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Intelligent Environmental Decision Support Systems

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CHAPTER EIGHT

Intelligent Environmental Decision Support Systems

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8.1. Introduction

8.1.1 Complexity of environmental systems

The increasing rhythm of industrialisation, urbanisation and population growth negatively affects environmental quality and hence plant, animal and human life. Whenever we attempt to tackle these environmental issues and to analyse the resulting tradeoffs between economic, ecological, social and technical interests, we are immediately confronted with complexity (see also Chapter 4). Environmental systems are stochastic and, very often, are multiscale, spatial- and temporal-dependent processes. They also tend to comprise complex interactions among social, cultural, physical, chemical and biological processes. These processes may not be known well and/or may be difficult to represent, causing considerable uncertainty. Some of the sources of this uncertainty can be tamed with additional data or further investigation, but this uncertainty becomes insurmountable especially when the systems of interest are characterised by chaotic behaviour or self-organising processes.

Therefore, advocating a single perspective that encompasses everything in a system is becoming increasingly difficult and ineffective. The consensus is developing that 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 a satisfactory description of the system. The second level would correspond to systems with a higher uncertainty degree where simple models can no longer provide satisfactory descriptions. Acquired experience then becomes more and more important, and the need to involve experts in problem solving becomes advisable. Finally, 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. As emerged in many of the previous chapters, it is then crucial to consider the need to account for a plurality of views or perspectives.

In this sense, it is important to realise that environmental problems are characterised 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 rarely been considered (Kinzig, 2001). Embracing a socioeconomic 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 of complexity cannot be tackled only with the traditional tools of mathematical modelling. To confront this complexity, a new paradigm is needed, and it requires new intellectual challenges.

8.1.2 New tools for a new paradigm

Over the last few decades, mathematical/statistical models, numerical algorithms and computer simulations have been used as an 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 has been applied to environmental management problems for a long time and with good results. The effort to integrate new tools to deal with more complex systems has led to the development of so-called Environmental Decision Support Systems (EDSSs) (Chapters 3 and 7; Guariso and Werthner, 1989; Rizzoli and Young, 1997).

EDSSs have generated high expectations as tools to tackle problems belonging to the second and third levels of complexity noted above. The range of environmental problems to which EDSSs have been applied is wide and varied, with water management at or near the top, followed by aspects of risk assessment and forest management. 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.

8.2. 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 support performed by EDSSs should be collaborative, not adversarial, and decision makers must inform and involve those who must live with the decisions. EDSS should be 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, Intelligent EDSSs or IEDSS 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. In the following we shall describe the nature of IEDSS.

From a functional point of view, and taking into account the type of problem that the IEDSS solves, two kinds of IEDSS can be distinguished but of course most systems of interest fall between these two categories. The first category are those IEDSS which aim to control or supervise a process in real-time (or almost real-time), facing similar situations on a regular basis (Sànchez-Marrè et al., 1996). They must guarantee robustness against noise, missing data, typos and any combination of input data. In general the end-user is responsible for accepting, refining or rejecting system solutions. This responsibility can decrease, thereby increasing IEDSS confidence over time, as far as the system is facing situations that were successfully solved in the past (real validation). In the second category are those that give punctual support to decision making, and are mainly used to justify multicriteria decisions of policy makers more than to make real decisions on a day-to-day basis (Comas et al., 2003). Here it is interesting for the end-user to play with what-if scenarios, to explore the response surface and the stability of the solution; for example how sensitive our decision is to small variations in the given weight and value of the relevant variables. The role of sociocultural and economic issues limits the use of standard databases. Confidence cannot be increased in the results when facing similar situations, because these IEDSS are very specific and sometimes are only built to take or justify one decision.

According to 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. Thus, an intelligent information system reduces the time in which decisions are made in a domain, and improves the consistency and quality of those decisions (Haagsma and Johanns, 1994).

Thus IEDSSs could be defined (Sojda, 2002) 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 conceptualising, or otherwise dealing with the entire problem (Boland et al., 1992; Brehmer, 1991). Other 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 economic components. Examples are the works by Dorner et al. (2007), Reichert et al. (2007) and Cortés et al.

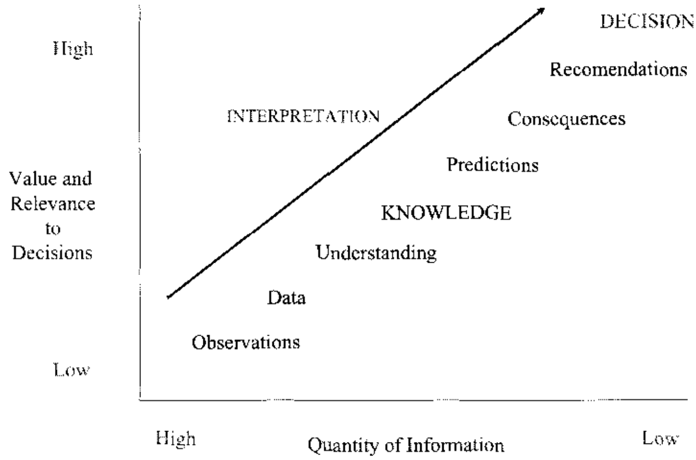

Figure 8.1 Interpretation process: from observations to decision.

(2002). 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 Figure 8.1, adapted from Wittaker, 1993).

8.2.1 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 (Poch et al., 2004). Their integration with numerical and/or statistical models in a single system provides higher accuracy, reliability and utility (Cortés et al., 2000).

This confers on IEDSSs the ability to confront complex problems in which the experience of experts provides 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 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 8.2 shows this methodology schematically.

There are inherent, open problems arising when running such systems and we discuss four of these. First, the *uncertainty of data* (1) being processed is intrinsic to the environmental system, which may be being monitored by several on-line sensors and off-line data. Thus, anomalous data values at the data gathering step, or even an uncertain reasoning process at later levels, such as in diagnosis, decision support or planning, can lead the environmental process to unsafe critical operation states. At

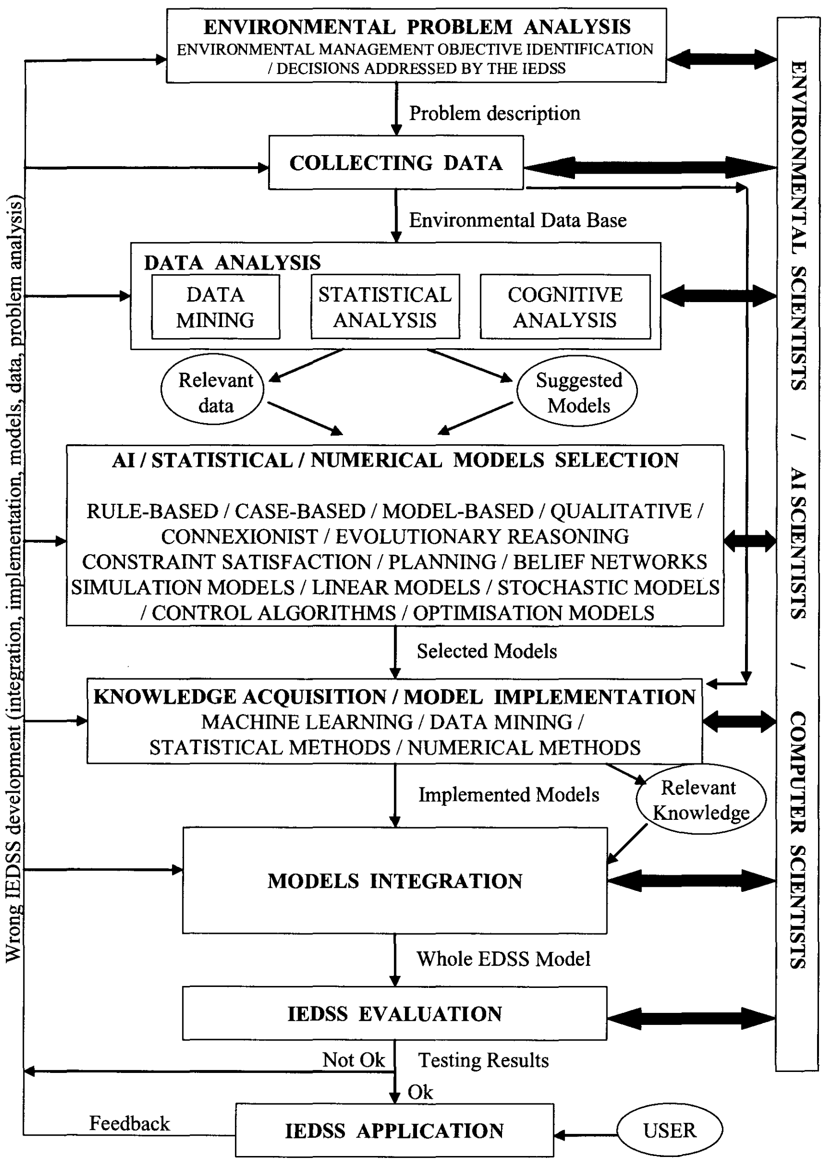

Figure 8.2 Flow diagram for development of an IEDSS.

the diagnosis step or even at the decision support step or planning step, *spatial reasoning* (2) or *temporal reasoning* (3) or both aspects can influence the reasoning processes undertaken by the IEDSS. To stipulate accurate and reliable assertions to be used within the diagnosis, decision support or planning processes, most 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. Finally, a related and crucial set of points: How reliable and safe are the decisions proposed by the IEDSS? Are we sure about the goodness and performance of proposed solutions? How can we ensure a *correct evaluation* (4) of the IEDSS?

The main goal of this chapter is to analyse the four issues mentioned above. Each of the following sections is devoted to one of these open challenges.

8.3. About Uncertainty Management

No matter whether the field of application is of closed-loop process control, diagnosis or more generally decision support, one has to deal with uncertainty (see Chapters 4–6). 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 about a system is always partial and incomplete due to system complexity. Lack of information, and also abundance of information, leads to uncertainty (van Asselt and Rotmans, 2002). Lack of information has been recognised for a long time as the main source of uncertainty in environmental systems but due to recent technical advances (in particular sensor development), there are now many situations where "the more we know, the more we don't know." Beck (1987) defines this paradigm for wastewater management as going from a "data poor, information rich" (i.e. few data available but they may be well analysed) to a "data rich, information poor" situation (i.e. much data available, in fact too much and their interactions are not carefully analysed and/or understood). 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 (e.g. Zimmermann, 2000) – but the above definition has the advantage that it leads to clearly different dimensions of uncertainty. For example for model-based decision support systems, Walker et al. (2003) 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 also has several levels ranging from determinism to total ignorance. From determinism, statistical uncertainty is followed by scenario uncertainty

(Chapters 4 and 9), then recognised ignorance and total ignorance, the frontier between these two last items being defined as indeterminacy (Walker et al., 2003).

Uncertainty appears at all stages of the decision-making process (see Chapter 5). Mainly, uncertainty can be distinguished at a *data or information level*, at the *model level*, or at the *user level*. One common and socially important case where uncertainty appears at the user level is in environmental policy decision making (Chapter 6). Also, uncertainty management depends on the modelling activity being carried out such as in predictive modelling, exploratory data modelling, communication modelling or learning modelling (Chapter 4).

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

The major approaches utilised to represent and manage uncertainty within the models developed in an IEDSS are belief or Bayesian networks, causal networks, certainty factors derived from expert systems, influence diagrams and fuzzy logic.

Representing uncertainty in a specific context leads to several questions, as pointed out by Walley (1996): What is the interpretation, calculus and consistency of the uncertainty representation in each of the theories? How can one evaluate, combine and adapt measures of uncertainty? How can one assess the consistency of the uncertain information? How can one use this measure in the decision-making process?

Comparison of these approaches can be found in several papers and books (Klir and Folger, 1988; Smithson, 1989; Sheridan, 1991; Krause and Clark, 1993). 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).

In addressing environmental issues, uncertainty management is clearly a main prerogative. A deep review of these aspects is out of the scope of the present chapter. But as an illustration of the increasing interest, Figure 8.3 presents the number of ISI 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 papers published per year and this tendency could be expected to continue.

8.4. Temporal Reasoning

Interest in the area of temporal reasoning and spatial reasoning is growing within the AI field, as well as within the geographic information systems area.

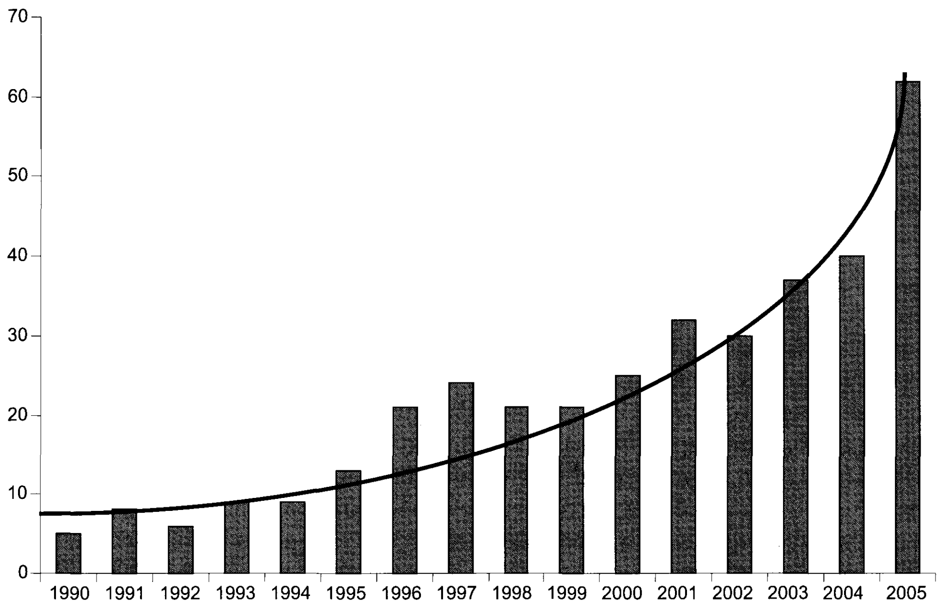

Figure 8.3 Number of scientific ISI publications dealing with "uncertainty," "environment" and "decision" in the title, abstract and/or keywords over the last 15 years.

This is probably due to the many application domains where temporal information, spatial information or both must be managed (Renz and Guesguen, 2004). The most common domains related to AI 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 station control, wastewater treatment plant 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, and the diagnosis and/or prognosis and cure of some medical diseases. Nevertheless, the necessity to deal with time and space is not restricted to artificial intelligence or geographic information systems (GIS). 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 current and past states of the environmental system constitute fundamental information to state accurate and reliable assertions to be used within the diagnosis process, 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. Temporal reasoning is therefore a necessary component within IEDSSs.

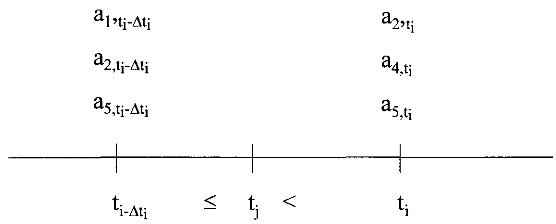

Figure 8.4 True assertions along the time line in a temporal domain.

In 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 minimisation 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 proven to be useful for different spatiotemporal 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.

8.4.1 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 is 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 their major characteristics, temporal domains could be defined as those domains where the truth of the logic assertions ($a_{k,ti}$) at a given time instant t_i depends both on the truth of logic assertions at the current time instant t_i, and on the truth of logic assertions ($a_{k,t_i-\Delta t_i}$) at a past time $t_i - \Delta t_i$. This is illustrated by Figure 8.4.

More formally, the domain could be considered as time dependent if and only if:

$$\begin{aligned} &\text{truth}(a_{k,t_i}) = f\big(\text{truth}(a_{h,t_j}), \text{truth}(a_{k1,t_i})\big) \\ &0 \leqslant k \leqslant la_{t_i},\ 0 \leqslant h \leqslant la_{t_j},\ 0 \leqslant k1 \leqslant la_{t_i},\ k1 \neq k. \end{aligned} \tag{1}$$

8.4.2 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:

- *Theoretically-oriented models*, which are basically inspired by certain kinds of logic or relation algebras. Outstanding models are the temporal interval logic by Allen (1983), generalised intervals by Balbiani et al. (2000), cyclic intervals by Balbiani and Osmani (2000), partially ordered time models (Anger et al., 1998) or the INDU calculus (Pujari and Sattar, 1999). They are highly concerned with the logical characterisation of the models of a given calculus and especially worried about the consistency and computational cost of basic operations over the domain knowledge.
- *Practically-oriented models*, which are more inspired by their application domains, and by the practical use of the models, such as with time series models, artificial neural networks, and mathematical models in statistics and in case-based reasoning (see Chapter 12). They are more concerned with the efficiency and accuracy of the queries to the domain knowledge.

The huge complexity of environmental systems makes modelling difficult with a theoretically-oriented model because many logic assertions should be stated and demonstrated before some reasoning mechanisms can be applied. On the other hand, practically-oriented models are mainly concerned with allowing effective and accurate reasoning capabilities in order to make the appropriate decisions about the environmental system.

8.4.3 Case-based reasoning for temporal reasoning

Case-based reasoning (CBR) (Kolodner, 1993) is becoming a promising framework to deal with temporal domains (Sànchez-Marrè et al., 2005; Martín and Plaza, 2004; Ma and Knight, 2003; Jaere et al., 2002). The main reason is that CBR itself operates by retrieving similar solutions within the realm of past experiences (past time actions) to solve a new unseen problem. Thus, it could be easier to incorporate the temporal component in this kind of system. For this reason, a new approach based on the concepts of temporal episodes is outlined. Sànchez-Marrè et al. (2005) propose 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*, termed *episodes*. In this kind of domain, 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 achieved, taking into account such temporal episodes of cases rather than analysing only the current isolated case.

Working with episodes instead of single cases is useful in temporal domains, but also raises some difficult tasks to be solved, such as how to:

- determine the length of an episode;
- represent the episodes, taking into account that they could be overlapping;
- represent the isolated cases;
- relate them to form episodes;
- undertake the episode retrieval;
- evaluate the similarity between temporal episodes of cases;
- 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 (Martínez, 2006; Sànchez-Marrè et al., 2005).

8.5. Geographic Information and Spatial Reasoning

8.5.1 Understanding spatial reasoning

Timpf and Frank (1997) suggested a definition of spatial reasoning: "... any deduction of information from a representation of a spatial situation." A definition is problematic partly because spatial relationships are thorny to delineate in themselves, and because reasoning has many components. An online resource for spatial reasoning with a bibliography can be found at http://www.cse.iitk.ac.in/~amit/other/spatsites.html. Hernández and Mukerjee (1995) list five properties of physical space: it is continuous and homogeneous, 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 neighbour." So developers of environmental decision support systems that incorporate spatial reasoning must take this in to account. As natural resource managers, we often think spatially, dealing with tightly controlled GIS representations in terms of X, Y, and Z dimensions, map projections, and relative datums. Still spatial representation and reasoning are not straightforward (Egenhofer, 1989; Mark, 1999). How can we couple knowledge with spatial information and reasoning? How do animals and humans perceive and move through their environment, and how do processes perceive, populate, and affect their environment? Finally, spatial and temporal reasoning share many commonalities, and often spatial problems must be represented in time steps or some other temporal framework. Although we

will not address individual techniques readily available in most GIS software packages, we do not wish to minimise their importance. AI can also be used as a basis for models themselves or as ways to communicate among model components, of which GIS could be one. AI-based software can be embedded within GIS, or vice versa.

Fonseca et al. (2002) make a compelling argument for using standard inheritance-based ontologies (Chapter 7) to handle not only aspects of granularity in spatiotemporal representations, but also for reasoning across granularities. Bettini and Montanari (2002) provide a summary of the related research needs and promote the linkage between GIS and AI. A similar problem seems inherent to the nature of the indivisibility of polygons, along with the discrete 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). De Serres and Roy (1990) and Argemiro de Carvalho Paiva and Egenhofer (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. Many methodologies 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 the plants of several small pothole wetlands tapping a common shallow groundwater source. Some such situations are based on significant biotic/abiotic feedback loops and are difficult spatial and temporal problems to model. 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; 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 characterisations 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.

8.5.1.1 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 colour 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 by Joy and Death (2004) in effectively linking a neural network and GIS for modelling aquatic species distributions. 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 inter-

nal models are also needed. Doing this in an iterative or recursive fashion can be computationally problematic if the number of steps is large. We agree with Sauchyn (2001) that spatial modelling of soil processes within a geologic time scale could be an important contribution and recognise 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. (1996, 1991) 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. However, it is unclear whether the soil experts used for system development were independent of the experts used for validation.

A GIS can also be coupled with modelling, optimisation or other methods (e.g. Crossman et al., 2007). Such systems can be used iteratively with varying inputs, with the varying GIS outputs representing spatial difference or change. Such spatial data outputs could be used to manually reason about, and explain, system relationships.

8.5.2 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 et al., 1999; Guo et al., 2003; Schneider et al., 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.

8.5.3 Representing change/time steps/feedback loops

There are mechanisms for capture of changing conditions within GIS software, often as a video representation of successive maps, and these can be most useful for visualisation of change. The need to incorporate feedback loops in interdisciplinary ecological modelling can be crucial. When seeking 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 embed 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.

8.5.4 Middleware, blackboards and communication protocols

There are numerous definitions of middleware, but we accept the generic one as software that provides an interface between other pieces of software (Brown et al., 2005), especially when distributed (Tripathi, 2002). Using middleware to connect AI-based process models with a GIS holds promise for computationally intense spatial models. Blackboards (Carver and Lesser, 1992; Corkill, 1991; Nii, 1986) allow 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. The AI-based agent communication protocols, KQML (Knowledge Query and Management Language, Labrou and Finin, 1997) and FIPA (Foundation for Intelligent Physical Agents, http://www.fipa.org), could provide the basis by which disparate spatial and temporal models could share information among themselves, if agent-based. 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.

8.5.5 Multiagent systems

Many AI-based methodologies, particularly those related to cooperative distributed problem solving and multiagent systems (Weiss, 1999), are designed to address temporally and spatially distributed problems, like those so common in natural resources. 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). We will accept the definition of an intelligent agent as a computer system based in AI, 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 inherent autonomous intelligence.

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. The belief-desires-intentions (BDI) agent architecture summarised by Wooldridge (1999) and Rao and Georgeff (1995) exemplifies the foundation upon which intelligent agents often are conceptualised and distinguished from non-AI 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. 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 a generic ecological modelling tool known as Gensim that incorporates interaction among agents, encompasses the definition of intelligent agents provided above, is domain independent, and can build and incorporate a large number of agents in a spatial framework. 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). A recent multiagent-GIS combination system of note is a crowd simulator (Moulin et al., 2003).

8.6. Evaluation of IEDSS and Benchmarking

The evaluation of an IEDSS is still an open problem and no clear strategies are well established yet for facing one of the more critical phases of the development of such systems. Ensuring that the performance of an IEDSS is good is critical to its use in the future and validation of IEDSS is devoted to this topic. Validation of IEDSS can be understood, at first, as the design of sets of tests to be applied in order to attest whether the systems are performing well, with good performance deemed as the capacity of the system to provide the right recommendation given a certain scenario.

There are generic approaches to validate IEDSS (Sojda, 2007) but previous experiences with several environmental sectors mainly related to water (Rodríguez-Roda et al., 2002; Heller and Struss, 2002; Struss et al., 2003) seem 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 sectors. Indeed, even considering a specific environmental sector, authors are not aware of standard validation protocols that are well established, except for some specific cases.

Nevertheless, it is possible and useful to develop a general methodology for evaluating IEDSS. In order to achieve that, the first thing to do is to identify the common elements to be considered for designing a generic evaluation schema. Thereafter 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 steps and criteria. This chapter presents a first approach towards this topic. In many ways, it complements the issues raised in Chapter 2, regarding good practice in modelling, and those in Chapter 7 regarding IEMFs.

In an IEDSS, a clear distinction can be drawn between its components and the tasks it can perform. Therefore, in order to design a standardised validation protocol it is required:

(1) To identify the components of the IEDSS as well as their characteristics (e.g. models available, data sources and data quality, knowledge base, user profile, system autonomy, open/limited situations faced, etc.).
(2) To identify the tasks performed by the IEDSS. Generally speaking, such tasks will fall into two main classes, namely: *diagnosis* which aims at assessing situations based on observations to determine "what is going on"; and, *recommendation* which aims at determining what can be done to achieve specified goals given a certain diagnosis.

It seems reasonable then to think of a general evaluation framework, which can be instantiated according to the characteristics of a specific IEDSS under evaluation, consisting of a structural, components-centred level and a functional tasks-centred level. These two evaluation levels are discussed in the following.

(a) *Structural* evaluation: this level is concerned with the components of the system and their interaction, comprising the following steps:
   (i) Evaluate the performance of each hardware and software component of the system separately (e.g. rules and inference engine, reception of sensor signals, etc.).
   (ii) Evaluate the interactions between components that take place in each diagnosis or recommendation process performed by the system. This requires the identification of such processes, each defined in terms of interactions within a certain subset of the system components (e.g. reading some data from a sensor, then sending a query to a certain knowledge base, then starting some approximate reasoning process, etc.).
(b) *Functional* evaluation: this level is concerned with the tasks performed by the IEDSS, comprising the steps:
   (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 (corresponding to situations in the target system) to be presented to the IEDSS, bearing in mind that complex as environmental systems usually are, it can be difficult to identify a reduced set of scenarios that guarantees a good representation of the system behaviour in entirety. Depending on the specificity of the IEDSS it will be important to include: real or simulated data, noisy or erroneous data, data from similar systems (to evaluate how easy it will be to transfer or adapt the IEDSS to another environmental system), and benchmarks, which are addressed below, can also be considered at this point. The IEDSS being of the kind that provides punctual off-line support or that controls a system in real time has an effect on the design of evaluation scenarios. In the former kind of IEDSS, the role of sociocultural and economic issues limits the use of standard databases in the design of scenarios, so comparison of results is not always possible. And confidence may not increase according to results obtained for similar scenarios

because such systems are very specific and sometimes are only built to take (justify) one single decision. For the latter kind of IEDSS, diagnoses can be previously validated by designing different scenarios that cover the whole response space, but it has to be taken into account that this may not be a trivial task.

(iii) Ask the IEDSS to provide diagnoses or recommendations for the designed scenarios.

(iv) Evaluate the performance of the system given a task and scenario. This step could range from classic multicriteria numerical techniques, such as sensitivity analysis of variables and weights, to qualitative approaches, such as cross-validation with different users, periodical revision of learning outcomes, etc.

Some specific criteria to be considered are that:

(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 with respect to noisy/erroneous data;
(g) the solutions can be reused for similar problems or sites;
(h) the transfer/adaptation to another system is easy.

Other criteria to be taken into account are: modularity, facilitating easy extension if new knowledge is obtained; monotonicity, with more information leading to better results; and scalability to realistic problems for efficiency. However, it is not easy to establish test cases for evaluating monotonicity, robustness, scalability, etc.

Summing up, an IEDSS evaluation framework ought to address not only the structural appropriateness of the system but also, and especially, the quality of the recommendations it provides. Ultimately, it is up to the end-user to accept, refine or reject solutions that the system offers. This responsibility can decrease as the confidence on the IEDSS increases over time, as long as the system incorporates situations that were successfully solved in the past (real validation). Although an 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 benchmarking procedure could be developed.

8.6.1 Benchmarking

First a concise definition of "benchmark" and/or "benchmarking" should be stated. An online dictionary (http://www.m-w.com/dictionary) provides 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 standardised 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."*

We are not aware of the existence of benchmarking databases for environmental systems. It should be a priority to build one – this would yield a better framework for comparison between IEDSSs, but some formal aspects should be agreed beforehand.

At present, we can distinguish at least two different kinds of benchmark. One kind consists of sets of scenarios for given sets of tasks. A set of scenarios specifies: the input data and/or knowledge, the set of acceptable results (diagnoses or recommendations), and a characterisation of unacceptable results. One of the most famous benchmarks of this type is the UCI machine learning repository (http://www.ics.uci.edu/~mlearn/MLRepository.html) within the Artificial Intelligence field. Benchmarks such as this are usually used to test whether a certain new technique is solving a known problem more efficiently, more quickly, more accurately, than the reference one. This sort of structure may be useful to build benchmarks for diagnoses provided by an IEDSS given a certain set of scenarios. However, the sort of information traditionally included in public benchmarking repositories may not suffice for evaluating IEDSS performances – an in-depth reflection on information representation issues is required. Moreover, our impression is that benchmarking based on sets of scenarios may not be suitable for evaluating long term effects of a control strategy on a dynamic system. Dynamics is one of the specific characteristics of environmental systems to be taken into account when designing good and useful benchmarks.

Another kind of benchmark exists which would be more suitable for evaluating treatments, control strategies, or any action recommended by an IEDSS related to the dynamics of the environmental system. It consists of prototypical system simulators with predefined sets of experiments to be evaluated. A set of experiments specifies: the characteristics of the simulated system, the conditional experiments to be simulated, and evaluation criteria to determine the success of the performed experiments.

As an example, 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 standardised simulation protocol to evaluate and compare different control strategies for a biological nitrogen removal process. The benchmark description provides details on the very well-defined structure, the simulation models, the influent disturbances (dry weather, storm and rain events), the simulation procedure, as well as performance evaluation criteria to determine the relative effectiveness of proposed control strategies. IWA/COST is an example of a simulation benchmark for designing control strategies for a specific environmental system. It does not matter whether control strategies are manually proposed by an expert or come from an IEDSS. Building a simulator for benchmarking an environmental system and providing a protocol to connect it to an IEDSS brings about the possibility of evaluating the consequences of taking the decision recommended by the IEDSS in the short, medium, and long terms. 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 less expensive approach seems to be to build a finite set of representative scenarios together with suitable recommendations, and evaluate the IEDSS responses in comparison. Clearly, selection of the set of testing scenarios is critical to guarantee that solving that set of situations correctly ensures a good performance in general. For the case of wastewater treatment plants, for example, this would be equivalent to building a set of scenarios representing dry weather, storm events and rainy days, together with a set of suitable control strategies for each scenario. This approach requires a good knowledge of the environmental system and of the suitable decisions to be made in each relevant situation. An interesting point arises from this: if the environmental system is so well known that we are able to signal which decisions are suitable for every situation, it might be useless to build an IEDSS to control the environmental system, as it could probably be controlled as well by deterministic software.

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 as well as their capacity to react to new situations. It is also clear that benchmarking has to be carried out for rather specific application domains.

8.7. Conclusions and Future Trends

Although IEDSS methodologies of the type depicted in Figure 8.2, are a systematic encapsulation of the basic steps and issues, there are inherent problems arising when developing and running such systems. During routine operation of IEDSS several open challenge problems appear. The *uncertainty of data* being processed is intrinsic to the environmental system, which may be monitored by on-line sensors and off-line data. Thus, anomalous data values at *data gathering level* or even uncertain reasoning processes 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* and *temporal reasoning* aspects can influence the reasoning processes undertaken by the IEDSS. Representation of most 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, decision support process or planning process. Finally, a related issue is a crucial point: how reliable and safe are the decisions proposed by an IEDSS? Are we sure about the goodness and performance of proposed solutions? How can we ensure adequate evaluation of the IEDSS?

As said before, validation of an IEDSS is as critical as the construction itself to ensure adequate performance in real applications. Yet few works are devoted to this specific part of IEDSS development. In this chapter, an analysis about the different aspects to be evaluated in an IEDSS and the possible tools to be used for that task have been addressed. Eliciting a general schema for IEDSS validation is not

straightforward but some general guidelines have been proposed. Benchmarking may be a promising way to avoid other complex validation methods, but much work needs to be done to find the appropriate structure of a benchmark oriented to IEDSS validation.

The main goal of this chapter has been to analyse these four issues mentioned above. It is suggested that these are really open problems and cutting edge tasks to be solved in the near future for a successful application of IEDSS. The major features involving each one of these problems have been outlined, and relevant work and possible approaches to tackle them have been discussed. Much interdisciplinary work remains to be done within the artificial intelligence, computer science (GIS, statistical and mathematical modelling) and environmental science community.

In summary, it has been indicated in this chapter that there are many open research lines for solving problems associated with the design and validation of really useful IEDSS. These include:

- 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.

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