchez-Marrè *et al*., 1999), a method for sustainable learning in continuous domains was proposed, based on a relevance measure.

There was not any approach proposing a mechanism for explicit representation for both temporal episodes and isolated cases, and addressing the problem of overlapping temporal episodes. Also the feature dependency among isolated cases forming an episode are not addressed by main known approaches, and rather they provide temporal logic reasoning mechanisms, which cannot solve all related problems. This means that classical individual case retrieval is not very accurate, as the dynamic domain is structured as a temporally related stream of cases rather than in single cases. The CBR system solutions should be also dynamic and continuous, and temporal dependencies among cases should be taken into account.

(Sànchez-Marrè *et al*., 2005) proposes a new framework for the development of temporal CBR systems: the Episode-Based Reasoning model. It is based on the *abstraction of temporal sequences of cases*, which are named as *episodes*. In this kind of domains, it is really important to detect similar temporal episodes of cases, rather than similar isolated cases. Thus, a more accurate diagnosis and problem solving of the dynamic domain could be done taking into account such temporal episodes of cases rather than only analysing the current isolated case.
Working with episodes instead of single cases is useful in temporal domains, but also raise some difficult tasks to be solved, such as:

- How to determine the length of an episode,
- How to represent the episodes, taking into account that they could be overlapping,
- How to represent the isolated cases,
- How to relate them to form episodes,
- How to undertake the episode retrieval,
- How to evaluate the similarity between temporal episodes of cases,
- How to continually learn and solve new episodes.

This approach answers almost all of these questions, and proposes a new framework to model temporal dependencies by means of the episode concept. The Episode-Based Reasoning framework can be used as a basis for the development of temporal CBR systems. This framework provides mechanisms to represent temporal episodes, to retrieve episodes, and to learn new episodes. An experimental evaluation has shown the potential of this new framework for temporal domains.

Main ideas can be summarised in figures 7 and 8.

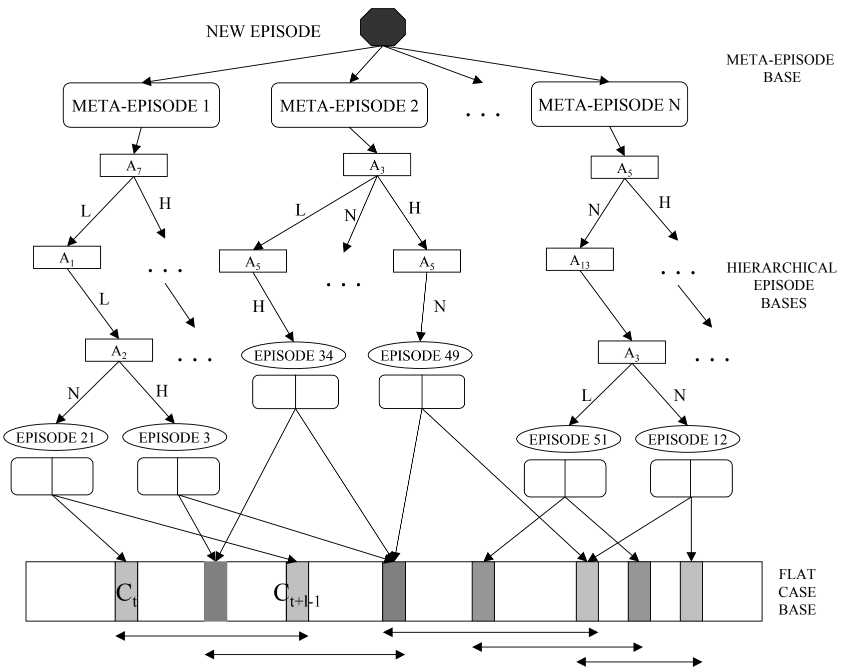

Figure 7. Hierarchical three-layered memory structure

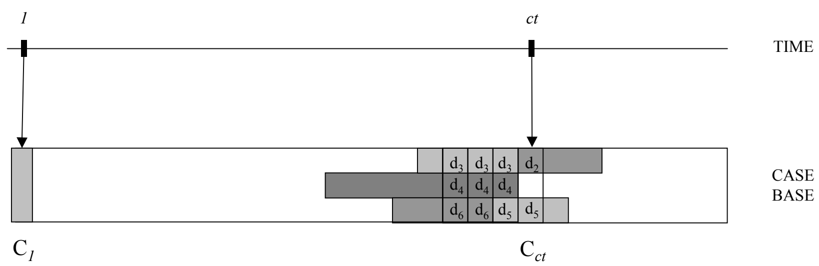

Figure 8. New and/or continued episodes arising from the current case

5. GEOGRAPHICAL INFORMATION AND SPATIAL REASONING

The design and use of GIS in natural resources research and management continues to proliferate throughout the world. This has been concomitant with the increase in computing power that has allowed increasingly complex spatial and temporal relationships to be utilized. Still, there appears to be potential for conceptual advancements. After discussing the intricacies of understanding and defining spatial reasoning, we will visit some of the approaches used and address some of the open issues and research needs. Our focus is on artificial intelligence methodologies and how they might link to GIS.

5.1 Understanding Spatial Reasoning

No single, concise definition exists for spatial reasoning. Timpf and Frank (1997) suggested the following intuitive one: "…any deduction of information from a representation of a spatial situation." A definition is difficult to develop partly because spatial relationships are thorny to delineate in themselves, and because reasoning has many components. We will examine both how to represent spatial relations and how to reason with and about them.

An online resource for spatial reasoning with a bibliography containing thousands of references can be found at http://www.cse.iitk.ac.in/~amit/other/spatsites.html , and we only will provide a cursory examination of some of the literature. Hernandez and Mukerjee (1995) list five properties of physical space: it is continuous and homogenous, objects relate to each other in terms of proximity and overlap, an object exists only once, each location coincides with at most one object, and movement is only possible to adjacent locations. They also differentiate several approaches to spatial reasoning, describing quantitative representations as those "expressed with respect to a predefined unit", and qualitative ones as representing "only those features that are unique or essential." Golledge (1992) has shown that people, in general, do not perceive and do not readily relate to fundamental concepts of geography and spatial reasoning such as "nearest neighbor". So, developers of environmental decision support systems that incorporate spatial reasoning must take this in to account. AI based interfaces might be of help.

A great deal of research attention has been given to qualitative spatial reasoning (see Freska, 1991, for an early review) because much of what people perceive about their spatial environment is not quantitative, e. g., the goose was observed flying between the two wetlands. This attention to qualitative aspects has many commonalities with yet unsolved issues in natural language processing, including nuance, context, and perspective. Robotics is another venue that has devoted attention to rapid and real-time processing of qualitative information to address problems of maneuvering through poorly understood environments. See Moratz and Wallgrun (2003) for a review of some of the literature. The blocks world and similar problems, so prevalent in early AI work, are often based on spatial reasoning and have been especially tied to search algorithms that examine large potential solution spaces. These have typically had representations of space that are tied to quantifiable spatial dimensions. As natural resource managers, we often think similarly, i.e., of spatial problems in regards to how they are represented in a GIS. We are usually dealing with tightly controlled representations in terms of X, Y, and Z dimensions, map projections, and relative datums. Still spatial representation and reasoning is not straightforward (Egenhofer 1989, Mark 1999), and we wish to further explore spatial reasoning in terms of GIS and artificial intelligence. How can we couple knowledge with spatial information and reasoning? We will not confine this to how animals and humans perceive and move through their environment, but also how processes perceive, populate, and affect their environment. We will also address the interaction of biotic and abiotic factors. Modelling of ecological processes within a spatial context has many indistinguishable features in common with spatial reasoning. Finally, spatial and temporal reasoning share many commonalities, and often spatial problems must be represented in time steps or some other temporal framework.

Fonseca et al. (2002) make a compelling argument and implementation for using standard inheritance-based ontologies to handle not only aspects of granularity in spatio-temporal representations, but also for reasoning across granularities. They recognize that processes and reasoning may be unique within, and among, levels of granularity. Bettini and Montanari (2002) provide a summary of the research needs in this important area and promote the linkage between GIS and AI. A similar problem seems inherent to the nature of the indivisibility of polygons, along with the discreet nature of polygons and the inherent conflict in using them to represent continuous data across space. This problem is typified in mapping soils and effectively discussed by McBratney (1992) and McBratney et al. (2002). One approach they put forward is using fuzzy set theory and related methodology for classifying polygons.

There are too many generic uses of GIS to list, but typical applications in natural resources include:

- combining data from layers to form a new layer
- pathway and nearest neighbor analysis
- buffering
- interpolation, kriging, and related analyses
- modelling ecological processes/graphical representation of process outputs
- locating objects that may be stationary or move over time
- integration of processes at multiple scales
- amalgamation (or the reverse) of objects or spaces (fields)
- changing topology or attributes over time

Although we will not address techniques readily available in most GIS software packages, we do not wish to minimize their importance to modelling. Artificial intelligence can also be used as a basis for models themselves or as ways to communicate among model components, of which GIS could be one. Artificial intelligence based software can be embedded within GIS, or vice versa. We see the following as particularly fruitful avenues for both natural resource application and further research and development in a modelling context. These all are potential areas where artificial intelligence and GIS can have a new or increasingly fruitful interface.

5.1.1. Altering Attributes/Databases and Topology

Models can be used to change the internal attributes of objects within a GIS, i.e., points, lines, and polygons, or cells. For example, the output from a snowfall model might alter the surface color or surface elevation associated with particular polygons. An alternative approach would be to have the model outside the GIS and have it alter a database held in common with the GIS. It appears that this is the approach used Joy and Death (2004) in effectively linking a neural network and GIS for modelling aquatic species distributions in relation to specific stream reaches in New Zealand. A slightly more intricate approach is where one layer's attributes are altered by a process model requiring data inputs from other layers. In such cases, autonomous agents within cells could be triggered by changing values in other cells. GIS approaches that can alter the actual shape, location, or identity of polygons, lines, and points based on either external or internal models are also needed. Doing this in iterative or recursive fashion can be computationally problematic if the number of steps is large. Liangyi and Baoli (2002) use the terms tight and loose coupling, respectively, to describe actual internal integration versus external database connections of GIS with expert systems. However, those terms have not be universally adopted. We agree with Sauchyn (2001) that spatial modelling of soil processes within a geologic time scale could be an important contribution and recognize the potential pitfalls they describe related to losing granularity with such extrapolations over time and space. We do not know of any spatial modelling efforts that have accomplished this.

The work of Skidmore et al. (1991) and Skidmore et al. (1996) in connecting expert systems and GIS for mapping forest soils in Australia combines AI and spatial reasoning and is particularly impressive because they conducted empirical validation, something not done frequently enough. They were unable to demonstrate a statistical difference in performance between the expert system and the mapping by experts, although accuracy of each approach was less than 75 percent. However, it is unclear whether the soil experts used for system development were independent of the experts used for validation.

5.2. Kriging and Variants

A key aspect of complex spatial representation of raster-based models is controlling how adjacent cells interact. Does (should) the value of one cell depend on the value of adjacent cells? The concept of a moving window has been commonly used in everything from wildlife habitat models to pedology to estimating land use change (Carroll 1999; Guo et al. 2003, Schneider 2003). GIS software can make this available internally. We are not aware of work using encoded ecological knowledge (e.g., an expert system, machine learning) to control the moving window process, itself, or of work where kriging mechanisms encapsulate such knowledge.

5.3. Representing Change/Time Steps/Feedback Loops

There are mechanisms for capture of changing conditions within GIS software, often as a kind of video representation of successive maps or images. These can be most useful for visualization of change. The need to incorporate feedback loops in interdisciplinary ecological modelling can be crucial. When needing to develop interdisciplinary models that are knowledge-based, the problem of how to incorporate feedback loops generally remains problematic. Although Bayesian belief networks and influence diagrams (Jensen 2001) can be effective for interdisciplinary modelling, their inherent nature as directed acyclic graphs makes it nearly impossible to effectively incorporate feedback. One current solution is to imbed the network within the loop control of some other program, but this is typically cumbersome. A second solution is to develop instances of a modular portion of the network, and allow those instances to operate in successive time steps. This might work well for annual cycles of vegetation growth in relation to their abiotic environment, e.g., where cattails (*Typha* spp.) might trap snow and the resulting increased water levels may affect growth. However, the approach does not work well for feedback triggered by either episodic or sporadic events. Nor does it work well when the time steps are small and therefore likely numerous.

5.4. Middleware, Blackboards, and Communication Protocols

There are too many definitions of middleware to list. The most generic can be described as software that provides an interface between other pieces of software (Brown et al. 2005), especially when distributed (Tripathi 2002). With a recent National Science Foundation initiative in the U.S.A. (www.nsf.gov/od/lpa/news/03/fs03_nmi.htm), middleware has come to include a component of providing the interface for distributed computing over the Internet. Armstrong et al. (2005) provide a GIS example. Middleware seems to hold great promise for connecting distributed software, models, and databases, because spatial modelling tends to be intensive from both a computational and a data storage perspective. Using middleware to connect artificial intelligence based process models with a GIS holds promise for computationally intense spatial models.

Blackboards are an artificial intelligence method that have been around for two decades (Carver and Lesser 1992; Corkill 1991; Ni 1986). Blackboard methodology allows entities that may or may not be intelligent agents to use cooperative distributed problem solving methods(Carver et al. 1991; Durfee et al. 1989) for solving common problems. Nute et al.(2004) used backboard methodology in their NED-2 decision support system for forest ecosystem management.

Labrou and Finin (1997) provided one of the early communication protocols, KQML (Knowledge Query and Management Language), for message passing among agents, but it was never completely standardized in the computer science community. This has morphed into FIPA (Foundation for Intelligent Physical Agents) which has produced protocols for agent communication, management and message transport (www.fipa.org). Such protocols are the foundation not only for agent communication, but provide the basis by which disparate spatial and temporal models could share information among themselves within an artificial intelligence structure. Purvis et al. (2001) describe a system that combines neural networks and GIS via CORBA (Common Object Request Broker), another common protocol based on object oriented programming, not intelligent agent communication. All such communication protocols could be exploited for managing both the embedding of GIS and AI, as well as implementing many aspects of multiagent systems.

Rossier and Scheurer (2002), in an interesting turn for ecological scientists, describe a system for mobile network applications inspired by ecosystem principles. Although not GIS-based, it does incorporate the middleware technology, blackboards, and FIPA protocols. The system is based on self-regulation in populations of mobile agents, and conceptually can be related to ecological population concepts.

5.5. Multiagent Systems

The term, multiagent system, implies more than one agent interacting with each other within an underlying communication infrastructure and without a procedural control mechanism; and, the individual agents often are distributed and autonomous (Huhns and Stephens 1999.) Scores of problems in natural resources are inherently distributed both temporally and spatially. Many artificial intelligence-based methodologies, particularly those related to cooperative distributed problem solving and multiagent systems (Weiss 1999) also are designed to address distributed problems. Wooldridge (1999) stated that no single, accepted definition of an agent exists, although his writings have helped to overcome this. We will accept the definition of an intelligent agent as a computer system based in artificial intelligence, that is autonomous, collects information about its environment (either virtual or real environment), and is capable of independently taking the initiative to react to that input as appropriate (Weiss 1999; Wooldridge 1999; Wooldridge and Jennings 1995). This differs from objects, cellular automata, and individual based models which lack the inherent autonomous intelligence embedded within agents. Anderson and Evans (1994) discuss the application of intelligent agents as an approach to modelling in natural resource management, stressing the need for autonomy and the ability of an agent to interact spatially and temporally with surrounding entities. They also underscore the equal importance of providing a satisfactory representation of the spatial world in which the agents are embedded. Although the belief-desires-intentions (BDI) agent architecture summarized by Wooldridge (1999) and Rao and Georgeff (1995) is not a requirement for this definition of an agent, it exemplifies the foundation upon which intelligent agents often are conceptualized and distinguished from non-artificial intelligence based approaches. For further clarification, we note that objects lack autonomy; cellular automata are not capable of movement; and individual based models are generally designed to represent biotic entities.

A recent multiagent-GIS combination system of note is a crowd simulator (Moulin et al. 2003). Torrens and Benenson (2005) provide an excellent review of the differences between automata and agents, and they discuss geographic automata systems which are a hybrid combination for representing human objects interacting with their environment. Similarly, Anderson (2002) reviews these differences and describes Gensim, a generic ecological modelling tool that incorporates interaction among agents, encompasses the definition of intelligent agents provided above, is domain independent, and can build and incorporate large number of agents in a spatial framework. Brown et al. 2005 state that they “know of no implementation of an ABM [agent-based model] embedded completely within a GIS environment.”

We will not review all the uses of agents that have been used in spatial modelling and GIS, but intelligent agents can be used to represent knowledge bases, pieces of software (Nute et al. 2004), independent models, individual biotic organisms (Dumont and Hill 2001), environmental (abiotic and biotic) characteristics (Medoc et al. 2004), geographic portions of landscape, human decision makers (Bousquet and Le Page 2004; Lei et al. 2005), and user interfaces (Nute et al. 2004).

Spatial models in natural resources often also involve a temporal component. In purely procedural programming approaches, modelling the simultaneous effects of processes on multiple entities or space is nearly impossible without massively parallel implementations. However, using intelligent, autonomous agents, this limitation is overcome. Multiple threaded architectures are becoming an increasingly common approach to implementing multiagent systems. The software, DECAF (Graham and Decker 2000; Graham et al. 2001) is such an implementation; and, trumpeter swan (*Cygnus buccinator*) movements in seasonal time steps have been modelled within a multiagent framework using DECAF (Sojda 2002; Sojda et al 2002).

5.6. Other Thoughts

De Serres and Roy (1990) and Argemiro de Carvalho Paiva et al (*in press*) provide unique and interesting approaches to spatial reasoning for determining flow direction in rivers on remote imagery. It is not clear if either effort was integrated with a GIS, but it is easy to envision such a coupling.

It would also seem that the early innovative work of Folse et al. (1989) regarding animal movement, memory, and habitat use would lend itself exceedingly well to a combination of AI methodologies and GIS. This could include agents to represent animals, with memory seeming to be a natural instantiation of a belief-desires-intention (BDI) architecture (Wooldridge 1999; and Rao and Georgeff 1995). The related habitat use models could be represented using Bayesian belief networks, expert systems, or other AI methods that access the underlying habitat data and characterizations held in a separate database or that are integral to a GIS. Movement could be modelled as agents in a spatial framework represented by a GIS, or a GIS could simply be used to provide a final graphical depiction of the movement and habitat use.

Many of the methodologies described could be used to address the issue of adjacent entities affecting a common resource, such as several moose (*Alces alces*) feeding on the same patch of willows (*Salix spp.*), or red-winged blackbirds (*Agelaius phoeniceus*) and sedge wrens (*Cistothorus platensis*)using the same bulrush

(*Scirpus sp.*) stand, or the plants of several small pothole wetlands tapping a common shallow groundwater source. Some such situations are based on significant biotic/abiotic feed back loops and are difficult spatial and temporal problems to model.

6. EVALUATION OF IEDSS AND BENCHMARKING

The evaluation of an IEDSS is still an open problem and no clear strategies are yet well established for facing one of the more critical phases of the development of an IEDSS. As a matter of fact, evaluation of the IEDSS is very important, since the later use of the system totally depends on the appropriateness of the recommendations it provides. Ensuring that the system is performing well is critical to its use in the future, and validation of the IEDSS is devoted to this topic.

It seems that *validation* of an IEDSS could be understood, as a first approach, as the design of a set of tests which ensure good performance of the system. For the specific case of IEDSS, good performance can be identified with the capacity of the system to provide the right recommendation in front of a certain scenario. There are generic approaches to validate IEDSS, such those described in (Sojda, 2006), but previous experiences in the development and evaluation of IEDSS for several domains mainly related to water such as operation of biological wastewater treatment plants (mainly activated sludge system) (Comas *et al*., 2003; Rodríguez-Roda *et al*., 2002; R-Roda *et al*., 2001), conceptual design of complex and multi-criteria processes (Flores *et al*., 2005), management of altered river basin to improve nutrient retention (Comas *et al*., 2003a), selection of the most adequate wastewater treatment for small communities (Comas *et al*., 2003b; Alemany et al 2005), selection of industrial discharge limits, solids separation problems in the activated sludge system (slow dynamics) (Martínez et al., 2006a; Martínez et al., 2006b), drinking water treatment (Heller and Struss, 2002) and problems caused by algal bloom in water reservoirs (Struss *et al*., 2003) seems to point out that evaluation has to be done for a rather specific application domain. We are convinced that this also applies to other environmental systems. It is probably more reasonable to think about specific validation protocols for different kinds of environmental systems, instead of trying to develop a general purpose protocol. Just consider that validation of an IEDSS oriented to support the control of a wastewater treatment plant probably needs quite different considerations than the validation of an IEDSS oriented to support migration of birds through a certain natural space. Indeed, even considering a specific environmental application domain, authors are not aware of standard validation protocols well established yet, except for some specific cases which will be presented below.

Nevertheless, it is possible and useful to develop a general methodology for evaluating IEDSS. To do it, first thing is to identify the common elements to be considered for designing the generic evaluation schema of an IEDSS. Afterwards, the specific validation protocol for a given IEDSS could be designed following this general schema. It seems that this requires a clear, domain-independent, technology-independent definition of tasks and criteria. This paper is presenting a first approach to this topic.

First of all it has to be taken into account that in an IEDSS two levels can be distinguished. So, for designing a standardized validation protocol it is first required:

1- Identify the components of the IEDSS as well as their characteristics (e.g. models available, data sources – sensors, laboratories, observations, opinions, etc.- and data quality, knowledge based or soft computing reasoning, learning capability, user profile, system autonomy, open/limited situations faced, etc.).
2- Identify the tasks performed by the IEDSS. As said before (see section 1), there are two main kinds of IEDSS that should be distinguished regarding its functionality:
    - Those which are controlling / supervising a process in real-time (or almost real-time)
    - Those that give punctual off-line support to decision-making.

However, in both kinds of IEDSS, two main processes or tasks can be identified:

- "diagnosis"/situation assessment: based on observation, and oriented to determine "what is going on?"
- "recommendation"/therapy proposal: based on a specification of goals, determine "what can be done to achieve the goals given a certain diagnoses?"

It seems reasonable to think about a two level validation process according to the different nature of the components and tasks related to an IEDSS. So, a general framework could be establishing different evaluation steps that should be fulfilled based on each IEDSS particularities. A simple proposal should be:

a. *Structural* evaluation: related to the components of the system and their interaction
   i. evaluate separately the performance of every component of the system (evaluation of rule-based systems, evaluation of reception of sensor signals, verification and robustness of software, etc)
   ii. Identify the processes involved in the environmental system for performing either diagnosis or recommendations. It will be possible to define those processes as some interaction between a certain subset of the components of the system (reading some data from a sensor, then sending a query to a certain knowledge base, then start some approximate reasoning process etc)
   iii. For each one of the processes identified, evaluate the communication between the involved components.
b. *Functional* evaluation: Evaluate the good performance of every task involved in the IEDSS.
   i. Identify the environmental processes involved in the environmental system for which the IEDSS has to provide intelligent support.
   ii. According to these processes, design a representative set of scenarios (situations in the real target environmental system) to be presented to the IEDSS. Depending on the specificity of the IEDSS it will be important to include:
      a. real or simulated data
      b. noisy or erroneous data
      c. data from similar systems (to evaluate how easy will be to transfer or adapt the IEDSS to another environmental system)
      d. Benchmarks, which are addressed bellow, can also be considered at this point.
   iii. Ask the IEDSS to provide recommendations for those scenarios.
   iv. Evaluate the performance of the system. This step should include from classical multi-criteria numerical techniques (sensitivity analysis of variables and weights, …) to qualitative approaches such as cross validation with different users (even trough the web), periodical revision of learning outcomes, etc. Some specific criteria to be considered are:
      a. The situation assessment (usually not unique) contains the expected /appropriate one
      b. The situation assessment does not contain wrong/implausible explanations
      c. The therapy proposal contains the expected/appropriate/cheapest ones
      d. the therapy proposal does not contain wrong/implausible ones
      e. The system provides a justification/explanation for the solution. It is intuitive
      f. robustness w.r.t noisy/erroneous data
      g. The solutions can be reused for similar problems or sites.
      h. The transfer/adaptation to another system is easy

If the environmental system is complex as usual, it is a hard task to identify the reduced set of scenarios to be used for evaluation that really guarantees a good representation of the whole system behaviour.

Other criteria to be taken into account:
- Modularity, easy extension if new knowledge is obtained
- Monotonicity: more information leads to better results
- Scalability to realistic problems, efficiency

However, it is not easy to establish test cases for evaluating monotonicity, robustness, scalability, etc. So, in the evaluation, not only structural appropriateness of the system has to be evaluated, but especially the quality of the recommendations provided by the system.

Validation of different types of IEDSS involves different requirements:

In those IEDSS designed for providing punctual support, the role of socio-cultural and economical issues limits the use of standard databases. Comparison of the results is not always possible. Confidence can not be increased according to the results when facing similar situations, because these IEDSS are very specific and sometimes are only built to take (justify) one single decision. In this cases, the validation of steps 2.1, 2.2, 2.3 are possible, but 2.4 is more difficult.

In the IEDSSs that control or supervise an environmental system in real time, diagnosis can be previously validated by designing different scenarios that cover the whole response surface, but it has to be taken into account that this may not be a trivial task. However, the consequences of the therapy proposal (or control strategy or suggested solution or recommendation) can not be simulated. In general the end-user is responsible to accept/refine/reject system solutions. This responsibility can decrease (thus, increasing IEDSS confidence) over the time as far as the system is facing situations that were successfully solved in the past (real validation). Although the IEDSS can be very specific for the target application, there could be similar processes and systems in the target domain to generate repository databases and scenarios, etc. In that case, a benchmark procedure could be developed.

6.1 Benchmarking

First a concise definition of "benchmark" and/or "benchmarking" should be stated. An online dictionary provides [http://www.m-w.com/dictionary] the following ones:

- "benchmark: 2 **a**: a point of reference from which measurements may be made **b**: something that serves as a standard by which others may be measured or judged **c**: a standardized problem or test that serves as a basis for evaluation or comparison (as of computer system performance)"
- "benchmarking: the study of a competitor's product or business practices in order to improve the performance of one's own company."

In our opinion, one of the most promising research lines in IEDSS development is the definition of benchmarks to assess and evaluate their performance in a set of well-defined circumstances, and their capacity to react to new situations. This will also allow the creation of a better framework for comparison between IEDSSs. We are aware of no attempt to do this. This validation of an EDSS in the appropriate context may simplify the tuning tasks and help to enhance the system's performance.

We are not aware of the existence of benchmarking databases for environmental systems. It is very convenient to build one, but some formal aspects should be agreed before in order to build a database really useful for benchmark on environmental intelligent decision support systems.

At present we can distinguish, at least, two different kinds of benchmarks:

1. A set of scenarios for a given set of tasks, specifying:
   1- The input data
   2- The set of acceptable results (situation assessments/therapies) and a characteristic of unacceptable results

One of the most famous benchmarks of this type is UCI repository (http://www.ics.uci.edu/~mlearn/MLRepository.html), within Artificial Intelligence field. These kinds of benchmarks are usually used to test whether a certain new technique is solving a known problem more efficiently, more quickly, with more accuracy... than the reference one. This kind of structure may be useful to build benchmarks for the diagnoses provided by an IEDSS in front of a certain set of scenarios. However, to evaluate the performance of an IEDSS, other criteria, as mentioned before, has to be taken into account, such as the quality and appropriateness of the suggested recommendation in front of a given scenario, the capacity of explaining why or how was the proposed solution found are more important aspects to be considered. The set of criteria mentioned before is a first proposal, but what really determines that an IEDSS is working well should also be identified.

Anyway, building a repository for environmental data bases is a possibility to be studied and developed to generate a reference for evaluating new IEDSS.

2. A prototypical simulator of a system with a predefined set of experiments to be evaluated specifying:
   1. The characteristics of the simulated system
   2. The conditional experiments to be simulated
   3. Evaluation criteria to determine the success of the performed experiments

As an example of this kind of benchmark, the IWA/COST simulation benchmark (Copp, 2002) is presented, although now there exists also a plant-wide benchmark:

It is used by the wastewater research community as a standardized simulation protocol to evaluate and compare different control strategies for a biological nitrogen removal process. It includes a plant layout, simulation models and parameters, a detailed description of the influent disturbances (dry weather, storm and rain events), as well as performance evaluation criteria to determine the relative effectiveness of proposed control strategies.

The benchmark plant layout has a very well defined structure and the models used for the simulation of the processes occurring in the plant, as well as basic operational conditions are provided within the benchmark description. (Figure 9) Henze *et al.*, 1987) (Takács *et al.*, 1991)

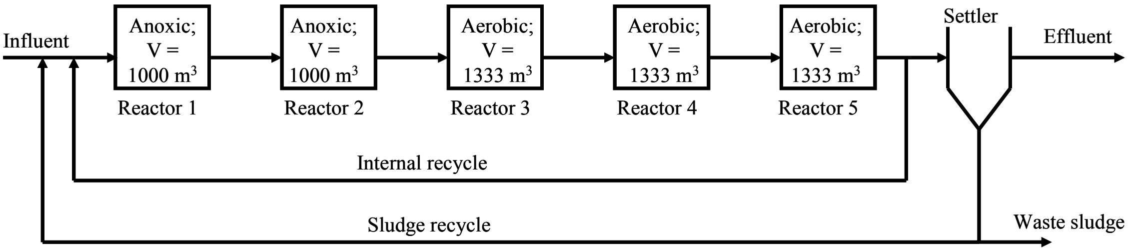

Figure 9. Lay-out of the IWA/COST benchmark plant.

The default control strategy or any other proposed control strategies are evaluated for three different pre-defined weather disturbance scenarios corresponding to dry weather, storm events and rainy days, respectively. In fact, the simulation process follows the protocol specified in (Coop, 2002) starting with 150-day steady-state to obtain adequate initial state values, followed by 14 days with dry weather scenario, then apply the dry, rain or storm conditions for another 14 days. Only the last week of the simulation is used for plant performace evaluation. The control strategy performance is evaluated by applying several performance criteria to the simulation output. These criteria include those defined in the original benchmark description (Copp, 2002) as well as the total operating cost index (TCI) proposed by Vanrolleghem and Gillot (2002).

This is an example of a benchmark for designing control strategies on a specific environmental system. It doesn't matter if the control strategies are manually proposed by an expert or they come from an IEDSS. In this sense it would be useful to evaluate if the treatment proposals (the recommendations) of a given IEDSS are right or not. In fact (3) (4) adds an extension of the IWA/COST simulation benchmark that allows the connection of an IEDSS and the benchmark to evaluate the IEDSS proposals.
So, this second kind of benchmarks is clear useful for benchmarking the second kind of tasks performed by IEDSS, the treatment proposal.

It seems clear that benchmarking has to be done for a rather specific application domain.

Building a simulator for benchmarking an environmental system and providing a protocol to connect it to a IEDSS provides the possibility of evaluating the consequences of taking the decision recommended by the IEDSS either in the short, medium and long term. However, this has an enormous cost and very often, the development of the simulator can take more time than the development of the IEDSS itself.

A cheaper strategy seems to build a finite set of representative scenarios together with the suitable recommendations, and evaluate which is the response of the IEDSS in front of them. Of course, the selection of the set of testing scenarios is critical to guarantee that solving correctly those set of situations ensures a good performance in general. For the case of wastewater treatment plants, this would be equivalent to build a set of scenarios representing dry weather, storm events and raining days together with a set of suitable control strategies for each one. This of course requires a good knowledge of the environmental system and a good knowledge of the suitable decisions to be taken in any case.

This arises an interesting problem: If the environmental system is so well known that we are able to signal which are suitable decisions in front of every situation it is probably useless to build an IEDSS to control the system and the environmental system can probably be controlled by deterministic software.

On the other hand, our impression is that benchmarks of type 1 are not very good for evaluating the long term effect of a control strategy on a dynamic system. This is one of the specific characteristic of environmental systems to be taken into account for designing good and useful benchmarks.

It seems that benchmarks of type one would be useful for evaluating diagnoses and those of type two would be suitable for evaluating treatments, control strategies, or any action recommended by the IEDSS related with the DYNAMICS of the environmental system.

However, the information included in a benchmark of type one may still be not enough for evaluating IEDSS performances. It is required a depth REFLEXION on the representation of the data in the benchmark. Will it be enough providing a set of scenarios together with the right recommendation for them?

The following items must be evaluated:

- The diagnosis is good
- The proposed treatment is acceptable
- The long term consequences of proposed treatment work well

We should think about including all the information required to evaluate these characteristics in the benchmark. So, present representation of public repositories as UCI is probably not enough for evaluating the performance of IEDSS.

Will this be enough independently of the technique used for inducing the knowledge used for building the IEDSS?

7. CONCLUSIONS AND FUTURE TRENDS

Although the IEDSS architecture depicted in figure 3, or even other possible architectures are very nice, there are inherent open problems arising when running such systems. During daily operation of IEDSS several open challenge problems appear. The *uncertainty of data* being processed is intrinsic to the environmental system, which is being monitored by several on-line sensors and off-line data. Thus, anomalous data values at *data gathering level* or even uncertain reasoning process at later levels such as in diagnosis or decision support or planning can lead the environmental process to unsafe critical operation states. At *diagnosis level* or even at *decision support level* or *planning level*, *spatial reasoning* or *temporal reasoning* or both aspects can influence the reasoning processes undertaken by the IEDSS. Most of Environmental systems must take into account the *spatial relationships* between the environmental goal area and the nearby environmental areas and the *temporal relationships* between the current state and the past states of the environmental system to state accurate and reliable assertions to be used within the diagnosis process or decision support process or planning process. Finally, a related issue is a crucial point: are really reliable and safe the decisions proposed by the IEDSS? Are we sure about the goodness and performance of proposed solutions? How can we ensure a correct evaluation of the IEDSS?

As said before, validation of an IEDSS is as critical as the construction itself to ensure right performance in real applications. Few works are devoted to this specific part of the IEDSS development. In this paper, an analysis about the different aspects to be evaluated in an IEDSS and the possible tools to be used for that task has been addressed. It has been elicited that thinking of a general schema for IEDSS validation is not easy at all and only some general guidelines have been exposed. Benchmarking may be a promising way to avoid other complex validation methods, but much work is to be done to find the right and successful structure of a benchmark oriented to IEDSS validation.

Main goal of this paper have been to analyse these four issues mentioned above. Within the text it has been justified that these are really open problems and cutting edge tasks to be solved in the near future for a successful application of IEDSS. Main features involving each one of these problems have been outlined, and relevant work and possible approaches to tackle them have been discussed. Main conclusion after this analysis is that much work must be done within the artificial intelligence, computer scientists (GIS, statistical and mathematical modelling) and environmental scientists interdisciplinary community.

In this paper it has been elicited that many open research lines requiring future efforts to solve the problems associated to the design and validation of real IEDSS. Any contribution to the following topics will greatly improve this field with great benefits on control and management of environmental systems:

- New uncertainty management techniques

- Techniques or tools to select the best uncertainty management tool for a concrete IEDSS
- New reliable and practical approaches for modelling temporal reasoning within IEDSS
- New reliable and practical approaches for modelling spatial reasoning and geographical information systems within IEDSS
- Integration of spatial and temporal reasoning aspects within a common approach for IEDSS
- Design of a general methodology of validation for IEDSS
- Building of public benchmarks for environmental systems and processes

8. ACKNOWLEDGEMENTS

This research has partially been supported by Spanish project TIN2004-1368.

9. REFERENCES

Allen J. and G. Ferguson. Actions and Events in Interval Temporal Logic. *The Journal of Logic and Computation*, 4(5):531-579, 1994.

Allen J. Towards a General Theory of Action and Time. *Artificial Intelligence*, 23:123-154, 1984.

Allen J. Maintaining knowledge about temporal intervals. *Communications of the ACM*, 26(11):832-843, 1983.

Anderson, J. 2002. Providing a broad spectrum of agents in spatially-explicit simulation models: the Gensim approach. *pages 21-58, in*: Gimblett, R., ed. Integrating Geographic Information Systems and Agent-based Modeling Techniques for Simulating Social and Ecological Processes. Oxford University Press. New York, New York.

Argemiro de Carvalho Paiva, J., and M. Egenhofer. *in press*. Robust inference of the flow direction in river networks. Algorithmica

Armstrong, M. P., M K. Cowles, and S. Wang. 2005. Using a computational grid for geographic information analysis: a reconnaissance. The Professional Geographer 57(3):365-375.

Beck M.B. Water quality modelling: A review of the analysis of uncertainty, *Water Resour. Res.* **23**(8), 1393-1442, 1987.

Belanche, Ll., Valdés, J.J., Comas, J., R-Roda, I. and Poch M, Towards a Model of Input-Output Behaviour of Wastewater Treatment Plants using Soft Computing Techniques, *Environmental Modelling & Software*, 14(5), 409-419, 1999.

Belanche, Ll., Valdés, J.J., Comas, J., R-Roda, I. and Poch, M., Prediction of the Bulking Phenomenon in Wastewater Treatment Plants, *Artificial Intelligence in Engineering*, 14(4), 307–317, 2000.

Brown, D. G., R. Riolo, D. T, Robinson, M. North, and W. Rand. 2005. Spatial process and data models: toward integration of agent-based models and GIS. Journal of Geographic Information Systems 7:24-47.

Bousquet, F., and C. Le Page. 2004. Multi-agent simulations and ecosystem management: a review. Ecological Modelling 176:313-332.

Cabanillas, D., Comas, J., Llorens, L., Poch, M., Ceccaroni, L. and Willmott, S. Implementation of the STREAMES environmental decision-support system. In: Pahl-Wostl, C., Schmidt, S., Rizzoli, A.E. and Jakeman, A.J. (eds.), Complexity and Integrated Resources Management, Transactions of the 2nd Biennial Meeting of the International Environmental Modelling and Software Society, iEMSs, Osnabruck (Germany), 2004. ISBN 88-900787-1-5.

Carroll, C., W. J. Zielinski, and R. F. Noss. 1999. Using presence-absence data to build and test spatial habitat models for the fisher in the Klamath Region, U.S.A. Conservation Biology 13(6):1344-1359.

Carver, N., Z. Cvetanovic, and V. Lesser. 1991. Sophisticated cooperation in FA/C distributed problem solving systems. pages 191-198 *in*; Proceedings of the Ninth National Conference on Artificial Intelligence. AAAI Press. Menlo Park, California.

Carver, N., and Lesser, V. 1992. The Evolution of Blackboard Control Architectures CMPSCI Technical Report 92-71, Department of Computer Science, Univ. Massachusetts-Amherst.

Corkill, D. D. 1991. Blackboard Systems. *AI Expert* 6(9): 40-47.

Comas J., Rodríguez-Roda I., Poch M., Gernaey K.V., Rosen C. & Jeppsson U. Demonstration of a tool for automatic learning and reuse of knowledge in the activated sludge process. *Water Science & Technology*, In press (2006a).

Comas J., Rodríguez-Roda I., Poch M., Gernaey K.V., Rosen C. & Jeppsson U.Extension of the IWA/COST simulation benchmark to include expert reasoning for system performance evaluation. *Water Science & Technology*, In press (2006b).

Comas J., Llorens E., Martí E., Puig M.A., Riera J.L., Sabater F, Poch M. Knowledge Acquisition in the STREAMES Project: The Key Process in the Environmental Decision

Support System Development. *AI Communications*, 16(4), 253-265, 2003a.
Comas J., Alemany J., Poch M, Torrens A., Salgot M. and Bou J. Development of a knowledge-based decision support system for identifying adequate wastewater treatment for small communities. *Water Science & Technology* 48 (11-12), 393-400, 2003b.
Comas J., Rodríguez-Roda I., Sànchez-Marrè M., Cortés U., Freixó A., Arráez J. & Poch M. A knowledge-based approach to the deflocculation problem: integrating on-line, off-line, and heuristic information. *Water Research* 37, pp. 2377-2387, 2003c.
Cortés, U., Sànchez-Marrè, M., Comas, J., Rodríguez-Roda, I. And Poch, M. Unpublished results, 2002.
Cortés, U., Sànchez-Marrè, M., Sangüesa, R., Comas, J., R-Roda, I., Poch, M. and Riaño, D. Knowledge Management in Environmental Decision Support Systems. *AI Communications*. 14(1), 3-12 2001.
Cortés, U., M. Sànchez-Marrè, L. Cecaronni, I. R.-Roda, and M. Poch, Artificial Intelligence and Environmental Decision Support Systems, *Applied Intelligence*, 13(1), 77–91, 2000.
Dempster A.P. Upper and lower probabilities induced by a multivalued mapping, *Annals of Mathematical Statistics,* 38, 325-339, 1967.
D'Erchia, F., C, Korschgen, M. Nyquist, R. Root, R. Sojda, and P. Stine. 2001. A framework for ecological decision support systems: building the right systems and building the systems right. U.S. Geological Survey, Biological Resources Division, Information and Technology Report USGS/BRD/ITR-2001-0002.
De Serres, B, and A. G. Roy. 1990. Flow direction and branching geometry at junctions in dendritic river networks. *Professional Geographer* 42(2):194-201.
Dubois D. and Prade H. What are fuzzy rules and how to use them, *Fuzzy Sets and Systems,* 84, 169-185, 1996.
Dumont, B. and D. R. C. Hill. 2001. *Ecological Modelling* 141:201-215.
Durfee, E. H., V. R. Lesser, and D. D. Corkill. 1989. Cooperative distributed problem solving. pages 84-147 *in*: Barr, A., P. R. Cohen, and E. A. Feigenbaum, eds. The Handbook of Artificial Intelligence, Vol. IV. Addison-Wesley. Reading, Massachusetts.
Egenhofer, M. J. 1989. A formal definition of binary topological relationships. *Lecture Notes in Computer Science* 37:457-472.
El-Swaify, S.A. and Yakowitz, D.S. (Eds). *Multiple objective Decision Making for Land, Water, and Environmental Management*. Lewis Publishers, 1998.
Flores X., Bonmati A., Poch M., Rodríguez-Roda I. & Bañares-Alcántara R. Selection of the Activated Sludge Configuration during the Conceptual Design of Activated Sludge Plants Using Multicriteria Analysis. *Industrial & Engineering Chemistry Research*, 44(10), 3556- 3566 (2005).
Fox, J. and Das, S. *Safe and sound. Artificial Intelligence in Hazardous Applications,* AAAI Press / The MIT Press , 2000.
Freska, C. 1991. Qualitative spatial reasoning. *pages 361-372 in*: Mark, D.M., and A. U. Frank, eds. Cognitive and linguistic aspects of geographic space. Kluwer Academic Publishers. Dordrecht, Netherlands.
Funtowicz, S.O. and Ravetz, J. R.: Science for the post-normal age, *Futures* 25(7), 739-755, 1993
Funtowicz, S.O. and Ravetz, J.R. Post-Normal Science – an insight nom maturing, *Futures* 31(7), 641-646, 1999
Graham, J. R. and Decker, K. S. 2000. Towards a distributed, environment-centered agent framework. *pages 290-304 in*: Jennings, Nicholas R. and Y. Lesperance, eds. Proceedings of the Sixth International Workshop on Agent, Theories, Architectures, and Languages (ATAL-99). Springer-Verlag. Berlin, Germany.
Graham, J. R., D. McHugh, M. Mersic, F. McGreary, M. V. Windley, D. Cleaver, and K. S. Decker. 2001. Tools for developing and monitoring agents in distributed multiagent systems. Lecture Notes in Computer Science 1887:12-27.
Guariso, G. and Werthner H., *Environmental Decision Support Systems*. Ellis Horwood-Wiley, New York, 1989.
Guo, Y., P. Gong, and R. Amundson. 2003. Pedodiversity in the United States of America. Geodema 117:99-115.
Haagsma, I.G. and Johanns, R.D. Decision support systems: An integrated approach. In Environmental Systems Vol. II. Zannetti, P.(Ed.),pp.205-212, 1994.
U.Heller, P.Struss. Consistency-Based Problem Solving for Environmental Decision Support. *Computer-Aided Civil and Infrastructure Engineering* 17 (2002) 79-92.
Huhns, M. N., and L. M. Stephens. 1999. Multiagent systems and societies of agents. pages 79-120 *in*: Weiss, G., ed. Multiagent systems. MIT Press. Cambridge, Massachusetts.
Jaczynski M. A Framework for the Management of Past Experiences with Time-Extended

Situations. In *Proc. of the 6th Int. Conference on Information and Knowledge Management (CIKM'97)*, pages 32-39, Las Vegas, Nevada, USA, November 1997.

Jaere M, A. Aamodt, and P. Shalle. Representing Temporal Knowledge for Case-Based Reasoning. In *Proc. of the 6th European Conference, ECCBR 2002*, pages 174-188, Aberdeen, Scotland, UK, September 2002.

Jensen, F. *Bayesian networks and decision graphs*. Springer-Verlag. New York, New York. 268 pages, 2001.

Kinzig, A. Bridging Disciplinary Divides to Address Environmental and Intellectual Challenges, *Ecosystems*, 4, 709-715, 2001.

Klir G.J. and Folger T.A. *Fuzzy sets, uncertainty and information.* Prentice-Hall, Englewood Cliffs N.J., 1988.

Krause P. and Clark D. *Representing uncertain knowledge.* Kluwer, Dordrecht, 1993.

Labrou, Y. and T. Finin 1997. A proposal for a new KQML specification. Technical Report TR CS-97-03. Computer Science and Electrical Engineering Department, University of Maryland Baltimore County. Baltimore, Maryland. 42 pages.

Lei, Z., B. C. Pijanowski, K. T. Alexandridis, and J. J. Olson. 2005. Distributed modeling architecture of a multi agent-based behavioral economic landscape (MABEL) model. Transactions of the Society for Modelling and Simulation International 81: 503-515.

Likhachev M, M. Kaess and R. C. Arkin. Learning Behavioral Parameterization Using Spatio-Temporal Case-Based Reasoning. *Procc. of IEEE Int. Conference on Robotics and Automation (ICRA 2002)*, 2002.

Ludwig D., The Era of Management Is Over, *Ecosystems*,4, 758-764, 2001

J. Ma and B. Knight. A Framework for Historical Case-Based Reasoning. In *Procc. of 5th Int. Conference on Case-Based Reasoning (ICCBR'2003)*, pages 246-260, LNCS2689, 2003.

J. Ma and B. Knight. Reified Temporal logic: An Overview. *Artificial Intelligence Review*, 15:189-217, 2001.

J. Ma and B. Knight. A General Temporal Theory. *The Computer Journal*, 37(2):114-123, 1994.

Mark, D. M. 1999. Spatial representation: a cognitive view. *pages 81-89, in*: Maguire, D. J., M. F. Goodchild, D.W. Rhind, and P. Longley, eds. Geographical Information Systems: Principles and Applications, v.1. Longman Scientific & Technical. Harlow, Essex, England.

Martínez M., Rodríguez-Roda I., Poch M., Cortés U. & J. Comas. Dynamic reasoning to solve complex problems in activated sludge processes: a step further in decision support systems. *Water Science & Technology*, In press (2006a).

Martínez M., Sànchez-Marrè M., Comas J. & Rodríguez-Roda I. Case-based reasoning, a promising tool to face solids separation problems in the activated sludge process. *Water Science & Technology*, In press (2006b).

Medoc, J., F. Guerrin, R. Courdier, and J. Paillat. 2004. A multi-modelling approach to help agricultural stakeholders design animal wastes management strategies in the Reunion Island. Transactions of the Environmental Modelling and Software Society 2(1):460-467.

Moratz, R., and J. O. Wallgrun. 2003. Spatial reasoning about relative orientation and distance for robot exploration. Lecture Notes in Computer Science 2825:61-74.

Morton A. Mathematical models: Questions of trustworthiness, *Brit. J. Phil. Sci.* 44, 659-674, 1993.

Moulin, B., W. Chaker, J. Perron, P. Pelletier, J. Hogan, and E. Gbei. 2003. MAGS Project: multi-agent geosimulation and crowd simulation. Lecture Notes in Computer Science 2825:151-168.

Nakhaeizadeh G. Learning Prediction of Time Series: A Theoretical and Empirical Comparison of CBR with Some Other Approaches. In *Proceedings of the Workshop on Case-Based Reasoning*, pages 67-71, AAAI-94. Seattle, Washington, 1994.

Nii, H. P. 1986b. Blackboard Systems: Blackboard Application Systems, Blackboard Systems from a Knowledge Engineering Perspective. AI Magazine 7(3):82-106.

Nute, D., W. D. Potter, F. Maier, J. Wang, M. Twery, H. M. Rauscher, P. Knopp, S. Thomasma, M. Dass, H. Uchiyama, A. Glende. 2004. NED-2: an agent-based decision support system for forest ecosystem management. Environmental Modelling and Software 19:831–843.

Olsson, G., H. Aspegren, and M.K. Nielsen, Operation and Control of Wastewater Treatment – A Scandinavian Perspective over 20 years, *Water Science & Technology*, 37(12), 1–13, 1998.

Ostrom, E. Governing the commons: the evolution of institutions for collective action. Cambridge University Press. 1991

Poch M., Comas J., Rodríguez-Roda I., Sànchez-Marrè M. & Cortés U. Designing and building real environmental decision support systems. *Environmental Modelling and Software*, 19(9), pp. 857-873 (2004).

Purvis, M. K., Q. Zhou, S. J. S. Cranefield, R. Ward, R. Raykov, and D. Jessberger. 2001. Spatial information modelling and analysis in a distributed environment. Environmental Modelling and Software 16:439-445.

Ram A and J. C. Santamaría. Continuous Case-Based Reasoning. *Artificial Intelligence*, 90:25-77, 1997.

Rao, A. S. and M. P. Georgeff. 1995. BDI agents: from theory to practice. pages 312-319 *in*: Proceedings of the First International Conference on Multiagent Systems. AAAI Press. Menlo Park, California.

Renz J. and Guesguen H.W. Guest editorial: spatial and temporal reasoning. *AI Communications* 17(4):183-184, 2004.

Rizzoli, A.E. and Young, W.Y. Delivering Environmental Decision Support Systems: software tools and techniques. *Environmental Modelling and Software* 12(2-3):237-249, 1997.

Rodríguez-Roda I., J. Comas, J. Colprim, M. Poch, M. Sànchez-Marrè, U. Cortés, J. Baeza and J. Lafuente, A hybrid supervisory system to support wastewater treatment plant operation: implementation and validation, *Water Science & Technology,* 45(4-5), 289-297, 2002.

Rodríguez-Roda, I., J. Comas, M. Poch, M. Sànchez-Marrè and U. Cortés, Automatic Knowledge Acquisition from Complex Processes for the development of Knowledge-Based Systems, *Industrial Engineering Chemistry Research*, 40, 3353–3360, 2001.

R-Roda I., Sànchez-Marrè M., Comas J., Cortés U. & Poch M.Development of a Case-Based System for the Supervision of an Activated Sludge Process. *Environmental Technology*, 22, pp. 477-486 (2001).

Rosenstein M. T. and P. R. Cohen. Continuous Categories for a Mobile Robot. IJCAI-99 Workshop on Sequence Learning, pages 47-53, 1999.

Rossier, D. and R Scheurer. 2002. An ecosystem-inspired mobile agent middle ware for active network management. Lecture Notes in Computer Science 2521:73-82.

Sànchez-Marrè M., U. Cortés, M. Martínez, J. Comas y I. Rodríguez-Roda. An Approach for Temporal Case-Based Reasoning: Episode-Based Reasoning. 6th International Conference on Case-Based Reasoning (ICCBR'2005). LNAI-3620, pp. 465-476. Chicago, USA, 2005.

Sànchez-Marrè M., U. Cortés, I. R.-Roda and M. Poch, Sustainable case learning for continuous domains. *Environmental Modelling & Software* 14:349-357, 1999.

Sànchez-Marrè, U. Cortés, J. Lafuente, I. R.-Roda, and M. Poch., DAI-DEPUR: a Distributed Architecture for Wastewater Treatment Plants Supervision. *Artificial Intelligence in Engineering*, 10(3), 275-285, 1996.

Sauchyn, D. J. 2001. Modeling the hydroclimatic disturbance of soil landscapes in the Southern Canadian Plains: the problems of scale and place. Environmental Monitoring and Assessment 67(1–2):277–291.

Schneider, A., K. C. Seto, C. E. Woodcock. 2003. Temporal patterns of land cover change in Chengdu, China, 1978-2002. International Geoscience and Remote Sensing Symposium 5:3365- 3367.

Shafer G. *A mathematical theory of evidence*, Princeton, USA, Princeton University Press, 1976.

Shanahan M.A. Circumscriptive Calculus of Events, *Artificial Intelligence*, 77(2):249-384, 1995.

Sheridan F.K.J. A survey of techniques for inference under uncertainty. *Artificial Inteligence Review* 5, 89-119, 1991

Shoham Y. Temporal Logics in AI: Semantical and Ontological Considerations, *Artificial Intelligence*, 33: 89-104, 1987.

Smithson M. *Ignorance and uncertainty.* Springer, Berlin, 1989.

Sojda, R. S. Empirical evaluation of decision support systems: needs, definitions, potential methods, and an example pertaining to waterfowl management. *Environmental Modelling and Software*. In Press, 2006.

Sojda, R. S. 2002. Artificial intelligence based decision support for trumpeter swan management. PhD Dissertation. Colorado State University. Fort Collins, Colorado. 183 pages.

Sojda, R. S., J. E. Cornely, and L. H. Fredrickson. 2002. An application of queuing theory to waterfowl migration. in: Rizzoli, A. E., and A. J. Jakeman. eds. Integrated Assessment and Decision Support: Proceedings of the First Biennial Meeting of the International Environmental Modelling and Software Society 1(2):232-238.

Struss P, M. Bendati, E. Lersch, W. Roque, P. Salles. Design of a Model-based Decision Support System for Water Treatment. Proceedings of the 18th International Joint Conference on Artificial Intelligence (IJCAI 03): Environmental Decision Support Systems, pages 50-59, Acapulco, Mexico. August 10, 2003. ISBN 0127056602.

Sydow, A., Rosé, H., and Rufeger. Sustainable development and integrated assessment. Ercim News (34), 32. 1998.

Timpf, A., and A. U. Frank. 1997. Using hierarchical spatial data structure for hierarchical spatial reasoning. Lecture Notes in Computer Science 1329:69-83.

Tripathi, A. 2002. Challenges in designing next-generation middleware systems. Communications of the Association of Computing Machinery 45(6):39-42.

Torrens, P. M., and I. Benenson. 2005. Geographic automata systems. International Journal of Geographic Information Science 19(4):385-412.

Turon C., Alemany J., Comas J., Bou J. and Poch M. Optimal maintenance of constructed wetlands using an environmental decision support system. *Water Science & Technology*, 51(10), 109-117, 2005.

van Asselt M.B.A. and Rotmans J. Uncertainty in integrated assessment modelling: from Positivism to Pluralism, *Clim. Change* 54, 75-105, (2002).

van Benthem J. *The Logic of Time*, Kluwer Academic, Dordrecht, 1983.

Walker W.E., Harremoës P., Rotmans J., van der Sluijs J.P., van Asselt M.B.A., Janssen P. and Krayer von Krauss M.P. Defining uncertainty – A conceptual basis for uncertainty management in model-based decision support, *Integrated Assessment* 4(1), 5-17, 2003.

Walley P. Measures of uncertainty in expert systems, *Artificial Intelligence* 83, 1-58, 1996.

Weiss, G. 1999. Prologue: multiagent systems and distributed artificial intelligence. pages 1-23 in: Weiss, G., ed. Multiagent systems: a modern approach to distributed artificial intelligence. MIT Press. Cambridge, Massachusetts.

Wittaker A.D. Decision support systems and expert systems for range science. In *Decision Support Systems for the Management of Grazing Lands: Emerging Lands*, edited by J.W. Stuth and B.G. Lyons, pp. 69–81, 1993.

Wooldridge, M. 1999. Intelligent agents. pages 27-77 in: Weiss, G., ed. Multiagent systems: a modern approach to distributed artificial intelligence. MIT Press. Cambridge, Massachusetts.

Wooldridge, M. and N. R. Jennings. 1995. Intelligent agents: theory and practice. Knowledge Engineering Review 10(2):115-152.

Zadeh L. Fuzzy Sets, *Information and Control* 8, 338-353, 1965.

Zimmermann H.-J. An application-oriented view of modeling uncertainty, *European Journal of Operational Research* 122 (2), pp. 190-198, 2000.