The role of fuzzy logic in GIS modelling

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DEUG de Science

Licence de Géologie appliquée

Maitrise de Géologie appliquée

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Graduate Diploma in Education (Secondary)

Graduate Diploma in Geographic Information

Faculty of Engineering, Health, Science and the Environment

Charles Darwin University

PhD thesis

2011

Thesis declaration

I hereby declare that the work herein, now submitted as a thesis for the degree of Doctor of Philosophy of the Charles Darwin University, is the result of my own investigations, and all references to ideas and work of other researchers have been specifically acknowledged. I hereby certify that the work embodied in this thesis has not already been accepted in substance for any degree, and is not being currently submitted in candidature for any other degree.

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Date: 7 April, 2011

ACKNOWLEDGMENTS

This research was carried out in Darwin, in the Northern Territory of Australia, between 2001 and 2010, while working full time on a variety of GIS projects in the Top End of the Northern Territory. During that relatively long period of time both my professional and my research environments changed.

Within that context, first and foremost, I am deeply indebted to my wife Patricia and my two sons, Julien and Guillaume, who provided a stability and support in my private life without which I would not have been able to complete this work.

Without the guidance and friendly encouragement of my two supervisors, Dr Diane Pearson and Dr Stefan Maier, this thesis would not have been written. I thank them for their unflinching support, their expert advice and their confidence in my capabilities.

In addition to those I named before, many more persons and organisations contributed to my research. Out of fear of unfairly forgetting some, I decided to express my deepest gratitude to all relatives, friends, colleagues, professionals and researchers who played a role in my endeavour.

GLOSSARY

AAGIS	Anindilyakwa Aquaculture GIS
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
BOM	Bureau Of Meteorology
CI	Consistency Index
COG	Centre Of Gravity
CR	Consistency Ratio
DAC	Darwin Aquaculture Centre
DEM	Digital Elevation Model
DOF	Degree Of Fulfillment
EDA	Exploratory Data Analysis
FCM	Fuzzy C-Means
FIS	Fuzzy Inference System
FKC	Fuzzy K-Clustering
GIS	Geographic Information System
GAM	Generalised Additive Model
GLM	Generalised Linear Model
GK	Gustafson Kessel (algorithm)
KBS	Knowledge Based System
KE	Knowledge Engineering
MAUP	Modifiable Areal Unit Problem
MCDA	Multi Criteria Decision Analysis
MF	Membership Function
MOM	Mean Of Maxima
NRM	Natural Resource Management
NT	Northern Territory
sciFLT	Scilab Fuzzy Logic Toolbox
SMI	Semantic Import Approach
TFN	Trapezoidal Fuzzy Number
TRF	Timor Reef Fishery
TS	Takagi Sugeno

UBC	University of British Columbia
XLFIS	Excel Fuzzy Inference System

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Abstract

This thesis investigates the application of fuzzy logic to geospatial problems. Fuzzy logic provides a means for dealing with vague information and sparse datasets inherent to many real world applications. A fuzzy site suitability analysis for prawn farming on remote Groote Eylandt demonstrates how fuzzy logic concepts can be incorporated into maps to facilitate site selection.

Another application presented relies on a published chemical plant operation dataset to illustrate how data driven modelling enables objective predictions on the basis of available information. In a third application, records of environmental variables associated with the foraging patterns of elephant seals are reinterpreted. The fuzzy rule-based data driven analysis of this small dataset of high dimensionality leads to an unambiguous conclusion more efficiently than other methods described in the literature.

Knowledge driven fuzzy rule-based modelling is illustrated by case studies aimed at improving the sustainability of the Timor Reef fishery. Firstly, the knowledge of experienced fishers is recorded to evaluate the fishing power of the Timor Reef fishery fleet to assess the need for recalibrating an existing map of productivity. Near constant fishing power across that fleet suggests that recalibration is not necessary. Secondly, a published fuzzy rule-based expert system is implemented. It can estimate fish susceptibility to fishing pressure from biological parameters only. The susceptibility to fishing pressure of target species of the Timor Reef fishery, estimated with this fuzzy expert system, differs from that estimated from globally averaged parameters. These discrepancies highlight the importance of local models for the development of sustainable fisheries.

Case studies in this thesis highlight the potential of fuzzy rule-based modelling in complementing statistical methods applied to spatial problems particularly when the uncertainty of the data is undefined. That potential is noteworthy in marine natural resource management.

CHAPTER 1

INTRODUCTION

Scope of this thesis

This thesis demonstrates that fuzzy logic simplifies GIS modelling by providing a generic approach to predictions on the basis of a wide range of data.

GIS models often rely on non spatial predictive capabilities including curve fitting, classification and multivariate analysis that are provided by a variety of statistical modelling techniques. This dissertation argues that fuzzy rule-based modelling offers, in one single coherent framework, a valid alternative to the variety of statistical modelling techniques currently relied on to perform these tasks. Fuzzy rule-based modelling can be either data, or knowledge driven, and therefore provides GIS modelling with additional flexibility, much needed in Natural Resource Management.

The objectives of this dissertation are to first provide an underlying rationale for the adoption of fuzzy logic instead of Boolean logic to describe uncertainty within the geographical context of GIS. The second objective is to introduce the reader to the fundamentals of fuzzy logic required to understand the case studies which support the central claim of this thesis. The third objective is to explore a non fuzzy rule-based modelling method, more intimately integrated in the GIS methodology, yet lacking the multi purpose capabilities of fuzzy rule-based modelling. The fourth objective is to explore case studies which support the hypothesis that fuzzy rule-based modeling offers a valid alternative to statistical modeling techniques. The last objective is to emphasise the relevance of fuzzy rule-based modelling in GIS models for the management of natural resources particularly aquaculture and fisheries in Australia, and more specifically in the Northern Territory, and other similar parts of the world.

1.1 Background

Geographic Information System (GIS) originated in Canada from the work of Tomlinson (Coppock and Rhind, 1991) in the 1960s. GIS was Tomlison’s response to an urgent need for substantial improvements in Natural Resource Management (NRM). Typical GIS outputs include maps and modern cartographic elements such as digital elevation models (DEM), as well as other derived datasets, with or without pictorial components. All are approximations of an infinitely complex natural world: they are models. This thesis is concerned with the growing complexity and diversity of methods adopted to develop these models. The sorites paradox (Fisher, 2000), later discussed in this chapter, expresses our inability to translate numerically the clear linguistic difference we make between a heap of sand and a dune. This contradiction highlights an underlying cause for the pervasive failure of GIS to adequately represent some fundamental geographical entities. The solution proposed here, suggested by this paradox, is a radical change in the modelling framework that prevails in GIS modeling. What fuzzy logic offers is a completely different definition of uncertainty leading to a single, simplified modelling strategy capable of complementing purely spatial components of GIS models as required. Non statistical by design, the method advocated does not suffer from limitations of more main stream strategies.

1.1.1 Trends in GIS modelling

Geography became more quantitative in the 1990s (Earickson and Harlin, 1994). As the role of statistics grew, the approach of geography, with the advent of GIS, became increasingly quantitative. Currently, predictive GIS modelling is generally statistical in nature. Typified by the sophisticated Geographically Weighted Regression (Fotheringham *et al.*, 2002) it relies more and more on complex statistics. Generalised Linear Models (Guisan *et al.*, 2002; Bradshaw *et al.*, 2004), as well as alternative statistics such as Bayesian modelling; (Guisan and Zimmerman, 2000) add to the plethora of statistical methods from which GIS modellers can choose.

GIS users in soil sciences (Burrough *et al.*, 1992), as well as in geosciences (Bonham-Carter, 1994), discovered the potential offered by fuzzy logic some time ago. While soil scientists immediately saw in fuzzy logic a way to better describe boundaries between soil types, geologists mainly saw applications for pattern recognition and expert systems (Bonham-Carter, 1994). Soil classification relies on strict definitions of materials resulting from gradual processes under highly variable natural conditions. Irrespective of efforts from soil scientists, boundaries between soil types cannot be made crisp. In the 1990s Burrough was joined by other soil scientists (Lagacherie *et al.*, 1996). They came to the conclusion that the “new” mathematical model proposed by Zadeh (1965), more than a quarter of a century earlier, was better suited to pedology than the traditional mathematical framework built on Boolean logic.

This dissertation proposes to revisit the concepts actively promoted by Burrough nearly 20 years ago and focus on a direction which, at the time, had not been sufficiently researched to reveal its full potential.

1.1.2 Fuzzy logic in GIS modelling

As GIS started to become more widely available (Leung, 1999), researchers became increasingly concerned by its over-simplified description of the inherent uncertainty of geographic data (Goodchild, 2000). They explored ways of designing more conceptually realistic GIS models. Their solutions remained generally impractical (Jeansoulin and Wurbel, 2003; Liu, 2003) and GIS, as we presently know it, still relies on Boolean concepts. This thesis consequently explores practical ways of merging the rather blunt, yet widely adopted, existing Boolean GIS framework with an improved approach to reality through the adoption of fuzzy reasoning.

Before the start of the new millennium, few papers on spatial analysis (Wegener and Fotheringham, 2000) refer to fuzzy logic. Only one paper by Wilson and Lorang (2000) focuses on fuzzy logic to reveal its great potential to improve GIS erosion modelling. The same year, a special issue of Fuzzy Sets and Systems presents 12 papers by some prominent GIS researchers. Goodchild (2000) is mindful of the negative impact of additional levels of complexity on GIS which owes much of its attraction to its simplicity. In 2000, research in applications of fuzzy logic to GIS modelling does not appear to reach GIS modelling circles where it receives less coverage than it deserves. Yet fuzzy logic researchers see in GIS a worthwhile domain of application. Dubois, in his preface to “Fuzzy rule – based modelling with applications to geophysical, biological and engineering systems” by Bardossy and Duckstein (1995) gives three reasons why the fuzzy-rule based models are worth considering. Firstly they apply to a large number of situations that cannot be described by linear functions. Secondly they remain comparatively simple. Thirdly, they can be interpreted verbally. These three arguments are of considerable relevance to GIS modelling where many “real life” environmental problems are hard to describe by mathematical formulations simple enough to be implemented in a GIS environment. The compatibility of fuzzy logic with human language is very advantageous as modelling can become more accessible to non mathematicians and more transparent to the public.

The quest for computational tools, that are conceptually more transparent to the wider community, has lead to the development of ‘soft computing’. This term was coined by Zadeh in the early 1990's (Yen, 1999) to describe a family of new computational tools, all aimed at improving existing computational techniques based on fuzzy-logic. Among the best known are neural networks and genetic algorithms. They have been associated with fuzzy logic, and particularly fuzzy rule-based modelling, to better match predictions and observations. These tuning algorithms often generate weightings that optimise model predictions. Although ‘soft computing’ techniques may play an important role in specific engineering applications, such as control systems, they have two major drawbacks. They substantially increase the complexity of the model and remove all transparency in fuzzy rule-based modelling. Consequently ‘soft computing’ is deliberately ignored in this thesis.

Fuzzy logic has been unnecessarily associated, through ‘soft computing’, with very different computational frameworks such as neural networks. The resulting confusion contributes to the difficulty of assessing the current standing of fuzzy logic in GIS modeling. As demonstrated by the publication of a special issue of Fuzzy Set (Cobb *et al.*, 2000) on uncertainty in GIS and spatial data, a number of leading GIS researchers are aware of the advantages offered by fuzzy logic. Yet, the role of fuzzy logic in GIS modelling remains insignificant. This thesis offers a solution to this apparent contradiction. Instead of focusing on the development of geographically specific implementations of fuzzy logic, this thesis explores how GIS modelling can benefit from simple and practical fuzzy logic techniques commonly used in engineering.

1.2 Geography and linguistic uncertainty

Paradoxes often reflect flaws in reasoning. Addressing inconsistencies in the logic underpinning cognitive processes, and derived computations, can only lead to improvements in the outcome. The ‘heap of sand’ paradox (Fisher, 2000) below is the first of two paradoxes which support the quest for an alternative GIS modelling paradigm that drives this thesis.

1.2.1 A ‘heap of sand’ to test fuzziness

When does a clump of trees become a forest? How can we tell the boundary between land and sea? We can all offer answers to these questions. However, they are likely to be different. They reflect a particular type of vagueness captured by Greek philosophers in the ‘heap of sand’ paradox (Fisher, 2000). The “heap of sand” (sorites in ancient Greek) paradox is defined in one question: What is a heap of sand? In other words what is the critical number of grains of sand that makes a collection of grains a heap. A geographical adaptation of this paradox could be: what is a forest? One cannot define a heap of sand by adding individual grains until we obtain a heap and nor can one define a forest by adding individual trees. This vagueness is not of numerical nature but reflects instead our perception of the world. Fisher (2000) concludes that this vagueness is better addressed by fuzzy logic, “Fuzzy set theory provides a framework in which vagueness can not only be developed and implemented, but can be analysed and sustained as a basis for exploration and explanation” (Fisher, 2000: p.15).

Fisher (2000) proposes the ‘sorites paradox’ as a simple test to assess the nature of the underlying vagueness of geographical entities. If the geographical object considered is affected by the sorites paradox, it cannot be defined by Boolean logic. Statistics are consequently incapable of quantifying its underlying uncertainty. However it is believed that fuzzy logic can.

1.2.2 A paradigm shift

“Fuzzy sets and fuzzy logic” (Klir and Bo Yuan, 1995) contains a comprehensive bibliography of 1731 titles. History and basic notions of fuzzy sets (Dubois *et al.*, 2000) are presented in the first of seven volumes making up the Handbooks of Fuzzy Sets. This encyclopedia of fuzzy logic compiled by experts recognised world wide for their contributions to fuzzy logic is a reference that reflects the interest generated by fuzzy logic as a result of remarkable technological achievements at the end of the twentieth century. Clearly, fuzzy logic is well documented and information on the subject is readily available. Dubois and Prade (1994) deplore misinformed attacks from proponents of statistics and Bayesian methods. To address the issue of misinformation they embarked on detailed comparisons between fuzzy logic and probability/statistics (Dubois and Prade, 1986, 1993). Hisdal (1988) offers an olive branch to all parties by relying on probabilities to demonstrate fuzzy logic. As respective merits of fuzzy logic and statistics have been so extensively debated elsewhere they are not discussed in this thesis. The title of the first chapter of the reference text “Fuzzy sets and fuzzy logic” reads “From classical (crisp) sets to fuzzy sets: a grand paradigm shift” (Klir and Bo Yuan, 1995: p.1). Parallels between Zadeh’s ‘fuzzy logic’ and theories such as Darwin’s ‘evolution of species’ or Einstein’s ‘relativity’ are unmistakable. Both represent grand challenges to well established, reputable domains of human knowledge. They are paradigm shifts. As such they are initially rejected, criticised, scrutinised and eventually recognised.

1.2.3 Relevance of fuzzy logic to geography

The seminal paper “Fuzzy sets” (Zadeh, 1965) by a professor of electrical engineering at Berkeley University stresses that “…, the notion of a fuzzy set is completely non statistical in nature” (Zadeh, 1965: p. 340). Consequently fuzzy logic should not suffer from any limitation of statistical modelling. Nearly 30 years later, the influence of Zadeh’s model of uncertainty is reflected in Bouchon Meunier's introduction to “La logique floue” (1993: p. 3): “La logique floue suscite actuellement un intérêt général de la part des chercheurs, des ingénieurs et des industriels, mais plus généralement de la part de tous ceux qui éprouvent le besoin de formaliser des méthodes empiriques, …”. Translated this means “Fuzzy logic generates much interest among researchers, engineers and industrialists but more generally among all those who need to formalise empirical methods,…”.

Researchers in geography (Robinson *et al.*, 1986; Leung, 1987; Robinson, 1988) started to look at the potential of fuzzy logic in GIS at a time which predates the rapidly growing research in fuzzy rule-based modeling which characterizes the 1990s. Robinson *et al.* (1986) explores the role of expert systems in four GIS domains: map design, feature extraction, database management and decision support systems. Robinson (1988) later focuses on the applications of fuzzy logic geographic databases. He only briefly mentions fuzzy logic. Leung (1987) focuses on the application of fuzzy logic to the definition of boundaries but later (Leung, 1999) considers spatial analysis as well. Burrough (1989) extensively explores this topic as well as the role of fuzzy logic in classification (Burrough *et al.*, 1992) in GIS. Applications of fuzzy logic to mining exploration in GIS (Bonham-Carter, 1994) appear. Research on applications of fuzzy logic to GIS has clearly been very active (Mackay and Robinson, 2000; Dragicevic and Marceau, 2000; MacMillan *et al.*, 2000; Cobb *et al.*, 2000; Guesguen and Albrecht, 2000; Robinson, 2000; Wang, 2000). However, only few practical applications emerged. A notable exception is the fuzzy functionality available in the decision support system of the commercial GIS software IDRISI (Eastman, 2009: p. 159). The effort committed to this domain of research was not reflected in the significance of derived practical applications.

1.3 Statistical uncertainty and quantitative geography

First, the ‘sorites’ paradox (Fisher, 2000) suggests that current GIS modeling incorrectly represents some geographical concepts. The second paradox, outlined below, indicates that our traditional statistical approach to uncertainty may have flaws, addressed to some extent by geostatistics. The growing disinterest in quantitative geography (Fotheringham *et al.*, 2000) may reflect the inadequacy of the current reliance on statistics to describe geographic uncertainty.

Karl Popper (2008), in his “Logic of Scientific discovery”, stumbles on a fundamental paradox in the theory of chance, central to probability, the very foundation of statistics. “The most important application of the theory of probability is to what we may call ‘chance-like’ or ‘random’ events, or occurrences. These seem to be characterized by a peculiar kind of incalculability which makes one disposed to believe – after many unsuccessful attempts – that all known rational methods of prediction must fail in their case. We have, as it were, the feeling that not a scientist but only a prophet could predict them. And yet, it is just this incalculability that makes us conclude that the calculus of probability can be applied to these events.” (Popper, 2008: p.138). The apparent paradoxical nature of probability calculations suggests that we may need to reconcile the unpredictability of chance events with predictions of their occurrence. Probabilistic reasoning developed from large numbers of observations which generally reveal a convergence of outcomes of random events such as getting a five when throwing a dice or drawing a queen of spade from a pack of cards. The ‘fundamental problem of the theory of chance’ (Popper, 2008: p.142) stems from the antithetic axioms of convergence, or limit, and randomness central to the theory of probability. Convergence is hardly compatible with randomness, as true randomness precludes the definition of a limit towards which a series of numbers may tend. The somewhat limited randomness of chance observations, from which probability taught in scientific courses emerged, betrays its initial association with gaming. By contrast, many complex natural systems may display a substantially more random behaviour resulting in a questionable convergence of measurements recorded to describe the process investigated.

Bertrand Russell, one of the most influential thinkers of the twentieth century was both a mathematician and a philosopher. His views cast some light on Popper’s paradox. Russel calls frequency theory the probability theory associated with statistical inference (Russel, 2009b: p.630) derived from gaming. Russel (2009b) does not consider that the frequency theory is characterised by the certainty expected from mathematics. He argues that the frequency theory is closer to science than to mathematics (Russel, 2009a: p.293). Russel (2009a), besides the frequency theory, considers two notable alternative theories of probability. They are the theory of mathematical probability and Keynes’s theory of probability. Keynes, better known for his work in economy, exposes in ‘Treatise of Probability’ (1921) his deductive logical-relationist theory of probability. The logical-relationist theory of probability does not abide by the true and false dichotomy. His theory of probability includes the concept of degree of rational belief assigned to a proposition, a concept already advocated by Leibniz (Keynes, 1921: p.2) at end of the eighteenth century. Keynes's theory of probability, like the theory of mathematical probability, hinges upon a logical relation between two sets of propositions (Keynes, 1921: p.8): a premiss and a conclusion. Knowledge too plays an important role in this logical-relationist theory (Keynes, 1921: p.18). Popper, Russel and Keynes grappled with unsatisfactory aspects of the treatment of uncertain events in the frequency theory of probability. Kolmogorov (1956), aware of inconsistencies in frequency theory, has made fundamental contributions to the current theory of probability. Regardless of its imperfections, no alternative to the theory has lead to numerical methods capable to compete with statistical modelling for the prediction of uncertain outcomes in domains. This statistical model, called statistical inference, consists in fitting the data representative of a population to a model from which parameters are derived, to infer uncertain properties of this population. Bayesian inference (Bayes, 1763), an alternative to statistical inference, relies on a more subjective approach as it proposes a prior distribution which, on the basis of new data, provides the basis for the inference of a posterior distribution. Both inferential and Bayesian statistics strive to predict uncertain events. The role of inferential statistics in linking cause and effect, through statistical methods such as the analysis of variance (Fisher, 1925), has substantially contributed to the advancement of science during the past century. Yet, scientific knowledge is not only hampered by uncertainty, initially exemplified by random outcomes in gaming, but by imprecision as well. The frequency theory, however, only applies to uncertainty.

Lofty Zadeh (1965: p. 339) describes the concept of fuzzy sets as "…a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria of class membership rather than the presence of random variables". Zadeh (1978) derives, from the concept of fuzzy sets, a theory of possibility which parallels the theory of probability (Dubois *et al.*, 2004) and extends it by creating a suitable framework for the treatment of imprecision. In one sentence, "… the imprecision that is intrinsic in natural languages, is in the main, possibilistic rather than probabilistic in nature" (Zadeh, 1978: p. 3), Zadeh hints at the major role that fuzzy sets can play in interfacing between human languages and scientific applications. The possibility theory complements the frequency theory. The former is best equipped to tackle uncertainty while the latter applies to both uncertainty and imprecision. Fuzzy logic, based on fuzzy sets, did not prompt the philosophical concerns expressed by Popper (2008) and Russel (2009). Like Keynes's theory of probability, fuzzy logic is not dichotomous but can easily accommodate binary logic. The formalism of fuzzy sets based reasoning relies on logical relations between an antecedent and a conclusion, a framework reminiscent of the logical-relationist probability (Keynes, 1921). The degree of fulfillment of a fuzzy rule and the degree of belief of Keynes's theory (Keynes, 1921) bear some resemblance. Fuzzy sets, as this thesis will demonstrate, offers a unified framework to process uncertainty and imprecision (Bouchon-Meunier, 1999: p. 5). One can therefore imagine that the domains of application of fuzzy logic overlap those of statistics as will be demonstrated in this thesis. Bouchon-Meunier's (1999) views suggest that fuzzy logic may complement statistics (Dubois and Prade, 1986) particularly when vagueness of information is more closely related to imprecision than to uncertainty or when advantages offered by a unified framework take precedence on the sophistication of statistical methods. In addition fuzzy logic may be useful in situations where the axiom of randomness, central to the frequency theory of probability, cannot always be verified.

Krige, a South African mining engineer (Upton and Cook, 2008), came to the conclusion that spatial processes cannot be ignored in the statistical description of mineral resources. The independence of events, directly related to the randomness that bothered Popper (Popper, 2008), rarely applies to geography. It turns out that there is much to gain in studying that non randomness caused in that instance by the spatial correlation of observations. In 1962 Matheron formalised Krige's work in his "Treatise of applied geostatistics" (Upton and Cook, 2008) where he describes the spatial interpolation called kriging. Although a clear departure from traditional statistics in the sense that they clearly acknowledge the peculiarity of spatial data, geostatistics still require data to be normally distributed, a frequent statistical prerequisite to the applications of a number of modelling techniques. The need for geostatistics suggests that, when it comes to spatial applications, statistical modelling requires substantial adjustments.

Fotheringham laments (Fotheringham *et al.*, 2000: p. xi) "…, at the end of the twentieth century, much of geography turned its back on quantitative data analysis just as many other disciplines came to recognize its importance." This statement reflects a certain frustration from a researcher dedicated to the development of advanced spatial statistical modelling frameworks such as the geographically weighted regression (Fotheringham *et al.*, 2002). Could it be that quantitative geography suffers from issues linked to unresolved paradoxes, the very concept of randomness already tackled by Krige for instance? Fuzzy logic may be able to help where inappropriate geographical representations or just spiraling complexity result from attempts to quantitatively circumvent spatial uncertainty with conceptually inappropriate techniques.

1.4 Outline of this thesis

The role of fuzzy logic in GIS modelling is explored through Chapter 2 to Chapter 6. Chapter 2 introduces the fundamentals of fuzzy logic which underpin this thesis. The representation of vagueness in fuzzy logic does lead to the development of non statistically based predictions. Fuzzy rule-based modelling is a well documented method successfully applied to both data and knowledge driven predictive modelling. This detailed description of fuzzy rule-based models provides the background knowledge required in subsequent chapters.

Chapter 3 establishes that alternative applications of fuzzy logic to GIS modelling can be very successful. The modelling technique adopted here presents a high level of integration in the actual GIS modelling process but lacks the universality of the method described in Chapter 2. Other fuzzy modelling systems may be better suited to specific applications, however, Babuska (1996: p.9) says "The most often used are rule-based fuzzy systems". Chapter 3 is a conscious digression which serves as a reminder of the variety of fuzzy modelling methods deliberately ignored in this dissertation. Despite their merits, these methods are not considered as they do not simplify GIS modelling. Instead, they add to the panoply of seemingly unrelated application specific GIS techniques. This chapter demonstrates however that fuzzy logic can be integrated in a spatial context with other methodologies, Saaty's (2001) Analytic Hierarchy Process (AHP) in that instance.

Chapter 4 is concerned with the development of predictive models from experimental data, a common component of GIS models. Data driven fuzzy rule-based modelling relies on semi automatic segmentation of multivariate datasets to make objective predictions. The absence of a relation between input and output variables leads to the impossibility of designing the corresponding input membership functions. This unambiguous sign of independence between input and output variables allows one to rapidly eliminate unnecessary input variables. A NRM case study, based on a small and complex dataset, demonstrates substantial advantages of this aspect of fuzzy rule-based modelling. Fuzzy systems developed in this chapter demonstrate how classical non linear models can be implemented through fuzzy rules.

Chapter 5 focuses on a particular strength of fuzzy modeling: the ability to make predictions based on human expertise. Recording human knowledge to develop a fuzzy rule-based model relies on carefully designed questionnaires and on suitable informants. A knowledge driven fuzzy rule-based model derived from questionnaires shows how this method can benefit fisheries, a domain of NRM applications where data is scarce and human expertise abundant. The result is an improvement in reliability of an existing GIS model of fish abundance. In addition, fuzzy rule-based expert systems can give managers of remote fisheries instant access to international expertise to help better understand the relative sensitivity to fishing pressure of the species they target. This chapter demonstrates that, although they are not generally concerned with uncertainty management in practice, fuzzy systems greatly facilitate the development of expert systems despite the inherent uncertain formulation of human knowledge.

Chapter 6 concludes that fuzzy rule-based modelling is a convenient implementation of fuzzy logic that provides a generic predictive framework well suited to non statistical predictions based on experimental data or human knowledge. Case studies demonstrate that fuzzy rule-based modelling is both practical and well adapted to GIS modelling needs. This chapter concludes that, in the case studies considered, fuzzy systems are not generally concerned with uncertainty management. They either replicate classical linear models or capture the imprecision of human language in expert systems.

CHAPTER 2

SOME FUNDAMENTAL CONCEPTS OF FUZZY MODELLING

Overview

The fundamental concepts of fuzzy logic introduced in this chapter provide the background knowledge required throughout this thesis. Models and modelling methods, fuzzy sets and membership functions as well as fuzziness and its links to statistics and uncertainty are reviewed first. GIS, raster and direct application of membership functions to GIS modelling are then introduced as they play an important role in Chapter 3. Finally the acquisition of membership functions, their design and applications to the development of fuzzy rule-based models are explored.

The principles of fuzzy rule-based modelling, of particular relevance to GIS modelling, are introduced through the approximation of an artificially generated dataset. An implementation of the universal approximator (Kosko, 1994) introduces the same fuzzy rule-based methodology which is adapted to a range a very different situations in subsequent chapters. The framework of this completely non statistical predictive modelling strategy is outside the experience of most GIS modellers. This initial familiarisation with fundamental aspects of fuzzy rule-based modelling is therefore crucial to understand the implementations of this method to case studies in Chapter 4 and 5.

2.1 Models and modelling methods

Models are simplifications of the real world. A simple dichotomous classification consists in differentiating between descriptive and predictive models. The latter often rely on empirical statistical models. The type of model used is generally dictated by the nature of the dataset. The study of spatial patterns, often complex and poorly understood, benefits from this approach largely independent from any pre existing knowledge of underlying processes. Like statistical modelling, fuzzy modelling is well suited to the development of empirical, data driven, predictive models. Babuska (1996) offers a useful overview of fuzzy modelling. Beyond the trade off between the necessary accuracy of models and their complexity, he warns that a model which is too complex is not practically useful. Two classification schemes help identify which type of model is best suited to the task at hand. One classification reflects the transparency of the model, the other its role.

Transparency is paramount if users need to understand the model they rely on either to improve it, or to adapt it to changing conditions. The most transparent are white-box models. They require a good understanding of the physical background of the problem: a serious limiting factor. Common difficulties with this type of model arise from poorly understood underlying phenomena, inaccurate parameter values and overall complexity. Most real processes are non linear and can only be approximated locally by linear models. Black-box models, on the other hand, are the least transparent as they avoid the complexity of the white-box model by developing an approximator that correctly captures the observed dynamics of the system. The structure of the model hardly reflects the structure of the real system. This type of model suffers from two serious drawbacks: it does not contribute to the understanding of the problem and is not scalable. Finally, somewhere in between white-box and black box-models are grey-box models. They combine the characteristics of white-box and black-box models. Most standard modelling approaches lack the ability to use extra information such as expert knowledge. “Intelligent” methodologies explore alternative representations involving natural language, qualitative models and human knowledge. Fuzzy modelling is one of these methodologies.

A second important classification differentiates between models which describe a process and those which predict values of a variable. Despite this dichotomy, predictive and descriptive models tend to be interdependent. A descriptive model is generally tested by evaluating its capability to predict experimental observations and predictive models identify influential variables in the system under investigation. The robustness of a predictive model combined with the relative importance of its components cast some light on interactions within the model thus contributing to the understanding of these interactions. Although fuzzy rule-based models are predictive, their natural compatibility with human knowledge predisposes them to contribute effectively to the development of descriptive models.

Babuska (1996) defines three types of fuzzy rule-based models all sharing the same core structure articulated around the following logical statement.

IF antecedent proposition THEN consequent proposition

The three classes of fuzzy rule-based models only differ by the type of consequent proposition. In the linguistic or Mamdani type fuzzy model both antecedent and consequent propositions are membership functions. The fuzzy relational model is a generalisation of the previous model where one antecedent proposition can be associated with multiple consequent propositions. Finally, in the Takagi-Sugeno (TS) fuzzy model, the consequent proposition, a crisp function of the fuzzy antecedent proposition, is often a linear equation. This model is often preferred for engineering applications.

A fundamental understanding of Mamdani type fuzzy rule-based modelling, the focus of this thesis, is best gained from a short four page paper (Kosko, 1994) where Kosko briefly demonstrates how an output domain can be mapped on an input domain to emulate any continuous function. In a compelling generic approach to multidimensional predictive modelling, Kosko shows graphically how to predict the behaviour of a dependent variable from the corresponding values of independent variables. The method is easy to understand and has at least two characteristics of interest to a GIS community very much aware of the power of the visual. Firstly, “A fuzzy system, or approximator, reduces to a graph cover with local averaging”. Secondly, regions of the graph, called fuzzy patches, associate input and output membership functions. The graphical nature of the fuzzy patch should appeal to GIS users generally tuned to visual reasoning. In addition, the title of Kosko’s article (1994) “Fuzzy systems as universal approximators” implies a wide range of possible applications. This non statistical method is multidimensional and therefore well adapted to natural systems where processes under investigation rarely have a single cause. Mamdani type fuzzy rule-based models are consequently the focus of this thesis as they are always applicable while closely related TS models are incompatible with knowledge driven models. Kosko’s graphical technique based on fuzzy patches is extensively used in visual representations of fuzzy rule-based models described in this dissertation.

2.2 Fuzzy sets and membership functions

“Fuzzy Sets” (Zadeh, 1965) challenges our traditional mathematical view of the world. In this paper Zadeh provides the mathematical framework for an alternative description of “fuzziness” or vagueness associated with “problems in which the source of imprecision is the absence of sharply defined criteria of class membership rather than the presence of random variables.” (Zadeh, 1965: p. 339) class membership or “fuzziness” no longer based on Boolean logic, like statistics, but on non binary, fuzzy, logic. Central to a novel approach to this type of uncertainty is the concept of membership function.

2.2.1 Membership functions, fuzzy logic and Boolean logic

Despite the existence of multi valued logics (Klir and Bo Yuan, 1995) such as Lukasiewicz's, mainstream mathematics relies on crisp Boolean logic. The fundamental aspect of this binary logic is expressed in a single rule: either an object belongs to a group or it does not. The value of the logical statement “x belongs to A” can only be 1 if x does belong to A or 0 if it does not. We are so familiar with this concept that we do not question it, at least mathematically. In our daily life, however, we can think of many situations which do not agree with this model. Fuzzy logic provides an alternative mathematical model of logic, closer to our experience of the world around us which cannot be described in black and white. Central to this alternative logic is the concept of membership function.

Membership functions provide a unified model where Boolean logic is merely a special, simpler case of fuzzy logic. To help visualise both the concept of membership function and the relationship between Boolean and fuzzy logic, let us consider an element x of a set X. All elements of X are characterised by a property P taking values between 0 and 20. How representative x is of set X can be expressed in familiar terms very low to medium, medium, medium to very high. All members of X can therefore be grouped in three classes reflecting how much, on the scale of 0 to 20, property P is expressed in their members. These classes are: Very Low to Medium (VLM); Medium (M) and Medium to Very High (MVH). VLM, M and

MVH are called membership functions. They represent the three levels of intensity of expression of property P observed in each element x of X as displayed in Figure 2.1. Membership functions are often represented by the symbol μ. The membership function μ measures the grade of membership, or level of belongingness, of x in each class. The grade of membership of an element in classes of a variable increases with its similarity to each class. To facilitate comparisons and computations, grades of membership are normalised to 1 throughout this thesis. Figure 2.1 shows that consequently grades of membership are always between 0 and 1 and add up 1.

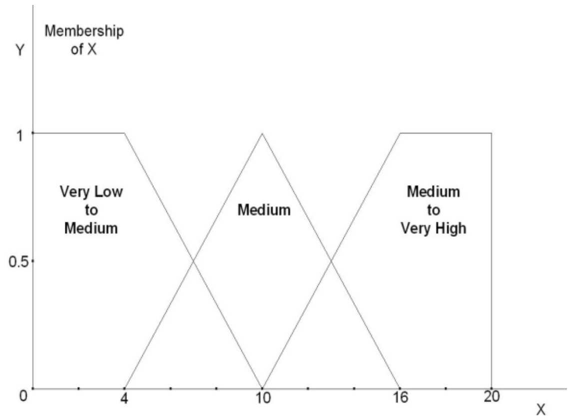

Figure 2.1: Fuzzy membership functions representing the belongingness of x to classes Very Low to Medium, Medium and High. Fuzziness increases when the membership of X approaches 0.5. For values of Y close to 0.5, X becomes equally representative of two of the three classes depicting overlapping fuzzy sets.

Let us now define μ_{f_VLM}, μ_{f_M} and μ_{f_MVH} as the membership functions describing the value of membership y of each element x of set X in the three classes VLM, M and MVH in Figure 2.1 above.

$x < 0$	=>	$y = \mu_{f\_VLM}(x) = 0$
$0 \leq x \leq 4$	=>	$y = \mu_{f\_VLM}(x) = 1$
$4 \leq x \leq 10$	=>	$y = \mu_{f\_VLM}(x) = - x/6 + 5/3$
$10 \geq x$	=>	$y = \mu_{f\_VLM}(x) = 0$

$x \leq 4$	=>	$y = \mu_{f\_M}(x) = 0$	
$4 \leq x \leq 10$	=>	$y = \mu_{f\_M}(x) = x/6 - 2/3$	
$x = 10$	=>	$y = \mu_{f\_M}(x) = 1$	Equation group 2.1

$10 \le x \le 16 \quad \Rightarrow \quad y = \mu_{f\_M}(x) = -x/6 + 8/3$

$16 \le x \quad \Rightarrow \quad y = \mu_{f\_M}(x) = 0$

$x \le 10 \quad \Rightarrow \quad y = \mu_{f\_MVH}(x) = 0$

$10 \le x \le 16 \quad \Rightarrow \quad y = \mu_{f\_MVH}(x) = x/6 - 5/3$

$16 \le x \le 20 \quad \Rightarrow \quad y = \mu_{f\_MVH}(x) = 1$

$20 < x \quad \Rightarrow \quad y = \mu_{f\_MVH}(x) = 0$

The equations of the linear segments of membership functions above are provided without explanation. Simple techniques to rapidly derive these equations from a graphic display of membership functions are described in section 2.2.2. Corresponding membership functions in binary logic are respectively μ_{b_VLM}, μ_{b_M} and μ_{b_MVH}. They are displayed in Figure 2.2. Equations of all membership functions displayed in Figure 2.2 are much simpler.

$x < 0 \quad \Rightarrow \quad y = \mu_{b\_VLM}(x) = 0$

$0 \le x < 7 \quad \Rightarrow \quad y = \mu_{b\_VLM}(x) = 1$

$7 > x \quad \Rightarrow \quad y = \mu_{b\_VLM}(x) = 0$

$x < 7 \quad \Rightarrow \quad y = \mu_{b\_M}(x) = 0$

$7 \le x < 13 \quad \Rightarrow \quad y = \mu_{b\_M}(x) = 1$ Equation group 2.2

$13 > x \quad \Rightarrow \quad y = \mu_{b\_M}(x) = 0$

$x < 13 \quad \Rightarrow \quad y = \mu_{b\_MVH}(x) = 0$

$13 \le x \le 20 \quad \Rightarrow \quad y = \mu_{b\_MVH}(x) = 1$

$20 > x \quad \Rightarrow \quad y = \mu_{b\_MVH}(x) = 0$

Membership functions are perfectly compatible with conventional binary logic. They are however a cumbersome mathematical description in binary logic where the only two possible values of membership are 0 and 1 as elements of a set either belong or do not belong to subsets of that set.

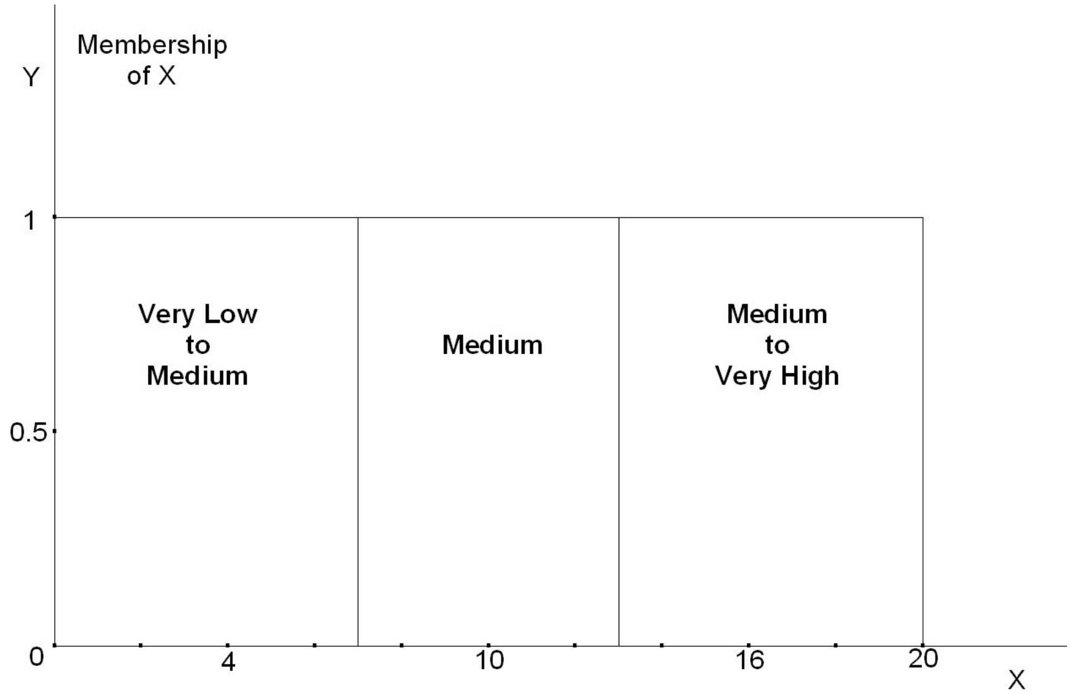

Figure 2.2: Membership functions in binary logic representing the belongingness of x to classes Very Low to Medium, Medium and High. These three classes are visualised by non-overlapping rectangular membership functions.

The case of fuzzy logic is clearly more complex. Equations are often necessary to calculate the membership of the value in a class. Membership values of all integers between 0 and 20 in Figure 2.1 and 2.2 are listed in Table 2.1. This table shows how Boolean logic simplifies fuzzy logic and therefore loses some of the initial information content. Where μ_f values are 0 or 1, μ_b values are respectively 0 or 1 too. Where μ_f values are neither 0 nor 1, μ_b values are the binary approximation of the corresponding μ_f values. There is clearly no contradiction between fuzzy logic and Boolean logic. The advantage of fuzzy logic is that it allows a more detailed description of classes. Taking for instance $x = 15$ in the above table, crisp logic only allows membership values to be 0 or 1. Fuzzy logic specifies that, in this instance 1 is actually 0.83, while one 0 value is more precisely 0.17. Fuzzy logic can therefore perfectly describe a situation where Boolean logic applies. Boolean logic, on the contrary, only provides a very blunt description of fuzziness. This leads to two important practical considerations. Crisp as well as fuzzy situations are both handled correctly by fuzzy logic. Fuzzy problems, however, when treated by binary methods lead to simplifications which may overshadow some crucial behaviour in complex systems.

Table 2.1: Comparison of membership values of all integer values of X in Figure 2.1 and 2.2.

X	μ_{b_VLM}	μ_{b_M}	μ_{b_MVH}	μ_{f_VLM}	μ_{f_M}	μ_{f_MVH}
0	1	0	0	1	0	0
1	1	0	0	1	0	0
2	1	0	0	1	0	0
3	1	0	0	1	0	0
4	1	0	0	1	0	0
5	1	0	0	0.83	0.17	0
6	1	0	0	0.67	0.33	0
7	0	1	0	0.50	0.50	0
8	0	1	0	0.33	0.67	0
9	0	1	0	0.17	0.83	0
10	0	1	0	0	1	0
11	0	1	0	0	0.83	0.17
12	0	1	0	0	0.67	0.33
13	0	0	1	0	0.50	0.50
14	0	0	1	0	0.33	0.67
15	0	0	1	0	0.17	0.83
16	0	0	1	0	0	1
17	0	0	1	0	0	1
18	0	0	1	0	0	1
19	0	0	1	0	0	1
20	0	0	1	0	0	1

Figure 2.1 and 2.2 could, for instance, adequately describe a coastal environment where each of the three classes VLM, M and MVH respectively correspond to terrestrial (Very Low to Medium number of days under water every year), intertidal (Medium number of days under water ever year) and marine environments (Medium to Very High number of days under water every year). The fuzzy model offers the necessary flexibility to compare coastal environments with different tidal regimes. Macro tidal regimes correspond to extensive overlaps between intertidal and terrestrial or marine environments while micro tidal regimes are represented by reduced overlaps. Fuzzy logic is well equipped to represent such differences. Boolean classes cannot easily capture transitional processes that play such an important role in the description of natural systems.

2.2.2 Drawing and describing membership functions

Membership functions can be displayed in three different ways (Turksen, 1991): as a contour function or by a horizontal or vertical representation. The contour function representation, the most useful for fuzzy rule-based modelling, was Burrough's focus (Burrough *et al.*, 1992) in applications of fuzzy classification of landscape properties for land suitability evaluation. In this paper, he considers a symmetrical bell shaped function as the "simplest model" of membership function. He proposed the equation below to define this bell shaped membership function represented in Figure 2.3.

$$\mu(x) = 1/(1+((x-b)/d)^2) \qquad \text{Equation 2.1}$$

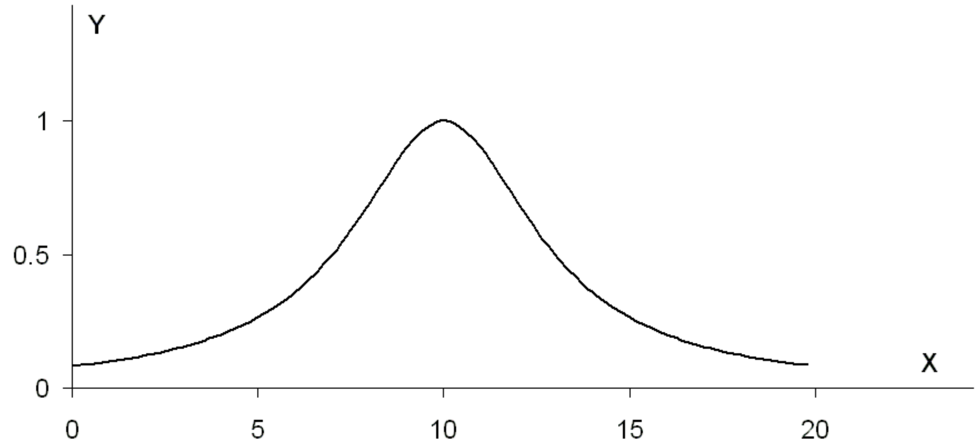

Figure 2.3: Bell shaped membership function proposed by Burrough, plotted for b=10 and d=3.

The views of Burrough (Burrough and McDonnell, 1998) on fuzzy logic have been influential in spatial sciences. He introduced membership functions as a new tool to handle the classification of soils in particular and landscape data in general. They display gradual variations by opposition to sudden changes and are consequently not well suited to traditional Boolean classifications. Burrough (Burrough *et al.*, 2000) continued to apply fuzzy logic to landscape studies for more than 15 years. Fuzzy logic, however, made little progress towards widespread acceptance in the GIS community. Surprisingly, Burrough in his 1992 article does not make any reference to Turksen (1991) who had already published a number of influential papers on various aspects of membership functions. The direction adopted by these spatial researchers focused mainly on representational applications of membership functions to geography.

Membership functions are often defined, for obvious practical reasons, by piecewise linear functions (Figure 2.4). They are more flexible and easier to adjust to specific datasets than Burrough's continuous functions. They consequently play a bigger role than continuous functions in fuzzy modelling. Unlike Burrough, who is more interested in the descriptive potential of membership functions, Bardossy and Duckstein (1995), Babuska (1996) and Kosko (1994) focus on computational applications where piecewise linear membership functions are preferred. Piecewise linear membership functions are consequently the focus of this thesis. These membership functions in Figure 2.4 can be defined in two ways. The first technique, which plays a crucial role in Chapter 3, consists in listing the y coordinates of their apices from left to right. The second technique involves defining the linear equation of each segment of the membership function. Once the coordinates of the apices are known, Bardossy and Duckstein (1995) introduce functions L(x) and R(x) respectively defining the left and right oblique sides of triangular and trapezoidal membership functions. All triangular and trapezoidal membership functions can be respectively represented by the triangular fuzzy number TiFN and trapezoidal fuzzy number TaFN defined as: TiFN = (a_1,a_2,a_3) and TaFn = (a_1,a_2,a_3,a_4). A general expression can be derived for L(x) and R(x) functions of triangular and trapezoidal membership functions.

for TiFN (a_1,a_2,a_3);

$L(x) = (x-a_1)/(a_2-a_1)$, $R(x) = (a_3-x)/(a_3-a_2)$; Equation group 2.3

for TaFN (a_1,a_2,a_3,a_4)

$L(x) = (x-a_1)/(a_2-a_1)$, $R(x) = (a_4-x)/(a_4-a_3)$.

Most engineering applications rely on piecewise linear functions as they allow rapid drawing of membership functions and easy derivation of analytic expressions used in fuzzy modelling. L(x) and R(x) equations, previously defined, were used to build in Excel (Kelly, 2006) the fuzzy modelling environment described in Appendix 1. Membership functions MF1(x) and MF2(x) are completely defined in Figure 2.4 by the x coordinates of their apices. Their respective fuzzy numbers TaFN and TiFN are:

TaFN(MF1) = (0,0,2,4) TiFN(MF2) = (6,8,12)

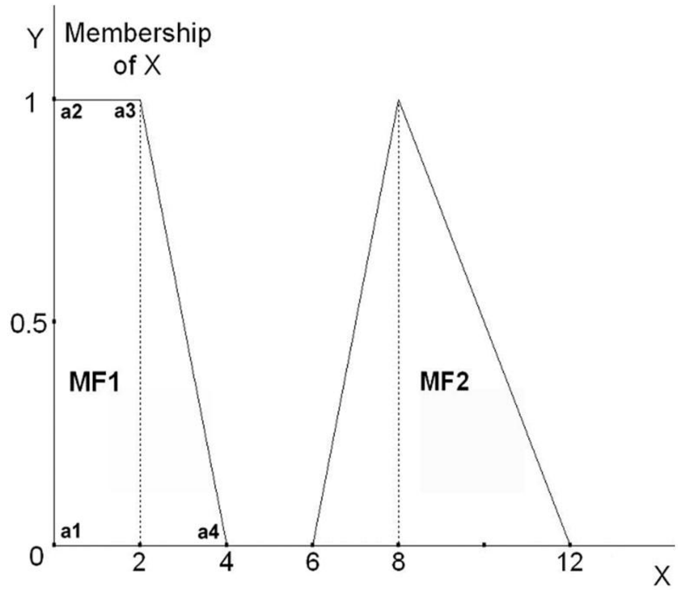

Figure 2.4: Two commonly used piecewise linear membership functions: trapezoidal (MF1) and triangular (MF2).

Notations introduced above are implemented below to derive the equations of the piecewise membership functions that make up MF1 and MF2.

$x < 0$	=>	MF1(x) = 0	
$0 \leq x \leq 2$	=>	MF1(x) = 1	Equation group 2.4
$2 \leq x \leq 4$	=>	$MF1(x) = R(x) = (a_4-x)/(a_4-a_3) = -0.5x + 2$	
$4 \leq x$	=>	MF1(x) = 0	

Once these equations are available, grades of membership of any value of x can easily be evaluated as demonstrated below for the four equations above.

x = -2	=>	MF1(x) = 0	
x = 0.5	=>	MF1(x) = 1	
x = 2.5	=>	MF1(x) = -1.25 + 2 = 0.75	Equation group 2.5
x = 3.5	=>	MF1(x) = -1.75 + 2 = 0.25	
x = 5	=>	MF1(x) = 0	

From these results we can draw a number of conclusions. For instance, the pair {-2, 5} represents elements that do not belong to the fuzzy set represented by MF1 while 0.5 is perfectly representative of this fuzzy set and 2 is more representative than 2.5.

Defining MF2 knowing its fuzzy number TiFN(MF2) = (6,8,12) is equally straightforward as shown below.

$x \leq 6$	=>	$MF2(x) = 0$	Equation group 2.6
$6 \leq x \leq 8$	=>	$MF2(x) = L(x) = (x-a_1)/(a_2-a_1) = 0.5x - 3$	
$8 \leq x \leq 12$	=>	$MF2(x) = R(x) = (a_3-x)/(a_3-a_2) = -0.25x + 3$	
$12 \leq x$	=>	$MF2(x) = 0$	

Triangular and trapezoidal fuzzy numbers are concise descriptions of membership functions particularly well suited to the conceptual development of both data and knowledge driven fuzzy rule based models. They are widely used as well during the exploration phase of a model to rapidly input the parameters of a fuzzy model in specialist software as will be demonstrated in section 2.8.

2.2.3 Vertical and horizontal representation of membership functions

Although the following concepts are not directly used in this thesis, they play an important role in algebraic operations on membership functions and in their general description. They do not have a direct bearing on applications of fuzzy rule-based modelling considered in this thesis but provide a broader understanding of membership functions and their description in the literature. Membership functions were so far defined through their functional representation: a function was drawn and the equation of that function was evaluated. Two other representations exist: the vertical representation and horizontal representation.

The vertical representation of a membership function, in Figure 2.5, is unique once the interval of possible membership values α is defined. In this thesis membership values are always normalised and therefore $\alpha \in [0,1]$. A horizontal slice across a membership function defines an α cut as a subset of the original fuzzy set. Grades of membership of this subset, by definition, are all above the grade of value α. This important concept of fuzzy set is discussed in texts (Kandel, 1986; Terano *et al.*, 1992) which deal with other advanced aspects of the theory of fuzzy sets. The horizontal representation, through a succession of α cuts, allows to completely define a membership function: this is the resolution principle.

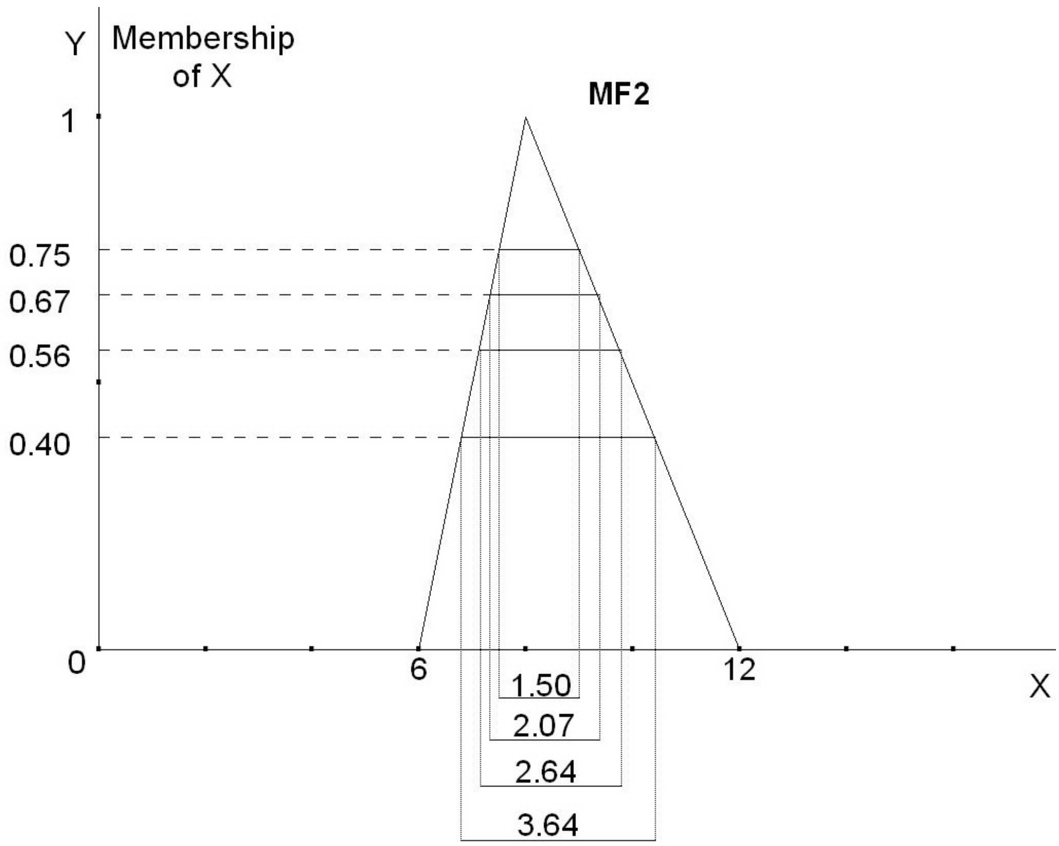

Figure 2.5: Definition of a membership function through a succession of α-cuts (horizontal lines across the membership function). Through α-cuts, a membership function can be defined by its vertical and horizontal representations.

The concept of addition of fuzzy numbers, derives from the extension principle (Terano *et al.*, 1992) directly based on α cuts. Only nested α cuts are possible as fuzziness decreases with increasing grades of membership. Non nested α cuts would indicate that the membership function is not convex and that locally, the rate of change in precision varies with changing grades of membership. Such an inconsistency would be a flaw the in the design of membership functions. Another important property of membership functions better explained by referring to α cuts is the inverse relationship between reliability of information and slope of equations defining the piecewise linear sides of triangular and trapezoidal membership functions. The wider a triangular membership function, the more fuzzy the information it conveys. This can be simply demonstrated by considering the extreme situation where the support of the membership is a single value of x. The membership function is then a single vertical line and all fuzziness has disappeared. The relative width of membership functions is therefore an important consideration when assigning weightings to individual rules in fuzzy rule-based models: the wider the membership function the less precise its information content. Consequently, if two membership functions belonging to the same variable are similar in all respects but their width, the narrower membership function should be assigned a higher weighting to reflect its higher precision and therefore reliability.

2.3 Fuzziness, statistics and uncertainty

Much has been written about statistics and fuzzy logic and it seems appropriate to consider how they can be related before discussing the acquisition of membership functions. Techniques proposed by authors like Hisdal (1988) are statistical while Zadeh (1965) emphasises that, although there are similarities between membership function and probability density function, there are essential differences. He adds that "In fact, the notion of a fuzzy set is completely non statistical in nature" (Zadeh, 1965: p. 340). Hisdal (1988) proposes the Threshold Error Equivalence (TEE) model to demonstrate that if the axiomatic statement 'fuzziness ≠ randomness' is ignored, statistics can replicate fuzzy logic. Her work is particularly relevant for at least two reasons. Firstly, gaps between theory and applications of fuzzy logic, inferred in the previous section, disappear. Secondly, the statistical origin of some sources of fuzziness related to informants' awareness, encountered in knowledge capture, no longer needs a justification. The latter consideration implies that when dealing with the capture of human knowledge, denying a link between statistics and some types of fuzziness is impossible. Deriving membership functions from questionnaires can be a statistical process as explained in 2.1.4. Why then is there a need to draw a line between statistics and fuzzy logic?

The existing divide between statistics and fuzzy logic, reflected in the emotional statement "I am constantly amazed at the amount of negative and often hostile information about fuzzy logic earnestly offered by scientists …" (Cox, 1999: p. 11) suggests that this line drawn between statistics and fuzzy logic may not be the outcome of a rational debate. A possible explanation is that “Fuzzy logic challenges the probability monopoly” (Kosko, 1994: p. 33). Some authors (Kandel *et al.*, 1995) felt the need to expose the actual differences between fuzzy and statistical methods. This educational campaign (Dubois and Prade, 1993), intended to reconcile the feuding parties by offering an olive branch, concluded that the problem is multifaceted. There are situations where fuzzy logic and probability have a lot in common, yet fuzzy logic does have a role to play as demonstrated by many practical applications. This thesis steers away from the previous controversy to focus on contributions of fuzzy logic, beneficial to GIS modelling, independently of the role played by statistical modelling.

2.4 GIS, raster and direct application of membership functions

After defining membership functions and explaining how to build them, we now explore their roles in general and more particularly in relation to GIS modelling. Two fundamental practical applications of fuzzy membership functions are considered in this thesis. Firstly they can be considered as individual repositories of information, a role explored in chapters 3 and 5. Secondly they are the building blocks of data and knowledge driven fuzzy rule-based models. Membership functions, in that context, will be dealt with in detail in chapters 4 and 5.

The practical application of fuzzy membership to GIS modelling is illustrated by two case studies. One represents a direct contribution of membership functions to suitability mapping in raster GIS. Here fuzzy membership functions are an integral component of a GIS based terrain modelling strategy. The other case study demonstrates how fuzzy membership functions can record expert knowledge required to improve the accuracy of fishery productivity maps in Chapter 5. Although not intrinsically spatial, this second case study has profound implications for spatial NRM modelling as explained in Chapter 5. Fuzzy rule-based modelling is the second, and arguably the most important, practical application of membership functions. Fuzzy modelling strategies explored in Chapters 4 and 5 do not involve any specific GIS functionality. Petry *et al.* (2005) conclude that, although there is currently a growing interest in fuzzy logic among GIS researchers, there are still few purely spatial practical implementations of fuzzy logic.

2.4.1 More realistic landscape modelling

Geographers saw in landscape modelling a domain of application for specific facets of fuzzy logic such as classification. Burrough *et al.* (2000) show how continuous classification by fuzzy k-means is a reproducible and objective method that can reduce spatial variation to a set of classes that summarise key information relevant to land based processes. Fisher *et al.* (2005) explore landscape information derived from DEMs. They assign DEM cells to one of six geomorphic/morphometric classes: pit, peak, pass, channel, ridge and plane. These six classes correspond to all possible permutations of first and second derivatives of a surface in two orthogonal directions in a cell surrounded by 8 contiguous cells. These units in a real landscape are easy to define but remain semantically vague concepts otherwise difficult to apply to a DEM. The Ben Nevis area of Scotland constitutes a good testing ground for their approach. Using the local to meso scale range, they obtain degrees of peakness, ridgeness and passness in good agreement with human perception. An article by Costa Fonte and Lodwick (2005) falls in a different category of landscape classification based on fuzzy logic. Their description of the contribution of membership functions to the capture of spatio temporal knowledge is practical. They consider three domains of application: classification of satellite imagery, DEM and visualisation of water bodies. The latter, detailed below, demonstrates how fuzzy logic can simplify the quantitative description of geographic entities.

Costa Fonte and Lodvick (2005) show how the combination of a DEM and gauging station records can provide a visual account of floods simultaneously in space and time. The authors compiled 2557 observations of water level in a river over the 1982-1990 period. Grids are derived from a DEM and water level measurements by assigning to each grid cell under water a value of 1 for each gauging record. The 2557 grids generated from 2557 gauging records are added. All cells in the resulting grid have a value between 0 and 2557. Once divided by 2557, the code of cells always submerged is 1 while cells never under water have a code of 0. The content of each grid cell can be interpreted as its membership in the river fuzzy set. The same approach can be used to define the membership function of other geographical entities that oscillate between two extreme states. This example plays three important roles. Firstly it demonstrates a more realistic visualisation of wandering geographical features (eg coastline, sand banks, dunes, glaciers, etc.) and non geographical features with a geographical expression (effects of disease, education, wars) while formalising the spatial representation of their changing nature. Secondly it shows the role of the raster format in bringing fuzzy concepts into a GIS context, thus introducing Chapter 3. Finally it represents a first step in the adaptation of fuzzy rule-based modelling to a GIS environment.

2.4.2 Raster: the GIS bridge between non spatial and spatial concepts

Fundamental principles of map fuzzification used in Chapter 3 are described here. They provide an excellent opportunity to define the spatial data structure that enables fuzzy models to have a cartographic expression. GIS maps rely on two fundamental data structures: raster and vector. Both have advantages and drawbacks familiar to all GIS professionals. The interested reader will find a comprehensive introduction to this topic in GIS textbooks (DeMers, 1997).

Raster is the format implicitly referred to in this thesis. A raster performs a systematic sampling of the spatial environment considered. Wherever a grid is laid over a variable defined across a plane, all points of (x,y) coordinates take the value of the corresponding grid cell. This representation is very convenient as it addresses three fundamental issues. Firstly the need for a way of visualising changes in values of a mapped variable is answered. Secondly it offers a transition between analogue transparency overlays and digital GIS. Thirdly it constitutes a general technique to apply mathematics to a geographical environment. Mathematically, a raster is an array conveniently represented as a matrix. Outputs of matrix calculations are therefore natively compatible with GIS through rasters. Software like Matlab (MathWorks, 1999) and Scilab (Campbell *et al.*, 2006), based on matrix computations, produce results easily exported into a GIS.

Throughout this thesis, unless stated otherwise, the fuzzy modelling techniques considered can have a spatial or non spatial expression. GIS is therefore rarely referred to outside Chapter 3 which is the only exclusively GIS oriented chapter. The corollary is that fuzzy analysis/modelling in this thesis does not require a GIS environment, except for Chapter 3 where the reader needs to be at least familiar with GIS and ideally have experience in GIS modelling in a raster environment.

2.4.3 Mapping vagueness with fuzzy numbers

Chapter 3 relies on key concepts detailed below. Malczewski relies on them in a book (1999) which was very influential in my discovery of fuzzy logic applications to GIS. Although Malczewski's approach to vagueness described here is limited in scope, its visual outputs are thought provoking and well adapted to the objectives of multi criteria suitability analysis.

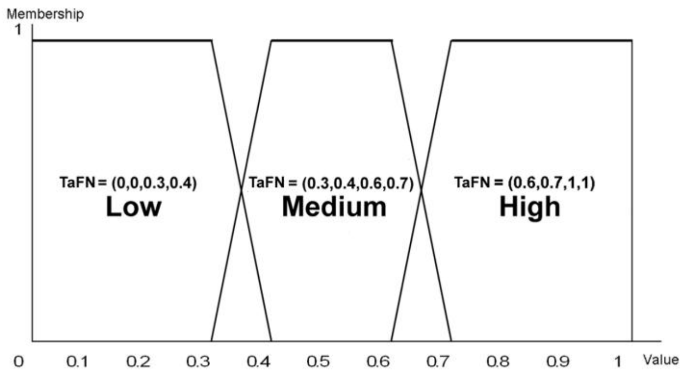

Figure 2.6: Trapezoidal membership functions defining three possible values of suitability in linguistic terms. The horizontal scale has no unit as it is normalised and does not represent the domain of a specific measurable attribute. Each of the three linguistic terms LOW, MEDIUM and HIGH is represented by a trapezoidal membership function defined by its coordinates recorded as a trapezoidal fuzzy number or TaFN.

Let us assume that the suitability of variables to some activity or process is to be estimated by a group of experts who prefer to evaluate the suitability of these variables in plain English. They rely on arbitrary linguistic terms such as low, medium and high. To ensure the consistency of meaning across variables and experts, the ranges of all variables are normalised. They are rescaled to start at 0 and their maximum value is 1. As such, the horizontal scale is no longer the domain of a measurable variable. Figure 2.6 displays fictitious membership functions applicable independently of actual measurable domain of the attributes as will be demonstrated in Chapter 3. In a GIS, the suitability defined in Figure 2.6 is depicted as a grid overlay in raster format by three classes of grid cells: Low, Medium and High represented by the three trapezoidal membership functions in Figure 2.6. Figure 2.6 uses concepts introduced in section 2.2.2 to quantify linguistic descriptions of suitability. Trapezoidal membership functions have two different domains. One domain is a plateau that covers all values with full membership of 1. In this region properties of the membership function are fully expressed. In Figure 2.6, for instance, the value 0.2 is fully representative of Low suitability. The other domain is a zone of overlap between two successive membership functions where values have intermediate properties. In Figure 2.6, 0.38 has a suitability intermediate between Low and Medium and closer to Medium. This value is only partially representative of Low and Medium suitability. Figure 2.7 summarises the concept of spatial fuzzy visualisation described by Malczewski (1999). This process is detailed in Appendix 3. Linguistic terms L, H, M in the top grid below respectively represent fuzzy suitability Low, Medium or High. Each of these terms is defined by its corresponding trapezoidal fuzzy number (TaFN): the x coordinates of all 4 vertices of the corresponding trapezoidal membership functions listed from left to right. Each of the three fuzzy suitability levels L, M, H can therefore be represented by the 4 coordinates (a,b,c,d) of its TaFN as shown below:

TaFN(L) = (0,0,0.3,0.4)   TaFN(M) = (0.3,0.4,0.6,0.7)   TaFN(H) = (0.6,0.7,1,1)

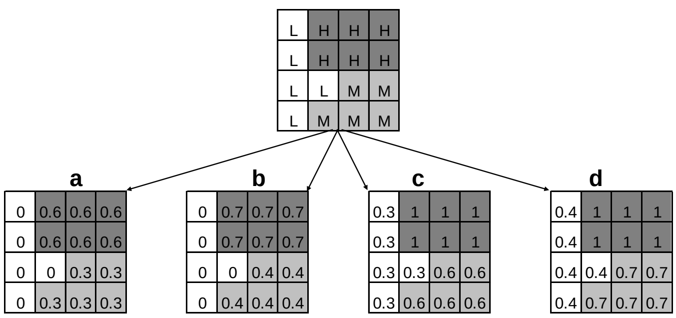

Figure 2.7: Breaking down a grid of linguistic suitability into 4 rasters. Dark grey, light grey and white cells respectively stand for High, Low and Medium suitability.

A single level of suitability has consequently 4 possible extreme numerical expressions. The first, corresponding to the lowest value of this range of suitability, is represented by the variable a. The second, b, is the lowest value in the range of values covered by the corresponding plateau in Figure 2.6. The third, c, is the highest value in that plateau. The fourth, d, is the highest value covered by the range of suitability considered. Visually, in a GIS, we can therefore replace a single map of suitability by 4 maps, each corresponding to one of four interpretations a, b, c and d, of the different levels of suitability displayed in the initial map. Practically, a single raster map is fuzzified by translating it into its four a, b, c, d fuzzy expressions. Although noteworthy as it provides a very flexible technique to visualise fuzziness, this graphical expression of fuzziness is rarely encountered.

Better known in GIS circles are graphical representations of fuzzy boundaries championed by Burrough (1998). Burrough's initial interest stemmed from the observations shared with other researchers in soil sciences (Lagacherie *et al.*, 1996) leading to the conclusion that crisp boundaries between soil types were very inadequate. His visualisation of fuzziness consists in gradual variations in colour intensity to reflect membership change with distance from lines separating two polygons. Well adapted to soil mapping, they are best suited to boundary studies. What Malczewski (1999) proposes is not driven by the needs of a specific branch of Science. Less application specific, his approach is more likely to appeal to a broader range of GIS professionals.

2.5 Acquisition of membership functions

Although the acquisition of membership functions is a fundamental step in the creation of a fuzzy model, no single methodology appears to exist. Two schools of thought prevail. One approach consists in creating membership functions independently for each input variable. Corresponding membership functions are then derived in the output variable. In the other approach, adopted in this thesis, output membership functions, obtained after segmentation of the whole dataset, are imposed on all input variables. Although rarely stated in the literature, the first technique applies best to knowledge driven modelling, where informants refer to specific input and output membership functions. In data driven modelling only output membership functions are initially defined, at least in terms of their number, if not in terms of their range.

2.5.1 Numerical data and knowledge require different methods

First, as a spatial scientist one must consider Burrough's views as they are likely to represent one's first encounter with fuzzy logic. Burrough (1998) distinguishes two methods of membership functions acquisition. He calls them semantic import approach (SMI) and fuzzy k-clustering (FKC). SMI does not appear to be used in fuzzy logic outside GIS. The underlying concepts still hold and reflect an important dichotomy. SMI consists in "importing" fuzzy classes based on expert knowledge while FKC relies on a semi automatic classification. FKC is less intuitive and less compatible with GIS visualisation, but has more scope when little is known of the investigated process. Burrough (1998: p. 270) states "Just as there are various types of probability distribution … so there can be different kinds of fuzzy membership functions". This comment, however, is slightly misleading as the selection of membership functions is generally driven by convenience and therefore leads to the overwhelming popularity of triangular membership functions in engineering applications. After Burrough's, the work of Civanlar and Trussel (1986) deserves a mention because of its purely statistical nature and the associated debate exposed in section 2.3. Their research refers to digital signal processing characterised by large data sets encountered, for example, in remote sensing. Reliance on large datasets however limits its applications in the context of this thesis.

2.5.2 Acquisition of membership functions for knowledge driven modelling

Turksen is well regarded for his work on membership functions. His 1991 article casts much light on the process of acquiring membership functions falling in Burrough's (1998) SMI category dedicated to the capture of human knowledge. Fuzzy logic faces little competition in this domain, as no other method provides the same flexibility. This explains why psychology researchers were among the first to embrace this new paradigm. Chameau and Santamarina are two additional researchers whose views, with Turksen's, are outlined below as they have been very influential in knowledge driven modelling.

Turksen (1991) lists four methods of membership function acquisition and construction. The first method, named direct rating, randomly selects elements of a set that are presented to informants who locate them with a pointer on a scale. They are then asked to find the lower and upper value of the corresponding variable. The same questions are randomly repeated (about 10 times) during the survey. Responses y for different values x of the variable provide an experimental distribution of membership values for each linguistic variable. The second method, referred to as polling, implies that semantic uncertainty is merely statistical. Values of membership functions are obtained by repeatedly asking the same questions to subjects and recording their binary answers. Graphed survey results automatically provide membership functions. Polling produces smaller fuzzy regions than direct rating. The third method, called set valued statistics, applies to a fuzzy set defined as an approximation of a random set. This approach however does not appear to be very practical. The fourth method, reverse rating, requires subjects to identify the grade of membership in a fuzzy set of randomly selected elements of that set. The same degree of membership is randomly presented to each subject a number of times during the survey. Membership values are then processed by techniques relying on the mean and standard deviations of recorded data for each linguistic variable.

Chameau and Santamarina (1987) conducted well documented experiments on university students. Their work is regularly quoted as it provides practical solutions to the capture of human knowledge in the form of membership functions. They compared four practical methods of extracting knowledge recorded in the form of questionnaires. The first method, point estimation, involves the selection of one element from a list or point on a reference axis. Membership is determined as a proportion of answers favouring the value considered. Membership values are normalised with respect to the largest value. This method is fast and the processing of answers is simple. The main disadvantage is in the crispness of the response that clashes with its inherent fuzziness. The second method, interval estimation, consists of selecting a range of values instead of one only. A segment is provided to represent the whole scale with a few intermediate values. Like point estimation, this is a binary direct rating method but it considers all levels in the response intervals. Fast and simple like point estimation, it is superior as it allows subjects to transfer the vagueness of their conceptualisation of the problem to the answer. This method results in lowest fuzziness. The main disadvantage is that it requires a number of assessors. The third method, membership function exemplification, records object membership estimates for set values in a questionnaire. This method, also called continuous direct rating, results in wider, and therefore fuzzier sets, than those obtained by point or interval estimation. No further processing is required but the method is cumbersome. The fourth method, pair wise comparison, records repeated informant's choice of the most representative element for all pairs of elements considered. This method has a number of disadvantages one of them being the involved mathematical processing of the results. To conclude their very informative paper, Chameau and Santamarina (1987) stress that the wider the scale given to assessors, the more inconsistent the answers and the fuzzier the final result. Of the four methods tested, interval estimation on a scale from 0 to 10 offers the best performance.

2.5.3 Acquisition of membership functions in data driven models

The first step in the design of a model consists of selecting all available independent variables that affect the output of the model. Dealing with the investigation of poorly understood natural processes in a GIS environment often makes this initial phase a lot more arduous than expected. Plots of Input versus Output are useful but the resulting correlation coefficient assumes a linear relation which may not apply. Exploring other possible relations between Inputs and Outputs is possible but not necessarily cost effective. Here we will assume instead that, when in doubt, all available variables making up a homogeneous dataset will be used. Four justifications for this approach can be put forward. Firstly, one variable may only have a localised, yet important effect on the output. Secondly, assessing which cut off value of the correlation coefficient decides if a variable should be retained is difficult. Thirdly, when evaluating membership parameters, inconsistencies often occur as a result of independence between input and output. This results in exceedingly noisy membership functions, which, as demonstrated in Chapter 4, are then discarded as they cannot be defined. Fourthly, identifying unnecessary variables is easier to achieve during performance evaluation when variables are removed from the model, one at a time, to explore their contribution to the overall predictive capability of the model.

The second step in the design of a model consists of grouping values belonging to each variable, into membership functions, on the basis of their similarity. This grouping process, called clustering, can be achieved in many different ways (Davis, 1986: p.502). The two main methods are partitional (Bezdek *et al.*, 1984; Bezdek *et al.*, 2005; Wang, 2006; Nuzillard *et al.*, 2007) and hierarchical (Johnson, 1967; Bar-Joseph *et al.*, 2001). The former, exemplified by the well known fuzzy c-means clustering method (Bezdek *et al.*, 1984), makes no assumption on the properties of the data but generally requires one to specify an initial number of clusters. Three situations can occur. Firstly, no reliable knowledge of interactions between variable exists and only experimental data are available. In this case, the identification of membership functions can only be data driven, or unsupervised, and relies generally on partitional methods used in this thesis. Secondly, insufficient experimental data is available but knowledge of interactions between input variables and output variable can be obtained. Then, the identification is knowledge driven. Thirdly, knowledge and data are available. Both knowledge and data driven identification methods can contribute to the identification of membership functions of the predictive model. This section concentrates on data driven identification methods which focused the effort of many researchers in the 1990s. Among those, Kosko and Babuska are notable for being frequently quoted in the fuzzy modelling literature.

Kosko (1994) and Babuska (1996) strived to rationalise membership function identification. The formalisation of the mathematical framework was important in putting to rest criticisms of subjectivity from fuzzy logic detractors. The acquisition method is depicted in Figure 2.8. Triangular membership functions are the simplest and most concise descriptors of a range of values [a,c]. Leftmost and rightmost coordinates a and c respectively represent the range of values, also called support, covered by the membership function. Membership values of a and c are 0. The spatial equivalent of the mean, the centroid b, is the apex. Coordinates of this point are the averages of x and y coordinates of all points in the fuzzy patch. As the most representative point of all in the patch, its membership is 1. A triangular membership function is defined by three coordinates (a,b,c), which make up its triangular fuzzy number. This fuzzy number uniquely defines this membership function. Although the median could be used instead of the mean to define b, its lowest sensitivity to extreme values is not always an advantage. Another reason for not using the median is the mismatch between points associated with the x median and those belonging to the y median. Consequently, the mean is generally the preferred estimate of a triangular membership function apex. Membership functions are generally normalised to 1 initially. Maximum values of membership functions can however be reduced by weightings in the model to reflect variations in reliability. Membership functions can be defined manually, although it becomes very tedious and rapidly impractical in large datasets of high dimensionality. Automatic segmentation, covered in the next section, is consequently often preferred in practice except when the number of records is very small.

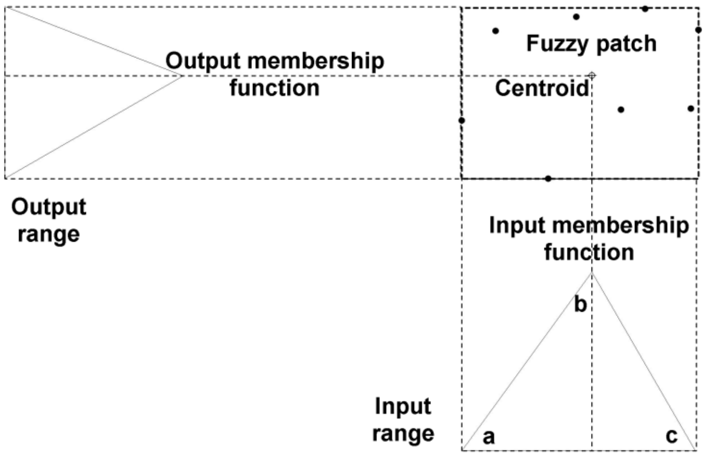

Figure 2.8: Graphical representation of a membership acquisition method utilising fuzzy patches. Two dimensional records in the rectangle called fuzzy patch can be projected horizontally on the y axis, or output dimension, and vertically on the x axis or input dimension. The projections of the centroid of all points in the fuzzy patch on the y and x axis are respectively the mean of y and x coordinates of all points in the fuzzy patch.

Guidelines on desirable number of fuzzy patches, patch size and patch overlap in most models are now required. Cox's (1994) practical recommendations provide some useful hints into practical membership function designs. There is no rule to determine degree of overlap between neighbouring regions. This overlap is not a shortcoming of fuzzy reasoning but a reflection of the ambiguous nature of the segmentation of the initially continuous space. Overlap for midpoint-to-edge should be 25% to 50% of the fuzzy set base. Much less or no overlap between neighbouring regions results in a choppy control surface and reflects an abrupt change in behaviour. An excessive overlap resulting in the edge of one fuzzy region crossing over the midpoint of another fuzzy region is to be avoided in knowledge modelling. The resulting epistemological problem consists in violating the Law of Non Contradiction, i.e. a value cannot be perfectly representative of one set and still be partially representative of a different set. The "Sum to One" rule of thumb aims at avoiding this semantic problem by requiring that the sum of membership functions does not exceed 1. A practical consequence of this rule is that a particular region should not be covered by more than two membership functions with a general upper limit of three.

A variety of specific applications may dictate the design of membership functions. From a control point of view, areas of membership functions decrease while their density increases in the region of desirable behaviour. The "Sum to One" rule of thumb no longer applies in the central zone of fine tuning to ensure that small variations are detected and handled properly. This situation is depicted in Figure 2.9. Other membership function design considerations are strongly influenced by human cognitive patterns. Humans often think in terms of low, medium and high with additional expressions in the lower and upper range if more detail is required. The number of membership functions a variable comprises, therefore, is often an odd number. To make the model more readable, this number is generally less than 11. This is typical of control engineering applications where the ideal state or most desirable operating range is represented by the narrowest membership function flanked on either side by membership functions gradually increasing in size. The preferred operational range needs to be precisely defined by a narrow membership function while domains of operation of decreasing importance are assigned membership function of increasing width. Although driven by the specific needs of system control engineering, Figure 2.9 shows a situation which would be acceptable in that context but not necessarily in others such as knowledge modelling, where a better match between centroids and membership function extreme values would be sought. Cox's (1994) recommendations outlined above may suffice in the case of manual segmentation. However, this will not be practical in cases of large dataset and high dimensionality typical of models involving satellite imagery. Automatic segmentation will then be required.

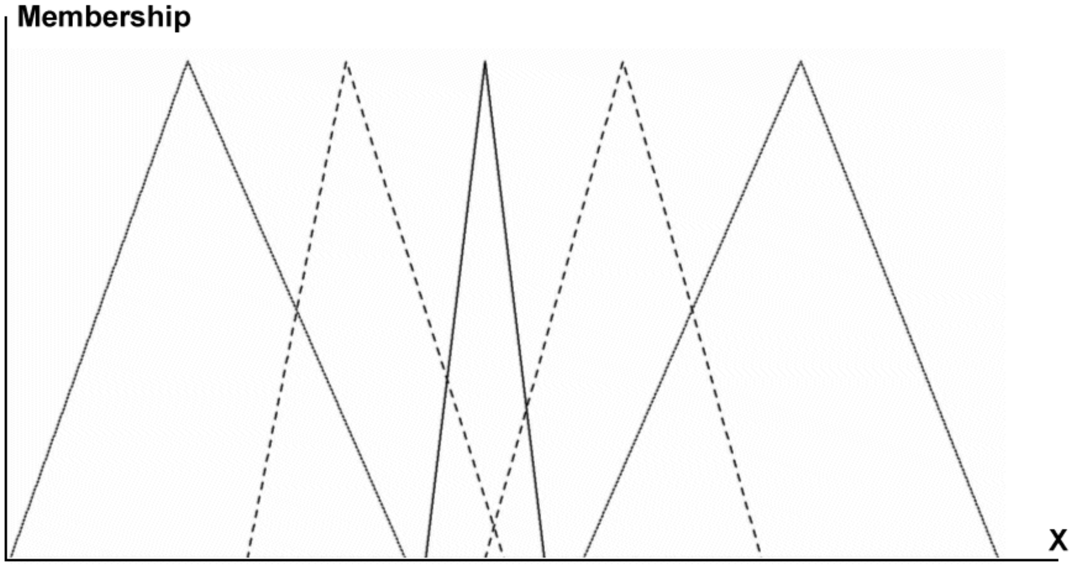

Figure 2.9: Example of membership functions demonstrating that for practical reasons, some rules of design may no longer apply. Here, the "Sum to One" rule is not enforced in the central zone to improve the handling of small but significant variations.

2.5.4 Automatic acquisition of membership functions

The automatic acquisition of membership functions relies on cluster analysis. Babuska (1996) describes cluster analysis as a classification of objects according to their similarities which is very useful in the absence of prior knowledge. Although clustering techniques can be applied to quantitative and qualitative data, here only quantitative data is considered. A cluster is a group of objects more mathematically similar to one another than to objects from other clusters. The mathematical similarity is generally expressed as a distance between data vectors, or to some reference. Clusters can have different shapes and can be hollow. The separation between clusters is influenced by the scaling and normalisation of the data. This partitioning, defined by the membership of each element to clusters, is dictated by the type of clustering applied to the data and therefore by the nature of the clustering algorithm selected to segment the dataset. For a given record, clusters change with the metric displayed on the horizontal axis. Although a detailed understanding of the mathematics of clustering algorithms is not required, knowledge of the respective strengths and weaknesses of available clustering algorithms is required to ensure that the segmentation adopted is compatible with the dataset considered and the purpose of the study.

There are three types of fuzzy clustering: hard, fuzzy and possibilistic partitioning. Possibilistic partitioning is characterised by elements with a sum of memberships to all clusters less than one if they are atypical (outliers). The more typical they are, the greater their membership. Most analytical fuzzy clustering algorithms are based on the minimisation of the fuzzy c-means function (FCM). The shape of the cluster is dictated by the type of distance measure. Two commonly used distance measures are the Euclidean and Mahalanobis distances. Euclidean distances create hyper spherical clusters while ellipsoidal clusters of unconstrained orientation are produced by Mahalanobis distance (Babuska, 1996). The main criticism of the fuzzy c-means algorithm is that it enforces a spherical shape on clusters regardless of the spread of data. A number of algorithms have been derived from the FCM to identify clusters that lie in subspaces of the data space. One of particular interest to identification is the Gustafson-Kessel (GK). Compared with the FCM clustering algorithm, the GK algorithm has three important characteristics. Firstly, clusters have similar volumes. Secondly, GK is better capable than FCM of detecting clusters of different shapes and orientations. Finally, GK is more computationally involved.

2.5.5 Desirable properties of membership functions

Membership functions representing linguistic terms are expected to meet at least two conditions. Firstly, their coverage must provide all data considered with a non zero membership value in at least one fuzzy set. Secondly, semantic soundness needs to reflect the validity of their linguistic meaning. Fuzzy sets should consequently be unimodal (they have only one meaning), normal (the value representing their exact meaning is the same regardless of the meaning), and in small number for each variable as we rapidly run out of words to describe increasingly subtle variations. The number of fuzzy sets used to capture the pattern of values taken by a variable determines the granularity or resolution of the model. A variable described with three membership functions is more granular than one made of five variables. Again compromise is a crucial concern in fuzzy rule-based modelling: granularity should be minimised as long as the cost of the resulting complexity does not negate the benefits of finer resolution. Practically, Mamdani type fuzzy rule-based models have no more than nine membership functions per variable. Some membership functions have ‘information hiding’ properties. In other words their shape does not reflect all changes in value. This is the case of trapezoidal membership functions in the plateau section. They are often used to describe the lowest and highest range of values of a variable as these may be domains where the behaviour of the variable is both poorly understood and difficult to document. In most other situations triangular membership functions are preferred, precisely because they are free of 'information hiding'.

2.6 Manual design of membership functions

Field data recorded for the purpose of natural resource management are often explored to produce predictive models. These models establish a relationship between the dependent variable y and independent variables $x_1, x_2, \ldots, x_n$, leading to the general expression

$$y = f(x_1, x_2, \ldots, x_n)$$

To estimate y on the basis of measurements of $x_1, x_2, \ldots, x_n$, one has to find a mathematical expression for f. A regression or a polynomial fit are mathematical methods often used to approximate experimental data. A strategy adapted to the problem at hand, especially with small datasets of less than fifty records, needs to be selected from a range of statistical methods.

A simple linear regression is often the best choice when little information is available. The result is a straight line through a cloud of points with a correlation coefficient generally difficult to interpret as it merely indicates that the experimental data at hand do not follow a linear equation. The polynomial fit is just as problematic as a sufficiently high degree polynomial can always be forced to match a cloud of points, thus embedding in the final equation all the variability of the data which may have little to do with the underlying process under investigation. The Generalised Linear Model (GLM), and its spatial counterpart the Geographically Weighted Regression (GWR), are statistical models created for multidimensional datasets. The mathematical complexity underpinning GWR and GLM (Stern *et al.*, 2004) is often unwarranted by the scope of the project and the reliability of the data. Although all calculations are automatically handled by some specialist software, not all users have the necessary statistical background required to confidently drive the software. The lack of transparency of these complex statistical models can be an additional drawback.

Within the context previously described, the universal approximator advocated by Kosko (1994) is a simple generic alternative worth exploring. This approach makes no assumption about the nature of the variability of the data. The data does not have to match a specific statistical distribution. Absence of autocorrelation, or spatial correlation and independence of the data are not prerequisites either. Kosko's (1994) concept of universal approximator is important as it introduces the procedure of membership functions acquisition adopted in this thesis.

2.6.1 Approximation of a non linear function by a rule-based model derived from fuzzy patches – A practical example of identification

Kosko (1994) briefly demonstrates how an output domain can be mapped on an input domain to emulate any continuous function. The principle is visualised in Figure 2.10. Fuzzy logic allows the same data to belong to two patches. This redundancy improves the capture of the characteristic pattern of a distribution of points. Rectangular fuzzy (as they overlap) patches in Figure 2.10 are created to cover the experimental dataset visualised by the black dots. Where patches overlap (double hatched area in Figure 2.10) fuzziness increases as membership functions drop below 1, data points no longer have characteristics of a single patch. Patches B1 and B2 relate the input domain to the output domain. Logical expressions describe this association between horizontal projections (segments A1 and A2 on the horizontal axis representing the input domain), and vertical projections (segments C1 and C2 on the vertical axis representing the output domain) of fuzzy patches. The graphical link through fuzzy patches between input values (horizontal axis) and output values (vertical axis) visually demonstrated in Figure 2.8 is formalised by logical relations displayed below.

Rule 1:	IF	antecedent A1 THEN consequent C1
Rule 2:	IF	antecedent A2 THEN consequent C2
…	…	…
…	…	…

Rules above are fuzzy as points, in the zone of overlap between two patches, belong to two different fuzzy classes at once. This logical structure is well suited to describe relations between environmental variables often of uncertain reliability. The construction of a fuzzy patch in Figure 2.8 is demonstrated on a dataset copied from a paper by Yager and Filev (1994) who refine their fuzzy model prediction with a tuning algorithm. Automatic adjustment of fuzzy rule-based models has grown in popularity and artificial neural networks and genetic algorithms (Recknagel, 2006) are frequently mentioned as performing well in this role. These tuning techniques are not considered in this thesis because the resulting models (D. Dubois, personal communication January 2005) are no longer preferable to other equally involved modelling techniques as they lose their main advantage: simplicity. The non linear function 2.4, defined by Yager and Filev (1994) in their paper, is used here to demonstrate the principles of a clustering method.

$$f(x) = (0.9\ x\ /(x + 0.2)) + \eta \qquad \text{Equation 2.2}$$

Noise, represented by η in Equation 2.2, is added to the initial function in brackets. The noise component, which randomly varies between –0.1 and 0.1, is assigned a normal distribution. The purpose of η is merely to mimic stochastic variations generally present in experimental data. According to the above equation, when x belongs to the interval [0,1], f(x) belongs to [-0.1, 0.85]. The presence of a stochastic component means that however good the model is, a perfect match between observed (modelled here) and predicted values, is mathematically impossible. The general fuzzy modelling predictive methodology proposed consists in 4 phases:

1/ data preparation results in dividing the experimental dataset in two subsets, called training dataset and evaluation dataset, and represented as A and B respectively in Figure 2.11;

2/ identification relies on the training subset to define all the numerical characteristics of the model such as number of membership functions per variable as well their type, size and position defined in panels C, D and E of Figure 2.11;

3/ model implementation;

4/ evaluation of model performance by comparing its output to actual values of the evaluation dataset: F in Figure 2.11.

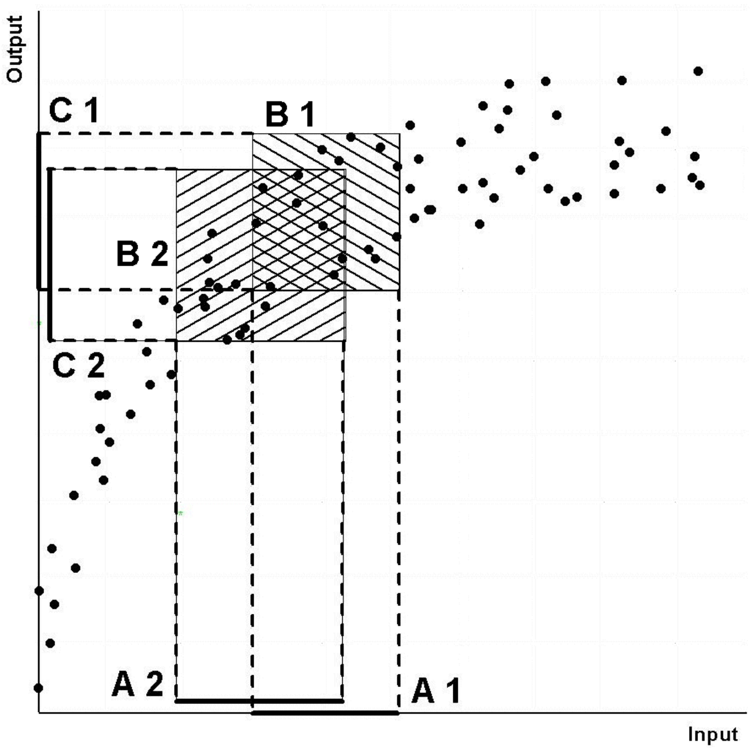

Figure 2.10: Graphical technique for designing membership functions using fuzzy patches. In this graph of equation $f(x) = (0.9\,x/(x + 0.2)) + \eta$, fuzzy patches (hatched) visualise graphical associations between Input and Output domain. The double hatched area contains points which belong to both patches.

The description below explains how, using the graphical technique in Figure 2.10, Kosko (1994) provides a simple framework to tackle the second phase of the general fuzzy modelling methodology outlined above. The diagrams in Figure 2.11 help the reader visualise this process.

Panel A shows the initial dataset as a combination of points and circles. The former represent the identification dataset comprised of 80 (x,y) pairs. The latter, the evaluation dataset, is made of the remaining 20 (x,y) pairs in this case. The training dataset generally comprises 1/4 to 1/3 of the overall dataset. Here the training dataset is only 1/5 of the data and the model still performs well which clearly demonstrates that this rule of thumb is not critical. These data are randomly selected with the exception of the minimum and maximum values which need to be incorporated in the training dataset in order to correctly define the boundaries of the model.

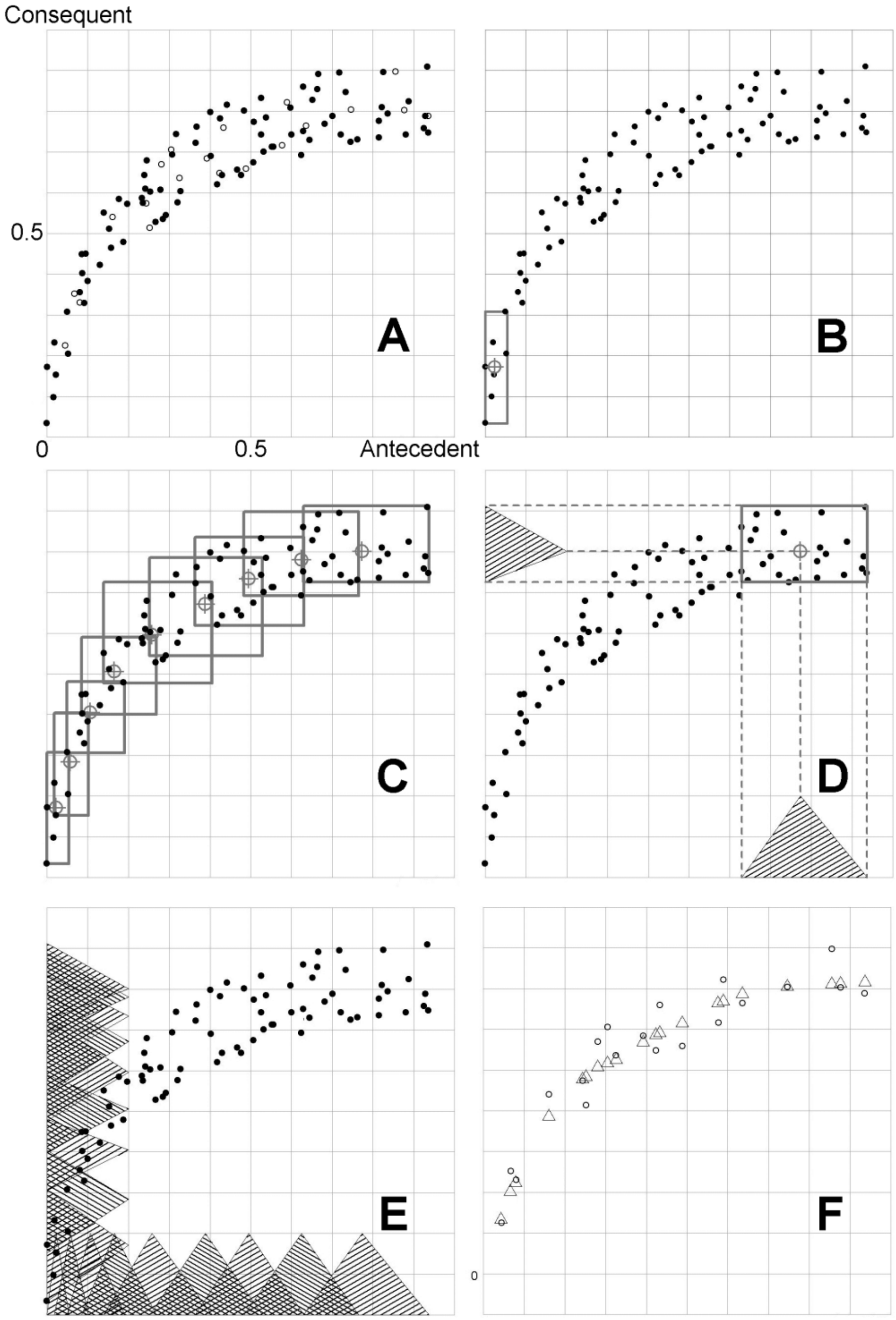

Figure 2.11: Stages of a graphical technique for designing membership functions using fuzzy patches. Solid dots and circles represent the whole dataset. Dots are used to train the model and circles to evaluate it. Panel F allows to visually estimate the performance of the model by comparing its predictions displayed as triangles, with the evaluation dataset shown as circles.

Panel B demonstrates how (x,y) pairs of the identification data set can be represented by the tightest box, or fuzzy patch, that contains them and its centroid (x_m,y_m)

defined by the averages of all x and y coordinates of the points in the fuzzy patch. Panel C extends the technique introduced in B to the whole dataset while ensuring that all successive fuzzy patches have a reasonable overlap. Panel D explains the relationship between fuzzy patches and triangular membership functions. Panel E provides an overview of the performance of the predictive fuzzy rule-based model derived from parameters embedded in triangular membership functions on the horizontal and vertical axes. F displays values of the training dataset as circles, identical to those in panel A, while triangles are the model predictions.

From the previous description of Figure 2.11, two questions immediately spring to mind. What dictates the size and location of a fuzzy patch? How many points should there be in a fuzzy patch? Both questions are answered by the principles previously outlined in section 2.5.3. Fuzzy patches should be designed to produce membership functions that follow these guidelines. If a reasonable model is obtained with five fuzzy patches and a negligible, improvement in predictive capability results from nine fuzzy patches, the five patch model is the best choice. Whether the improvement is negligible or not is dictated, on a case by case basis, by a more or less formal cost/benefit analysis. However, the procedure in n dimensional models is a lot more labour intensive and will be dealt with by a semi automatic approach described further in this chapter. To create the first patch, one must first decide on which axis to draw it. Although there is no total agreement on this matter, Bilgic and Turksen (2000, p. 215) write "Apply clustering on the output data and then project it into the input data". The vast literature on fuzzy logic teems with opinions that do not all carry the same weight. This statement, however comes from the first volume of the Handbook of Fuzzy Sets (Dubois and Prade, 2000), a series described by Zadeh (2000: p. 1) in his foreword of the seventh volume as "…an integrated, authoritative and up-to-date exposition of the entire body of knowledge centred on fuzzy set theory and its wide-ranging applications …". Mackinson (2000), a fishery research scientist with experience in practical applications of fuzzy logic, does not support the technique recommended by Bilgic and Turksen (2000) (written personal communication, July 2006). Disagreements among recognised experts on practical implementations of fuzzy logic are not unusual. They often reflect requirements specific to different domains of expertise. In this instance Mackinson (2000) is probably influenced by his work on knowledge modelling where membership functions are directly shaped by informants' answers. Bilgic and Turksen (2000) are more interested in data driven modelling where their approach considerably reduces the number of output membership functions. Bilgic and Turksen’s (2000) advice is adopted in the procedure detailed below.

The first patch, on panel B of Figure 2.11, starts at the origin of the y axis and extends up to the sixth point. This determines the height of the first patch. Its width is dictated by the range of x coordinates of all points in this patch. This initial patch aims at capturing the behaviour of the system described by this dataset for the lowest x values. This patch can be summarized by its centroid (x_{av},y_{av}) where x_{av} and x_{av} are respectively the average of x coordinates and y coordinates of all points in the patch considered. Narrow patches are better as they minimise the uncertainty of graphical association between x and y values. The second patch starts at the centroid of the first patch. The process is repeated in panel C until all points are covered by fuzzy patches. Panel D shows how each patch associates a range of x values (the projection of the patch on the x axis) to a range of y values (the projection of the patch on the y axis). These two projections are further refined by the centroid projections on the x and y axes. The projections of the patch and its centroid are summarised as a triangular membership function. The link between these two triangular membership functions is the fuzzy patch. This can be described in the statement below. This single logical expression is the building block of fuzzy rule-based modelling.

IF Membership Function X THEN Membership Function Y

Panel E in Figure 2.11 displays all triangular membership functions generated by this process. Their parameters are listed in Table 2.2 below. A minimum overlap of 20% is a general rule of thumb. While patches should be small enough to be associated with specific clusters of points that capture important details of the pattern of experimental data, their number must be kept as small as possible for practical reasons. A successful design therefore corresponds to a good compromise between number of patches, sufficient overlap and adequate coverage of distribution peculiarities by individual patches. Many possible arrangements of fuzzy patches can be proposed for the same dataset. Experience, however, proves that only a few trials are necessary to come up with a solution that only marginally improves with further refinements. The risk, in traditional statistics, of over fitting the noise rather than the signal is thus minimised. Table 2.2 below lists the coordinates of the membership functions displayed in panel E of Figure 2.11. Consequent membership functions (on the vertical axis in panel E) and antecedent membership functions (on the horizontal axis in panel E) left are defined by the apex coordinates. Table 2.2 summarises all information required to define the membership functions of the of the fuzzy rule based model that will represent the point distribution in Figure 2.11. Characteristics of the fuzzy patches themselves may be incorporated as weightings in the model to modulate the relative influence of the rules.

Table 2.2: Membership function coordinates derived from panel E in Figure 2.11.

Membership Function (mf)	x(Antecedent or Input)			y (Consequent or Output)		
	a	b	c	a	b	c
1	0.00045	0.02363	0.054	-0.06639	0.07227	0.20765
2	0.01889	0.05829	0.10236	0.05211	0.18402	0.30428
3	0.04893	0.10739	0.19031	0.20613	0.30494	0.38089
4	0.08494	0.16584	0.2692	0.30097	0.40658	0.48961
5	0.13918	0.25817	0.40485	0.37782	0.4954	0.62569
6	0.25244	0.38907	0.5286	0.44389	0.57191	0.68486
7	0.36391	0.49513	0.63068	0.51852	0.63377	0.73586
8	0.48272	0.62506	0.76514	0.59127	0.68044	0.79801
9	0.62886	0.77337	0.93755	0.62501	0.7004	0.81243

2.6.2 Membership functions, fuzzy patches and accounting for the relative reliability of rules

Narrow membership functions are more precise than wide membership functions. The wider a membership function the less specific it is. A membership function containing only a few values is not as representative as one containing many values for the same width. Intuitively, the higher the density of information, the more important the rule is. Therefore, the density of values in fuzzy patches, in absence of additional information, is an important consideration when designing a fuzzy rule-based model. This density of information in fuzzy patches can be translated into weightings, displayed in Table 2.3, that reflect the reliability of each rule relatively to the other rules. These weightings are calculated by dividing values in the Points column by values in the Area column to obtain figures in the Density column. Weightings are normalised by dividing all density values by the maximum density to obtain weightings between 0 and 1. The highest weighting in Table 2.3 corresponds to the patch at the bottom of panel C in Figure 2.9. Patch data density may be normalised for each variable or across the whole dataset. Either way, issues unfortunately arise regarding the ability of this ranking to reflect the actual influence of the respective variables on the output.

Table 2.3: Fuzzy patch properties derived from panel E in Figure 2.11.

Patch	Area	Points	Density	Weighting
1	0.015	7	466.67	1.00
2	0.021	8	380.95	0.82
3	0.025	10	400.00	0.86
4	0.035	13	371.43	0.80
5	0.066	20	303.03	0.65
6	0.067	18	268.66	0.58
7	0.058	23	396.55	0.85
8	0.058	24	413.79	0.89
9	0.058	24	413.79	0.89

More objective methods of weighting evaluation rely on soft computing (Dubois and Prade, 1998; Ishibuchi and al., 2002). However, these methods are not considered in this thesis as the resulting additional level of complexity imparted to fuzzy rule-based modelling is detrimental to its ease of implementation. In addition, Chapter 5 explores a knowledge driven model where weightings appear to have little influence on predictions which suggests that although weightings reflect important properties of a variable and are easy to generate, they may not always be effective. Their role is most important where datasets are not too noisy and contributions of input variables to the output are clear. Weightings are used in subsequent chapters and their contribution discussed on a case by case basis.

2.6.3 From membership functions to fuzzy rules

The first phase of the design of a fuzzy rule-based model consists in identifying input and output variables. The second phase, called identification, defines all properties of the membership functions of each variable in four steps. Firstly the original dataset is segmented into a training dataset and an evaluation dataset. Secondly the number of fuzzy patches is set to adequately capture all aspects of the dataset considered. Thirdly the shape and coordinates of the corresponding membership functions are derived. Finally rule weightings are evaluated when appropriate. Below, nine rules are defined.

Rule 1	IF	Input MF 1	THEN	Output MF 1	Weighting = 1
Rule 2	IF	Input MF 2	THEN	Output MF 2	Weighting = 0.82
Rule 3	IF	Input MF 3	THEN	Output MF 3	Weighting = 0.86
Rule 4	IF	Input MF 4	THEN	Output MF 4	Weighting = 0.80
Rule 5	IF	Input MF 5	THEN	Output MF 5	Weighting = 0.65
Rule 6	IF	Input MF 6	THEN	Output MF 6	Weighting = 0.58
Rule 7	IF	Input MF 7	THEN	Output MF 7	Weighting = 0.85
Rule 8	IF	Input MF 8	THEN	Output MF 8	Weighting = 0.89
Rule 9	IF	Input MF 9	THEN	Output MF 9	Weighting = 0.89

The above set of rules defines how fuzzy antecedents relate to fuzzy consequents. The next section details the functions of a fuzzy model which turn these fuzzy rules into a predictive framework.

2.7 Structure and functions of a fuzzy rule-based model

An abundant literature on fuzzy rule based-modelling (Dubois and Prade, 1996), ranging from superficial but practical (Von Altrock, 1995) to advanced (Kandel, 1986), is not always relevant to the intent of this thesis, which is to simplify GIS modelling by providing a unified predictive framework in GIS modelling. Four sources of information were very influential in shaping sections of this chapter and the overall fuzzy rule-based modelling strategy detailed in this thesis. Bardossy and Duckstein (1995) provide a complete and readable coverage of applied fuzzy-rule based modelling. Klir and Bo Yuan (1995) offer an excellent background on a wide range of aspects of fuzzy logic and fuzzy modelling. Babuska's (1996) study of fundamental differences between Mamdani and Takagi-Sugeno type fuzzy rule-based models contains clear and in depth coverage of important technical issues. Cox (1999) focuses on practical aspects of the implementation of fuzzy rule-based models. Research in alternative interpretations of fuzzy rules (Shepard, 2005; Jones *et al.*, 2009) reveals an interesting evolution of fuzzy rule-based systems. While Shepard (2005) describes fuzzy rule-based systems in perfect agreement with previous references, Jones *et al.* (2009) reflect in their work the growing interest in fuzzy rule-based systems of gradual implicative rules. These systems are not considered in this thesis as they do not have many applications yet. However, since they lead to a different type of knowledge representation (Jones *et al.*, 2005) they may well provide practical improvements to current fuzzy rule-based models.

Sections 2.7.1 to 2.7.6 of this Chapter rely on the sources of information cited above to explore the structure of fuzzy rule-based models. The four functions of a fuzzy rule-based model are in chronological order fuzzification, implication, aggregation and defuzzification. The implementation and integration of these functional blocks was initially explored in Excel (Kelly, 2006). A functional fuzzy rule-based modelling application called EXFIS (Excel Fuzzy Inference System), described in Appendix 1, was implemented. Detailed expressions for operators described in sections 2.7.1 to 2.7.6, including rule weighting algorithms, can be found in Appendix 1.

2.7.1 Diagrammatic representation of fundamental processes in a fuzzy rule-based model

The diagram in Figure 2.12 refers to the Mamdani inference system (Babuska, 1996) which represents the first practical implementation of Zadeh's (1965) principles of fuzzy logic. Mamdani, who worked on the development of control systems in the 1970's at Queen Mary College in London, devised a fuzzy controller for cement kilns built in the early 1980s. Mamdani’s inference system is associated with the first industrial implementation of fuzzy logic. Other models are not discussed in this thesis as they have very few practical applications to natural systems and NRM. These include the singleton model, the fuzzy relational model and the Takagi-Sugeno (TS) model (Babuska, 1996). The TS inference system is very popular in engineering where the general shape of the output is often known. The output of natural systems can rarely be represented by a simple mathematical expression. Mamdani type inference systems do not require predefined output mathematical expression. What follows focuses therefore on Mamdani type inference systems which are better suited to GIS modelling. Adding membership degrees to the conclusion, as depicted in Figure 12.2, however is to be attributed to Kosko (1994), as Mamdani and Assilian

(1975) used maximum instead of sum and centroid defuzzification to evaluate the output in Figure 2.12.

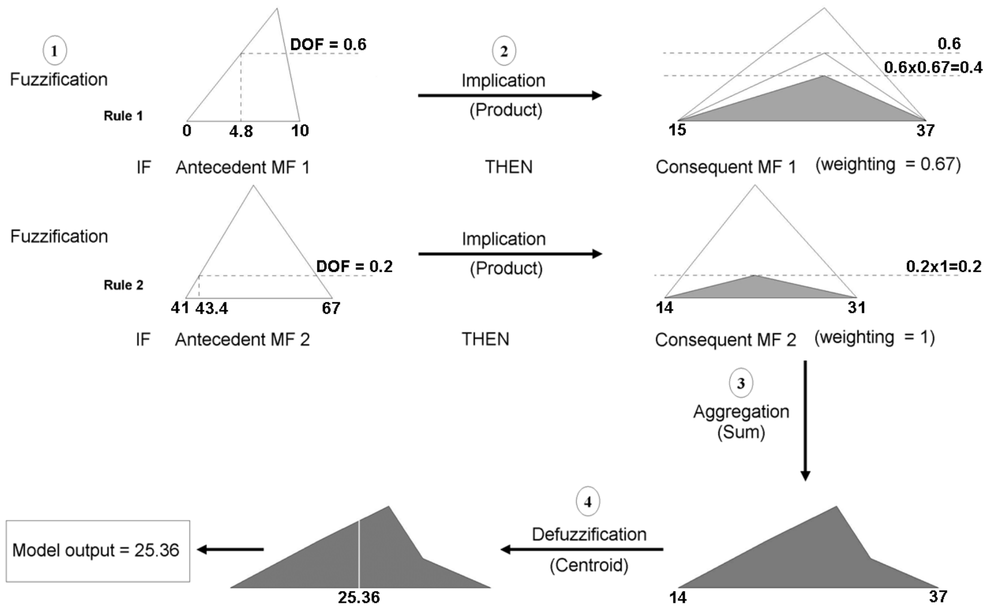

Figure 2.12: Succession of processes in the development of a fuzzy rule-based model, also called Fuzzy Inference System (FIS). There are only 2 rules defined by 4 membership functions. The Output is 25.36 and the Input vector (4.5, 43.4).

Figure 2.12 is the diagrammatic representation of a simple fuzzy rule-based model with multiple inputs and a single output (MISO). This type of model can be considered as the fundamental building block of fuzzy rule-based predictive models. All membership functions of the model in Figure 2.12 are triangular. Only two rules fired by the input value are displayed in this model. Four sequential tasks are successively completed by four separate operators. Rule 2 carries a higher weighting than rule 1 as a result of decisions made during the identification process. The prediction of this model for the input vector (4.8, 43.4) is 25.4. The Degree of Fulfilment of Rule (DOF) is the level to which a rule applies. This degree is measured by the membership of the input value in the antecedent membership function of the corresponding rule. In this model, the value 4.8 fires Rule 1 to only 60% of its maximum effect and its DOF is therefore 0.6. The value 43.4 fires Rule 2 at only 20% of its maximum capacity: rule 2 has a DOF of only 0.2. As they are only partially fired they are vertically rescaled in proportion. These results are combined through the graphical addition of the two membership functions. The output therefore is a shape which grows in size with the number of rules fired. The answer remains vague and needs to be defuzzified if it has to have any practical application. The defuzzified result is the single value which accounts best for the respective contribution of all rules fired. Here the centre of gravity (COG) is the defuzzification method used. It consists in projecting the centre of gravity of the sum of all rule membership functions, modified by their DOF and weighting, on the horizontal axis, as the clustering of the output variables is generally imposed on the input variables (Bilgic and Turksen, 2000: p.215). This position corresponds to the x coordinate of the largest combined contributions of all fired rules to the final result. Here the final output of the model is 25.36.

The model in Figure 2.12 has only two variables and only two rules are fired. In reality a minimum of two rules are frequently fired in each variable as a result of membership functions overlap. Real models generally have a minimum of three rules per variable. The model in Figure 2.12 is a MISO model. A combination of MISO models can achieve the same outcome as any multiple input multiple output (MIMO) model. The resulting model is less compact but more transparent. MISO high dimensionality predictive models are more readable and are therefore preferred in this thesis. Natural systems are typically described by a large number of parameters in addition to geographical dimensions. The architecture of fuzzy rule based models and their ability to tackle high dimensionality problems is consequently well suited to predictive modelling applications for natural resources management in a GIS environment.

2.7.2 Fuzzy rule-based modelling operations

The four steps of processing in a fuzzy rule-based model, displayed in Figure 2.12, rely on algebraic operations that need to be defined. These operations often lead to a great deal of confusion. Venn diagrams provide the basis for the definition of the two fundamental operations on sets called union and intersection. Union and intersection are operations on sets similar to addition and multiplication on real numbers, respectively. This however, casts little light on the algebraic expression used to evaluate the following fuzzy logic statement.

V1_MF1(0.5) AND V2_MF2(23)

In other words, how do we algebraically express AND/multiplication and OR/addition to perform operation(s) on degrees of membership? A number of texts (Kandel, 1986; Terano *et al.*, 1992; Bouchon-Meunier, 1993; Bardossy and Duckstein, 1995) provide in depth discussions of theoretical considerations leading to the choice of fuzzy operators available. The last reference is probably the most relevant to our needs. Bardossy and Duckstein (1995) give a concise and clear justification of the unusual variety of pairs of operators playing in fuzzy logic roles equivalent to those of addition and multiplication on real numbers. Firstly, the problem consists of finding practical mathematical expressions of addition and multiplication on membership functions that have all the desirable theoretical set properties. Secondly, these expressions need to be mathematically tractable. Thirdly, they need to make sense when applied to real problems. The fuzzy logic literature offers many operations which can perform the four steps in Figure 2.12.

Only some of the operations described in the literature are available in the fuzzy modelling software used in this thesis. Brief discussions of some theoretic aspects of fuzzy logic are necessary for two reasons. Firstly, fuzzy modelling is often dismissed (Dubois and Prade, 1994; Cox, 1999) by proponents of alternative mathematical models of vagueness who do not share the same scientific background (Dubois and Prade, 1993: p.1059). They fail, for instance to appreciate the synergy of merging statistical and fuzzy modelling to simultaneously address both uncertainty and imprecision as explained in Chapter 1. Secondly, a software like Matlab and Scilab, used to construct and evaluate fuzzy models, requires to make a number of choices including t-norm and t-conorm, implication and aggregation operators as well as defuzzification methods. The following sections are therefore necessary for the implementation fuzzy rule-based models discussed in Chapters 4 and 5.

2.7.3 t-norm (fuzzy intersection) and t-conorm (fuzzy union) operators

As mentioned earlier, familiar algebraic addition and multiplication do not apply to sets. Union and intersection are their equivalent in set theory. Union and intersection, are readily compatible with logic operators OR and AND used to combine membership functions. They do not however apply to membership values contributed by the respective antecedent membership functions in the rule below.

IF Input1 AND Input2 OR Input3 THEN Output1

In the context of fuzzy rule-based modelling, logical operators AND and OR are assigned algebraic expressions called t-norm, or fuzzy intersection, and t-conorm or fuzzy union ((Klir and Bo Yuan, 1995: p.62). Algebraic expressions generally need to satisfy at least the four conditions of commutativity, associativity, monotonicity and idempotency. Among all possible contenders, only a small number of algebraic expressions meet these four conditions and lead to meaningful results when applied to the physical world. The first pair of t-norm and t-conorm operators proposed by Zadeh (1965) were the minimum and maximum functions. Below is a brief discussion of some practical implementations of t-norm and t-conorm operators.

Once a t-norm (multiplication like operator) has been selected, the t-conorm (addition like operator) is fixed as they are mathematically linked by the two equations below where c and t respectively represent t-conorm and t-norm.

$t(x,y) = 1-c(1-x, 1-y)$ Equation 2.3

$c(x,y) = 1-t(1-x, 1-y)$ Equation 2.4

Researchers strived to propose t and c expressions with realistic outcomes. Among them, Yager, Dubois and Prade (Klir and Bo Yuan, 1995: p.74, p. 82) proposed suitable expressions meeting the conditions defined in Equations 2.3 and 2.4. Bardossy and Duckstein (1995) consider t-norms and t-conorms performance within the context of fuzzy rule-based modelling applied to geophysical, biological and engineering systems. They propose a short list of 5 norm conorm pairs (Bardossy and Duckstein, 1995: p.13). The choice of norm conorm pair reflects the type of application as well as the modeller's preference. Bardossy and Duckstein (1995) prefer the product-sum defined by the two equations below where x and y are membership values.

$t(x,y)$: x AND y $= xy$ Equation 2.5

$c(x,y)$: x OR $y = x + y - xy$ Equation 2.6

In addition to being mathematically simpler than alternative expressions, the algebraic product-sum is supported in Matlab and Scilab, both used in case studies discussed in this thesis. The algebraic product-sum is therefore the (norm, conorm) pair used in this thesis.

2.7.4 Implication: degree of fulfilment of a rule (DOF) and product inference

The level of truth of IF …THEN statements is called the degree of fulfilment (DOF) of the corresponding rule. Fuzzy rule-based modelling does not directly deal with fuzzy sets but with the membership values of elements in fuzzy sets which ultimately dictate the DOFs of all rules of the model. Figure 2.12 shows simple logical statements lead to straightforward DOF calculations. One fundamental concern is therefore the evaluation of the level of truth of a logical statement combining at least two antecedent variables.

IF Hot AND Humid OR Dusty THEN Uncomfortable

The antecedent premise above, like those displayed in Figure 2.12, does not necessarily combine multiple fuzzy sets such as ‘Hot’ and ‘Humid’ in the rule above. Data driven models rarely do as they generally rely on direct associations between input and output variables while knowledge driven models, on the contrary, often do as they replicate logical associations between multiple causes and effects common in human languages. Mathematical expressions are therefore required to evaluate the level of truth of the above logical statement from the DOFs of antecedent premises.

Bardossy and Duckstein (1995) offer clear guidelines to evaluate the DOF of the statement above for all possible combinations of antecedent premises. Following their terminology, the Greek letter ν is the symbol used for DOF. Let us assume that we are interested in evaluating logical statements involving the memberships $\mu_{A1}(a_1)$ and $\mu_{A2}(a_2)$ of elements a_1 and a_2 in fuzzy sets A_1 and A_2. We need to translate, into an algebraic expression, the DOF of fundamental logical operators AND, OR, NOT, XOR. Based on product-sum expressions in Equations 2.5 and 2.6, the following expressions are proposed.

$\nu(A_1) = \mu_{A1}(a_1)$

$\nu(\text{NOT } A_1) = 1 - \mu_{A1}(a_1)$

$\nu(A_1 \text{ AND } A_2) = \mu_{A1}(a_1).\ \mu_{A2}(a_2)$ Equation group 2.7

$\nu(A_1 \text{ OR } A_2) = \mu_{A1}(a_1) + \mu_{A2}(a_2) - \mu_{A1}(a_1).\ \mu_{A2}(a_2)$

$\nu(A_1 \text{ XOR } A_2) = \mu_{A1}(a_1) + \mu_{A2}(a_2) - 2\ \mu_{A1}(a_1).\ \mu_{A2}(a_2)$

The algebraic expression of an antecedent with any combination of the 4 logical operators above can be derived from Equation group 2.7 above. In addition to these familiar logical operators, Bardossy and Duckstein (1995) offer additional operators such as MOST OF THE PROPOSITIONS and at AT LEAST A FEW that play important roles in special applications of fuzzy logic such as the control of traffic lights. These belong to a group of linguistic expressions, called hedges, which include linguistic terms such as MORE, SLIGHTLY, etc. They modulate fundamental linguistic terms such as GOOD, BAD. A number of mathematical definitions have been proposed (Bardossy and Duckstein, 1995: p. 15) for a variety of hedges. Their objectivity, however, appears questionable. They may play a useful role in knowledge modelling but it seems difficult to ascertain that informants agree with the way ‘hedges’ modify the information they contribute. Hedges are not considered in this thesis as I believe that they would add an unnecessary level of subjectivity detrimental to the overall transparency of the final model.

Applications considered in this dissertation do not require complicated logical combinations of antecedents, and nor does the complete fuzzy rule-based expert system of Cheung *et al.* (2005) described in Chapter 5. In all examples considered in this thesis, data as well as knowledge driven fuzzy rule-based models can be exclusively built from rules associating a single antecedent membership function to a single consequent membership function. If this approach is unsuitable, equations in this section enable the derivation of appropriate algebraic expressions suited to the most complicated logical statements. Simple and short fuzzy rules remain one of the most desirable features of a good fuzzy rule-based model. Increasing the number of rules appears to be a better option than increasing their complexity. Transparency and simplicity guide models discussed in this thesis.

2.7.5 The role of implication in fuzzy rules

Implication consists in reflecting the DOF of a rule in the output membership function of this rule. The implication operator THEN thus transfers the DOF of the antecedent which can be, as discussed in the previous section, either a single membership function or a series of membership functions linked by logical operators. The DOF of the output membership function, as shown in Figure 2.12, rescales the output membership function. Practically this rescaling is achieved, in triangular fuzzy number for instance, by multiplying the central value by the DOF. A triangular output membership function of a rule whose antecedent has a DOF of 0.5 is therefore only half of its maximum height of 1. For a DOF of 0 the output membership function has a height of 0. Consequently the corresponding rule is not expressed. A DOF of 1, on the contrary, means that the output membership function has its maximum size and is therefore fully expressed. The implication process therefore modifies the height of the output membership function, and therefore its centre of gravity.

2.7.6 Rule combination

Bardossy and Duckstein (1995) outline three important properties of rule combination. The first property, idempotence, ensures that a rule can be combined with itself without changing its outcome. The second and third properties, associativity and symmetry, are necessary to ensure that rules can be combined in any order. Out of all possible rule aggregation methods the most commonly used are minimum, maximum and addition. The latter is often preferred because all rule contributions are incorporated. Minimum and maximum, on the contrary, fail to account for repeated consequences. This lack of sensitivity to smaller individual contributions, even if they occur in large number, amounts to a loss of information. The sum combination does not suffer from this limitation and can be weighted as well while weightings clearly play no role in minimum or maximum aggregation methods. There are good reasons to explore in detail aggregation methods and the type of logical operator used. The Combs method (Cox, 1999) for instance addresses the combinatorial rule explosion problem by a clever replacement of AND by OR. This thesis however steers away from such advanced concepts to provide a robust and simple approach to the development of rule-based models.

2.7.7 Defuzzification

The output of a Mamdani type fuzzy model (Mathworks, 1995) is the graphic sum of individual membership function polygons contributed by each rule of the fuzzy rule-based model. The output is therefore a polygon positioned within the range of output values. This polygon provides, through its size, shape and position on the output axis, a vague indication of what the corresponding output value should be. Defuzzification transforms this polygon into a number. Defuzzification, contrary to other facets of fuzzy rule based modelling does not appear to be supported by a robust theoretical framework. Cox (1999: p 31) stresses that defuzzification methods are not derived from fuzzy theory. They are merely acceptable empirical recipes to translate the position of a polygon on a horizontal axis into a single number. Justifications for the different methods proposed are directly linked to the performance of the model. As performance is a compromise between efficiency and accuracy, algorithms preferred in the 1970s, such as maximum, were largely driven by computational constraints of the time. However, since the 1970s, due to a remarkable evolution of information technology, the overall best algorithms can now be adopted instead. The three most popular methods of defuzzification (Klir and Bo Yuan, 1995; Babuska, 1996; Cox, 1999; Bardossy and Duckstein, 1995) are the centre of area, also called centre of gravity (COG), the mean of maxima (MOM) and the maximum. COG and MOM are compared in Figure 2.13. Although results are close, MOM prediction only changes if the maximum rule value changes.

COG is more sensitive as any modification of grey triangles in Figure 2.13 will affect the COG position and therefore model prediction. COG is generally preferred as it combines, contrary to maximum, the output of all rules. Furthermore COG is part of the methodology described by Kosko (1994) in his seminal paper on fuzzy rule-based systems as universal approximators. COG is the defuzzification method used in all applications described in this thesis. Well supported by both Matlab and Scilab fuzzy toolboxes, the underlying principle is intuitively more acceptable than any value read from the position of local maxima or minima.

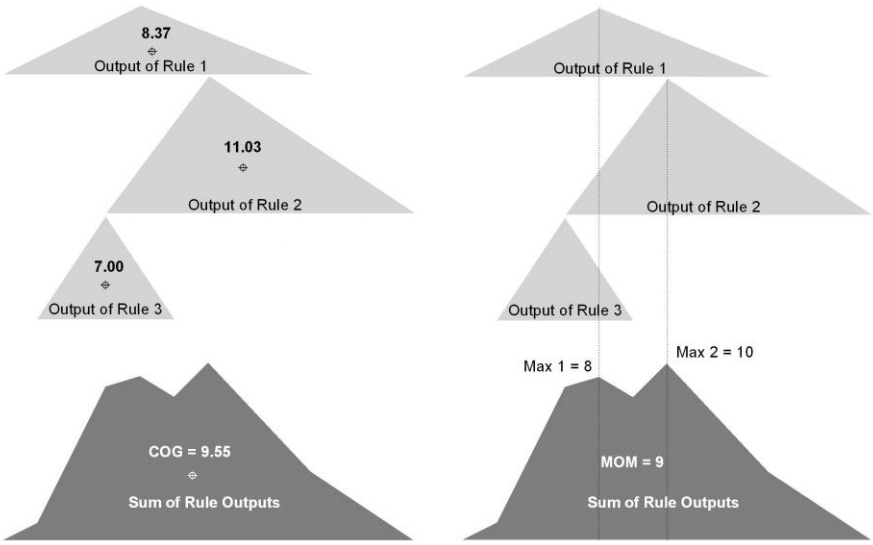

Figure 2.13: Comparison of two defuzzification methods - Centre of gravity (COG) on the left and mean of maxima (MOM) on the right. Rule outputs of the fuzzy rule-based model are the three grey triangles. The overall output of the model is the dark grey polygon obtained by adding up the three light grey triangles.

2.8 Implementation of a fuzzy rule-based model

The fuzzy rule-based strategy detailed in section 2.7 is applied to the problem defined in section 2.6. Fuzzy rule-based modelling is computationally demanding and therefore relies heavily on specialist software. Five different pieces of software were used to build the models described in this thesis.

ArcView 3.2 (Lee and Wong, 2001), with various extensions, is the only GIS software used in this thesis. The role of ArcView 3.2 is described in Chapter 3 and Appendix 3. Fuzme (Minasny and McBratney, 2002), a clustering freeware created at Sydney University, provided the segmentation capability required in Chapter 4. Excel (Kelly, 2006) was used to develop a fuzzy rule-based modelling environment detailed in Appendix 1. This proved to be a very useful training environment. Matlab (MathWorks, 1999) and Scilab (Campbell *et al.*, 2006) are the applications most fuzzy rule-based models described here were built in. Scilab is a free Matlab clone. A step by step implementation of fuzzy models in Scilab is presented in Appendix 4.

The problem defined in section 2.6 is solved in Scilab using sciFLT (Urzua, 2004), the Scilab Fuzzy Logic Toolbox.

2.8.1 Model implementation in Scilab

Figure 2.14 to 2.17 visualise all information described in section 2.7 that need to be entered in Scilab to build the model in Figure 2.11.

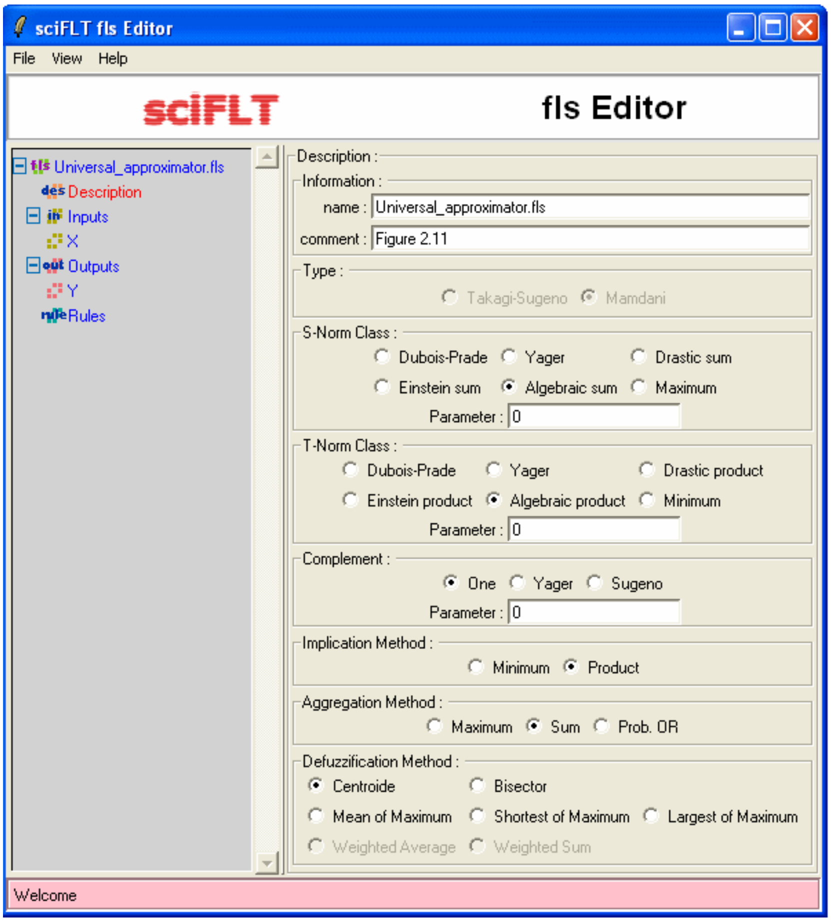

Figure 2.14: Screenshot of fls Editor of sciFLT showing the Description panel where the type of model and its parameters can be easily selected.

The Description panel, in Figure 2.14 above, enables the selection of suitable parameters including t-norm and t-conorm pairs, implication, aggregation and defuzzification operators to completely describe the Mamdani type fuzzy rule-based model required. Although there is little doubt that some combinations perform better in some specific contexts, the selection of operators displayed in this panel was used in all applications considered in this thesis.

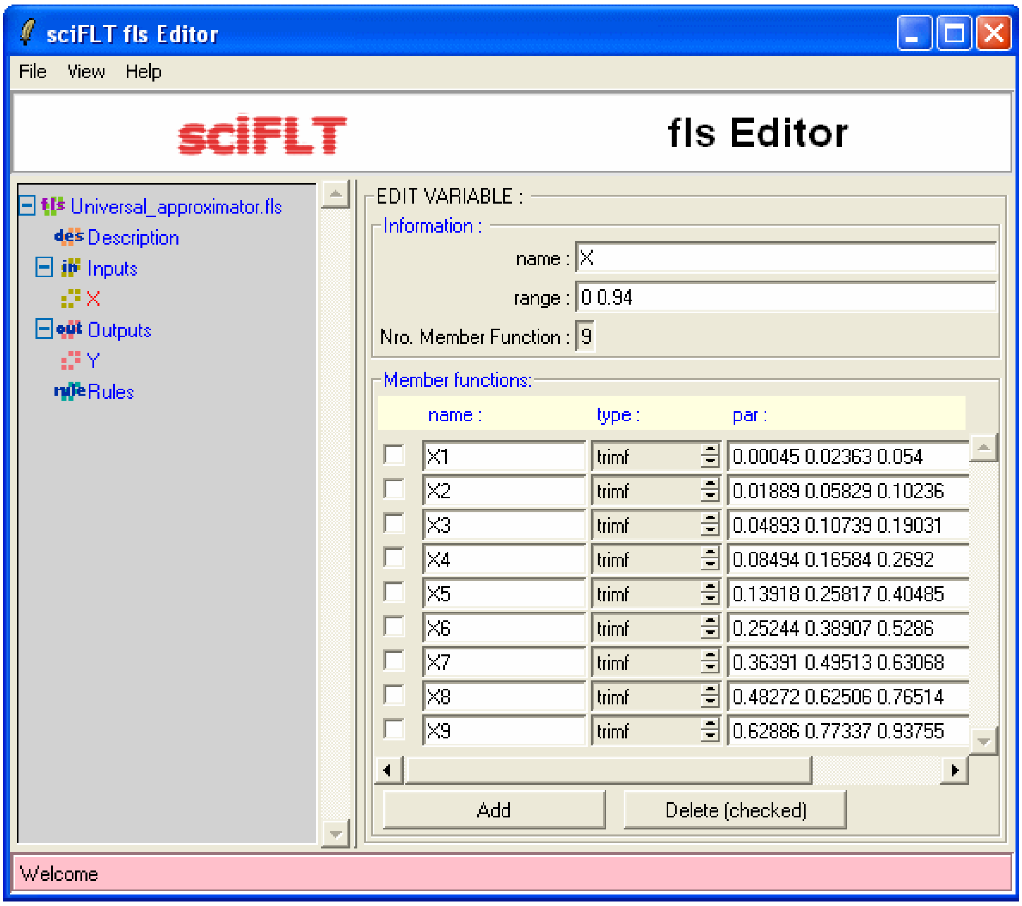

Figure 2.15: Screenshot of fls Editor of sciFLT showing the Rule definition panel where the type of membership, its parameters and the name of the corresponding rule are entered.

Figure 2.15 shows the nine membership functions (X1 to X9) of X, the only input variable in this model. The scilab toolbox sciFLT offers several membership function types. The type selected here is “trimf” which stands for triangular membership function. Once the type is selected the range of values covered, [0,0.94] in this case, and the coordinates of the three apices of each membership function are entered in the column under “par” for parameters. The same procedure is adopted to define the Y output variable. All input and output membership functions parameters are entered as shown in Figure 2.15. The model requires five operators to be defined from the sciFLT window in Figure 2.14. The algebraic sum and algebraic product for the (norm, conorm) pair are picked from the ‘S-Norm Class’ group and ‘T-Norm Class’ groups respectively. One is selected from ‘Complement’ for the maximum membership value. The ‘Implication Method’ is set to product. Sum is the ‘Aggregation Method’. Finally centroid (COG) is selected for the ‘Defuzzification

Method'. Most default settings are kept with exception of the aggregation method which is Maximum by default.

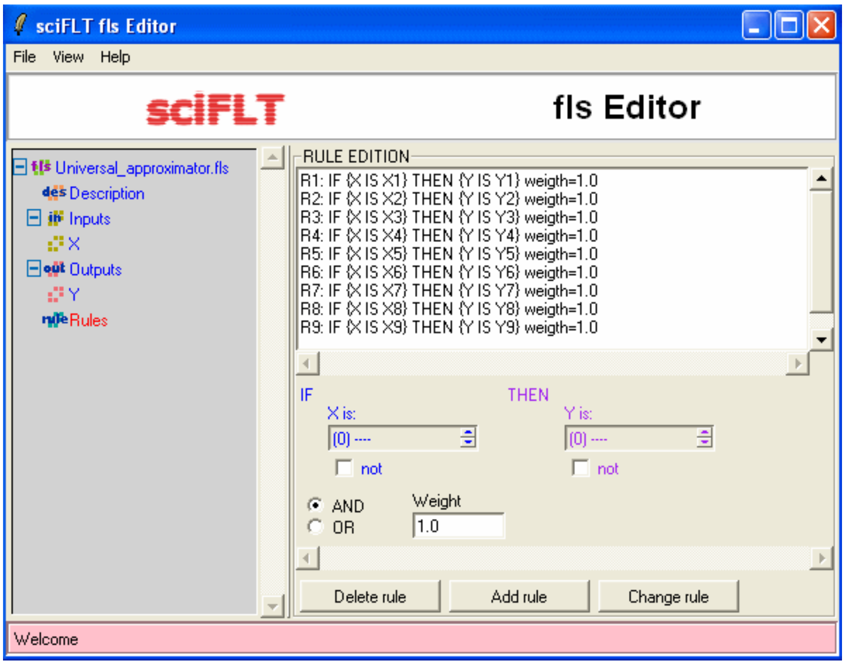

Figure 2.16: Screenshot of fls Editor of sciFLT showing the Rule definition panel where membership functions defined in Figure 2.15 are embedded in rules.

All possible associations between input and output membership functions defined by the fuzzy model are expressed as rules. This model is completely defined by nine rules displayed by the fuzzy logic system (fls) editor in Figure 2.16. All rules have the same default weighting 1. Figure 2.17 summarises this model as Mamdani (m) type model with 1 input, 1 output and 9 rules.

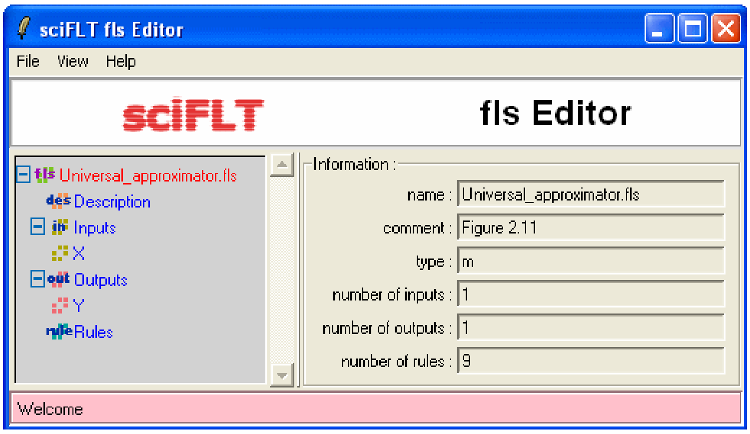

Figure 2.17: Screenshot of fls Editor of sciFLT showing a summary of the characteristic features of this universal approximator model.

2.8.2 Model evaluation

Figure 2.18 compares the values of the evaluation dataset, represented by circles in panel F of Figure 2.11, with model predictions based on the x coordinates of these records. The cloud of points is well aligned on the diagonal through the origin. This first impression is confirmed by the high correlation coefficient is 0.964. Any improvement on this model would require additional time and effort which a cost/benefit analysis may show to be unwarranted within that context. The dataset considered, like most real NRM datasets, contains a stochastic component that no model can replicate, thus making a correlation coefficient of 1 beyond the reach of models of natural systems. The model once completed is still a fuzzy rule-based model. It does not have an equivalent algebraic expression. Outputs, however, can then be fed into algebraic expressions downstream from the modelling process.

Y experimental	Y modeled
0.231	0.233
0.414	0.489
0.606	0.524
0.797	0.713
0.548	0.589
0.704	0.713
0.126	0.146
0.705	0.709
0.536	0.533
0.570	0.513
0.584	0.572
0.665	0.691
0.475	0.483
0.616	0.667
0.722	0.672
0.440	0.394
0.253	0.207
0.560	0.616
0.660	0.593
0.689	0.713

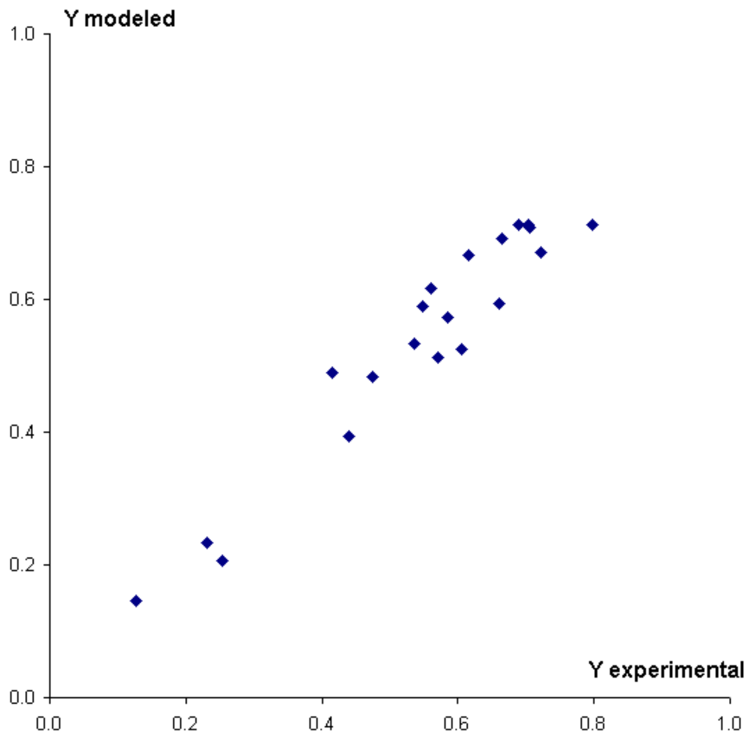

Figure 2.18: Model predictions plotted against experimental values.

The performance of the model is assessed by plotting, in Figure 2.18, the model predictions against experimental values. Although not forming a perfect straight line at 45 degrees gradient through the origin, this plot is representative of a good predictive model.

Summary

Predictive models are classified as white, grey or black box type. Owing to the direct association between rules and modelled processes, the transparency of fuzzy rule-based models puts them in the grey box category. Membership functions, a key component of fuzzy models, play a crucial role in making rules highly readable particularly when linguistic terms are used. A comparison of Boolean and fuzzy logic sheds some light on the contribution of membership functions to an improved description of natural processes. Membership functions allow fuzzy predictive models, unlike their Boolean counterparts, to be built from the very linguistic terms humans naturally rely on in their predictive reasoning. The versatility of membership functions comes at a price. There are many designs to choose from. Fortunately the simplest of all, the triangular membership is the most widely used as it performs well in most situations.

Much as been written about the statistical nature of membership functions as fuzzy and statistical representation of uncertainty have often been pitted against each other. Although Zadeh (1965) initially declared the concept of membership function to be non statistical, Dubois and Prade (1993) consider that the issue is multifaceted. Regardless of the controversy, membership functions offer real advantages in the GIS representation of geographic entities. These encompass a variety of sources of uncertainty better accounted for by a combination of statistics and fuzzy logic than by statistics alone. Although membership functions are particularly well suited to the representation of the linguistic terms, they are equally well suited to stochastic uncertainty. Owing to the importance of their role, the acquisition of membership function deserves some attention. Kosko's (1994) concept of fuzzy patches and universal approximator is widely implemented in this thesis. Fuzzy patches are graphical visualisations of the fuzzy association between input and output data. They provide a generic framework for membership function design, thus a universal technique to make predictions on the basis of observations and therefore to predictive modelling. The method is articulated around three processes which are in chronological order: identification, implementation and evaluation.

Identification is concerned with the definition of all components of the model. Input and output variables are all translated into membership functions. Parameters describing each membership functions are calculated. Rules and their corresponding weightings, if necessary, are directly derived from associations observed in the training dataset between input and output data.

Implementation consists in applying the fuzzy rule-based model previously defined to input data. Four successive processes are involved: fuzzification, implication, aggregation and defuzzification. These steps are better summarised diagrammatically as a flowchart. A range of possible mathematical operators is available to perform each of the four processes. Although both Takagi-Sugeno and Mamdani fuzzy rule-based models are widely used, only the latter is considered in this thesis. The implementation is computationally demanding and therefore relies on purpose built software. Scilab fuzzy logic toolbox is the main software used in case studies of this thesis.

Evaluation consists in assessing the performance of the model by comparing predictions and actual values. The evaluation metric used in this thesis is the correlation coefficient between observations and model predictions. This familiar metric confirms that, in the case study considered in this chapter, the fuzzy rule-based model created has very good predictive capabilities. Its correlation coefficient of 0.96 is very close to 1 which corresponds to a perfect model.

CHAPTER 3

GIS FUZZY MULTICRITERIA DECISION ANALYSIS

Overview

Fuzzy multicriteria decision analysis in a GIS is not a mainstream application of fuzzy logic. Although well adapted to GIS functionality, its scope remains limited in comparison with fuzzy rule-based modelling, the focus of this thesis. This chapter introduces a purpose specific implementation of fuzzy logic well integrated in the GIS modelling procedure. This high level of integration, however, results in a more complicated GIS modelling framework. Chapters 4 and 5, in contrast, demonstrate that fuzzy rule-based modelling does not impact on the modelling simplicity which makes GIS so attractive (Goodchild, 2000).

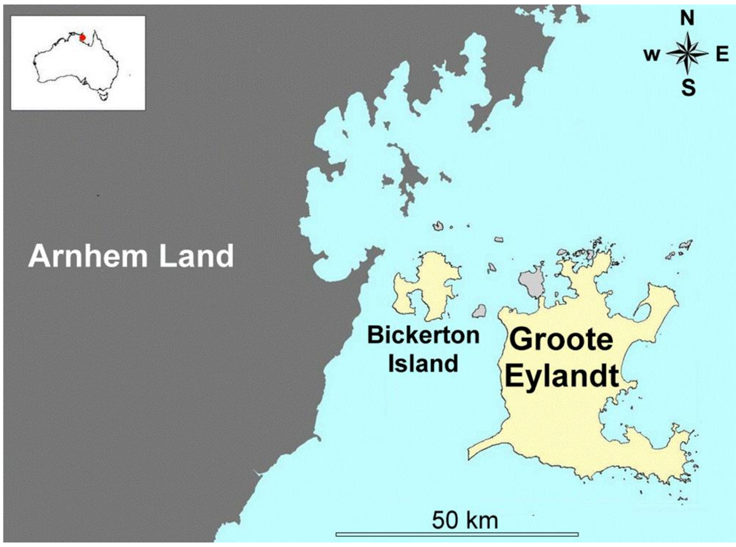

Figure 3.1: Map of the study area of the Anindilyakwa Aquaculture GIS (AAGIS). AAGIS relies on fuzzy logic to identify prospective sites for the development of prawn aquaculture on Groote Eylandt and Bickerton Island, in the remote North East of the Northern Territory.

The case study explored in this chapter brings to the front land management issues that can be well addressed by multicriteria decision analysis (MCDA). The integration of fuzzy and spatial concepts in aquaculture is demonstrated in an analysis of site suitability for prawn farming. The geographical context is Groote Eylandt, a remote island on Aboriginal Land in the Gulf of Carpentaria of Northern Australia (Figure 3.1). GIS plays a crucial role in this investigation by combining conflicting spatial requirements embedded in multiple geographic overlays. MCDA in this case study relies on Saaty’s analytic hierarchy process (AHP) used in many domains including management (Saaty, 1982) and GIS (Eastman, 2009). The principles of AHP, merely mentioned in Chapter 3, are detailed in the literature (Saaty, 2001).

The main role of fuzzy logic in this case study is to facilitate the definition of suitability rankings applied to the different classes of criteria considered. Linguistic terms are used instead of more abstract numerical values thus facilitating the merging of specialist knowledge with environmental data. The visualisation of spatial uncertainty introduced in section 2.4.2 offers an unusual geographic summary of all vague information considered.

Mapping fuzziness as four separate interpretations of each linguistic term of suitability is the most conspicuous characteristic of this approach (Puig, 2001). In the process of generating these maps, the fuzzy technique adopted better accounts for the uncertainty inherent in site selection by providing visual representations of the range of meanings implied by linguistic terms. Constraints, criteria, ranks and weightings can all be expressed in linguistic, non-technical terms more accessible to lay persons than mathematical expressions. Although the approach may appear complicated, underlying processes rely on simple mathematical operations known as grid algebra.

All leading professional GIS software offer the same essential functionality required by grid algebra (DeMers, 1997) extensively used in the Anindilyakwa Aquaculture GIS (AAGIS) (Puig, 2008). Wherever a grid is laid over a variable defined across a plane, values of the variable transferred to the corresponding grid cells can be combined with other values, in the same location in other grids, by using algebraic expressions. A raster representation of geographic entities is therefore very convenient as it addresses fundamental needs. Changes in values of a mapped variable can be displayed in grid format to facilitate the conceptualisation of complex underlying processes. Grid algebra adapts the technique of transparency overlays to GIS. Mathematical operations, required to provide the rigour attached to complex geographical reasoning, become readily available through the GIS. Through grid algebra, all fuzzy logic based models discussed in subsequent chapters are all directly relevant to GIS modelling.

3.1 Background

As a professional Spatial Scientist, I completed commercial projects pertinent to this thesis. Below is a case study adapted from an investigation I carried out for the Government of the Northern Territory of Australia.

This case study explores scientific aspects of a commercial GIS project, focused on some remote islands of Northern Australia. This case study is taken from a project commissioned by the Northern Territory Department of Fisheries. The GIS solution had to reflect the specificity of the location. The aim was to provide Aboriginal traditional owners with an incentive to prompt the business sector into investigating the potential of aquaculture on Aboriginal Land. This aquaculture GIS had to be fully capable of merging Aboriginal and Western knowledge into one single output. These knowledges differ in many ways. The former is qualitative, holistic, timeless and oral (Malloch, 1989; Smith and Marsh, 1990; Chaloupka, 1993; Castellano, 2000) while the latter is quantitative, reductionist, short-term and written (Tsuji and Ho, 2002). This project intended only to address the last difference. Interfacing with knowledge and linguistic differences was therefore crucial. Fuzzy logic is well suited to translate human knowledge into quantitative models. Issues of culture and therefore language are distinctive features of Aboriginal land. Fuzzy logic therefore became a key feature of this project.

3.1.1 Purpose of the project

The project consisted of GIS identification of the best prawn farming sites on the coasts of Groote Eylandt and Bickerton Island displayed in Figure 3.1. The outcome of this GIS desktop study was to map environmental variables considered to be crucial for prawn farming. Once prime locations are identified field surveys need to be carried out by interested developers to confirm suitability. The purpose of the GIS investigation is therefore to limit fieldwork to the most promising locations. The GIS approach minimises the high cost of feasibility studies in such remote locations.

3.1.2 A unique geographical and cultural context

The Anindilyakwa Aquaculture GIS, named after the local Aboriginal Council, provides a site suitability analysis designed to facilitate the identification of potential aquaculture sites. This low cost management tool is well suited to aquaculture development at local, regional and national scales. The GIS handles tedious and time consuming tasks while aquaculture specialists concentrate on the identification of physical and economical constraints including the assessment of their relative importance. Owing mainly to the abundance of rocky outcrops, ongoing mining activity and seasonal weather patterns, nearly 3/4 of the area of interest is unsuitable for aquaculture. The most promising locations are concentrated in the south of Bickerton Island and Groote Eylandt.

Few interpretative environmental maps of this area exist. Maps of aquaculture suitability produced by the GIS are therefore an important element in the development of integrated coastal management plans. An inventory of aquaculture sites in the Northern Territory is part of the Government’s strategic approach to aquaculture development. AAGIS represented a deliberate effort to improve technical communication with indigenous stake holders. Explanations to traditional owners were greatly facilitated by the reliance on visual information readily available from the GIS.

3.2 Method and data

The AAGIS is articulated around the effective mapping of prawn aquaculture site suitability based on environmental data and expert knowledge. First the method adopted to map the fuzzy suitability derived from the available information is outlined. Then the dataset used in this study is described. Finally the technique used to capture knowledge of the two aquaculture experts who steered this project is investigated. Complementary information related to the source of the data and other technical issues is available in Appendix 2.

3.2.1 Mapping fuzziness

Mapping areas of high potential for prawn farming consisted first of excluding unsuitable locations. Mangroves, sacred sites, mining infrastructure and their immediate surrounding, fall in that category. Aquaculture experts involved in this project then identified suitability criteria including slope, access, proximity of infrastructure, distance to the coast, soil depth, ground water availability, susceptibility to flooding. Each criterion is initially represented as a vector layer. Here, the GIS representation relies both on AHP and fuzzy logic. This approach introduced by Banai (1993) was subsequently adopted by other researchers (Gemitzi *et al.*, 2006; Vahidnia *et al.*, 2008; Farzanmanesh, 2010). This duality may explain why, although concise, this thematic mapping described in this thesis does not translate into simple mathematical procedures. However, the combination of AHP, fuzzy logic and GIS, widely used in natural resource management (Mc Bratney and Odeh, 1997; Schmoldt *et al.*, 2001; Chang *et al.*, 2008) has been successfully implemented in IDRISI (Eastman, 2009), one of the most sophisticated commercial raster based GIS software.

The GIS implementation of the method described in this chapter requires translating the various vector maps of environmental criteria described in Appendix 2 into grids. Suitability, defined by aquaculture experts in linguistic terms, is fuzzified for each criterion into 4 grids (a,b,c,d) as displayed in Figure 2.7. All 4 grids, for each criterion, are assigned the same weighting estimated by pair wise comparisons of all suitability criteria performed by the aquaculture experts. All weighted grids of type a are then added to produce a final grid of suitability A. Final grids B, C and D are similarly generated. Although the 4 maps carry crucial information, a single summary capable of guiding field investigations is required. Defuzzification plays this role.

Defuzzification is performed, in this case by adding maps A, B, C and D, as recommended by Malczewski (1999). However, only zones where the highest suitability persists across the four grids A, B, C and D were considered. In addition, aquaculture experts required areas covering no less than 1 ha. All prime targets for future investigation therefore display the highest suitability across the four maps and cover no less than 1ha of contiguous grid cells.

3.2.2 Source data

This site suitability analysis is based on variables listed in Table 3.1. These variables were derived from the digital datasets in Table 3.2

Table3.1: Source data sets of AAGIS.

	Source of prawn farm site suitability criterion
C1	four 1:50,000 vector topographic maps
C2	1:250,000 Land Systems from Arnhem Land
C3	1:250,000 Water Resources of Eastern Arnhem Land
C4	sites of Aboriginal significance (from Aboriginal Area Protection Authority)
C5	1:250,000 vector topographic map
C6	CAD drawings of Aboriginal communities
C7	personal notes from Perkins shipping company
C8	117 oblique photos of the coast of Groote Eylandt and Bickerton Island
C9	one Landsat TM image with 40m pixels
C10	one 1:300,000 marine chart

Source data and suitability criteria, although explored in Appendix 2, are listed here to stress the high variability of the type of information and format used in this GIS fuzzy model. A systematically high level of uncertainty is generally associated with GIS modeling for two reasons. Firstly data in vector and raster formats are often combined resulting in additional errors with each format change. Secondly differences in scale imply that the nominal scale of the final product is downgraded to that of the poorest dataset resolution used.

Table 3.2: Site selection criteria used to assess the suitability of a site for prawn aquaculture.

Criterion	Prawn farm site suitability criterion
C1	Slope
C2	Access by air & land
C3	Access by sea
C4	Proximity to infrastructure
C5	Risk of flooding
C6	Proximity of creek
C7	Pond size
C8	Distance to coast
C9	Soil depth
C10	Ground water availability

Knowledge capture, based on existing datasets listed in Appendix 2, is the most important phase of development of the AAGIS. This 3 step process comprises the identification of suitability criteria, the evaluation of criteria weightings and the definition by two DAC experts of ranges of suitability for all 10 criteria listed in Table 3.2. The resulting model therefore captures expert knowledge through three processes: environmental variables selection, weightings and translation of each variable to membership functions. Complementary information on the source of the data and other technical issues are available in Appendix 2.

3.2.3 Capture of knowledge derived from pair wise comparisons

Weightings are a key component of the expert knowledge captured in this model. They summarise the knowledge embedded in pair wise comparisons. DAC experts stressed that all criteria included in the model do not have the same importance. Evaluating the relative importance of each criterion is difficult because experts with different backgrounds have different views. The AHP (Saaty, 2001), well suited to decision making (Saaty, 1990) and natural resource management (Schmoldt *et al.*, 2001) provides an appropriate knowledge acquisition framework in this case study.

Views expressed by DAC experts during the project are summarised in the relative importance of site selection criteria listed in Table 3.3. These highlight the importance of facilitating strategies to ensure the effective cooperation of those involved. After working independently and obtaining conflicting weightings, the two experts finally agreed to adopt a pair wise comparison method structured to ensure maximum consistency. The importance of each suitability criterion is compared to that of every other suitability criterion using the scale in Table 3.4. Values of relative importance in Table 3.4 are all larger than 1 and the first criterion is always assumed to be the most important. The order of the comparison between criteria is therefore adjusted to always start with the most important of the two criteria. Alternatively the inverse of values of relative importance can be used instead as demonstrated in Table 3.5. Each criterion is compared to the remaining criteria. Calculations of relative importance for 5 criteria are demonstrated in Table 3.5.

Let us assume, using the terminology and values in Table 3.4, that we consider 5 hypothetical criteria C1 to C5. Their relative importance is defined in Table 3.3 below.

Table 3.3: Relative importance of 5 criteria assessed by pair wise comparisons.

	C1	C2	C3	C4	C5
C1	1	2	1/2	3	4
C2	1/2	1	5	1/4	4
C3	2	1/5	1	9	8
C4	1/3	4	1/9	1	2
C5	1/4	1/4	1/8	1/2	1

C1 is of equal to moderate relative importance compared with C2
C1 is of moderate relative importance compared with C4
C1 is of moderate to strong relative importance compared with C5
C2 is of strong relative importance compared with C3
C2 is of moderate to strong relative importance compared with C5
C3 is of equal to moderate relative importance compared with C1
C3 is of extremely strong relative importance compared with C4
C3 is of very to extremely strong relative importance compared with C5
C4 is of moderate to strong relative importance compared with C2
C4 is of equal to moderate relative importance compared with C5

Pair wise comparison values are displayed in Table 3.5. Understanding these calculations is important as they are the basis of weightings assigned to each criterion. These weightings ultimately decide the level of suitability of a site for the establishment of a prawn farm by taking into consideration all criteria in Table 3.2.

Table 3.4: Values of relative importance used in suitability criteria pair wise comparisons.

Value	Relative importance
1	equal relative importance
2	equal to moderate relative importance
3	moderate relative importance
4	moderate to strong relative importance
5	strong relative importance
6	strong to very strong relative importance
7	very strong relative importance
8	very to extremely strong relative importance
9	extremely strong relative importance

The evaluation of weightings is a tedious task handled semi automatically by a single spreadsheet derived from that presented by Malczewski (1999). Experts start by evaluating the relative importance of all selection criteria (C1 to C5 in Table 3.5) identified. They fill in the green cells in Table 3.5 with a number read from Table 3.4. Once two criteria Ci and Cj are compared, the spreadsheet automatically writes the reciprocal value for the comparison of Cj and Ci in the appropriate cell below the grey cells. All grey cells contain 1. They represent the importance of each criterion relative to itself which is 1 according to Table 3.4. Criteria weightings (Malczewski, 1999: p.177) derived from pair wise comparisons are implemented in Table 3.6. Values displayed in Table 3.6 are automatically calculated from numbers entered in Table 3.5 for all weightings in blue cells. Details of calculations linking Tables 3.5, 3.6 and 3.7, as well as derivations of parameters listed below, are presented in Appendix 2.4 as they require a description of spreadsheet formulas.

The consistency of pair wise comparisons (Malczewski, 1999: p 184) is measured by the Consistency Ratio (CR). CR is derived from λ and the Random Inconsistency (RI) index. The eingenvalue associated with the principal eigenvector of the pair wise comparison matrix (Eastman, 2009: p.138) is λ. Malczewski (1999: p.186) tabulated values for RI for up to 15 criteria. A good approximation of CR is given by Malczewski's formula below:

$$CR = \frac{\lambda - n}{(n-1) \times RI} \qquad \text{Equation 3.1}$$

Calculations of the CR (Malczewski, 1999, p. 186), and λ, the average value of the consistency vector, are detailed in Appendix A 2.4. Saaty (1990: p.13) provides additional information on the role of λ in assessing the consistency of the comparison matrix including table in Table 3.5.

Malczewski (1999) states that CR values larger than 0.1 reflect inconsistent pair wise comparisons. The following numerical demonstration helps understand the importance of CR. The value of RI for 5 criteria (Malczewski, 1999: p. 186) is 1.12. Based on calculations displayed in Tables 3.6 and 3.7, the consistency ratio for the rankings of Table 3.5, using equation 3.1, is therefore:

$$CR = \frac{7.858 - 5}{(5-1) \times 1.12} = 0.638$$

There are therefore incompatible values of relative importance in Table 3.5. In this example we can conclude that, because CR ≥ 0.1, weightings displayed in Table 3.6 are incorrect. Pair wise comparisons displayed in Table 3.5 need to be revisited until CR < 0.1. In this instance there is at least one clear inconsistency in the three leftmost green cells of Table 3.5: C1 cannot be more important than C2 and less important than C3 while C2 is more important than C3. Although CR is useful in checking the consistency of pair wise comparisons, maintaining CR below 0.1 is virtually impossible as the number of criteria increases. With 55 pair wise comparisons for 10 criteria, informants find it difficult to identify which pair wise comparisons are contradictory. After a few attempts to bring CR below 0.1, they retained the combination of relative importance ratings which minimizes CR. The consistency ratio (CR), calculated from figures entered in Table 3.5, is derived from the value of λ in Table 3.7. Using the method previously described, the two DAC experts obtained the weightings in Table 3.8.

Table 3.5: Input spreadsheet to calculate values of relative importance of suitability criteria. Rows record values of the relative importance of criteria on the horizontal axis compared to corresponding criteria on the vertical axis.

	C1	C2	C3	C4	C5
C1	1	2	0.5	3	4
C2	0.5	1	5	0.25	4
C3	2	0.2	1	9	8
C4	0.333	4	0.111	1	2
C5	0.25	0.25	0.125	0.5	1

Values of relative importance of the 5 hypothetical criteria C1 to C5 are entered in the calculation spreadsheet above. Pair wise comparisons are successively carried out between each row criterion and the corresponding column criterion. Values of relative importance read from Table 3.4 are entered in green cells at the intersection of the corresponding row and column. All grey cells contain 1 as the relative importance of any criterion compared with itself is 1. If the importance of the row criterion is larger, the value in the corresponding green cell is larger than 1. For instance, the importance of C1 relative to C2 is equal to moderate. The corresponding value of 2, read from Table 3.4, is typed in the cell at the intersection of row C1 and column C4. If the importance of the column criterion is larger, the inverse of the value read from Table 3.4 is entered instead. For instance, the intersection of row C1 and column C3 has a value of 0.5 which implies that C3 is more important than C1 and its relative importance is 2. All values in the white cells are automatically calculated as the inverse of the value of the corresponding green cell symmetrical about the diagonal of grey cells.

Table 3.6: Spreadsheet to calculate weightings of suitability criteria. The first five columns show the relative importance values for suitability criteria C1 to C5. The last column shows the calculated weightings.

	C1	C2	C3	C4	C5	Weighting
C1	0.245	0.268	0.074	0.218	0.211	0.203
C2	0.122	0.134	0.742	0.018	0.211	0.246
C3	0.490	0.027	0.148	0.655	0.421	0.348
C4	0.082	0.537	0.016	0.073	0.105	0.163
C5	0.061	0.034	0.019	0.036	0.053	0.040

The value of relative importance in cells of Table 3.5, divided by the sum of column values, is written in the corresponding cells of Table 3.6. The weighting of each criterion C1 to C5 is the average of the values in the corresponding row. As values in each column are normalised, weightings of all criteria in the blue column are normalised to 1.

Table 3.7: This spreadsheet calculates λ from results in Tables 3.5 and 3.6 following the steps described below. Coefficient λ, the average of the values in the blue column, is used to calculate the consistency ratio CR.

C1	0.203	0.491	0.174	0.488	0.162	7.469
C2	0.102	0.246	1.741	0.041	0.162	9.328
C3	0.407	0.049	0.348	1.463	0.324	7.442
C4	0.068	0.982	0.039	0.163	0.081	8.192
C5	0.051	0.061	0.044	0.081	0.040	6.857
					λ =	7.858

A detailed description of the calculation of λ in Table 3.7 is provided in Appendix A2.4.

Table 3.8: Weightings obtained by two DAC experts by applying the pair wise comparisons methodology to the 10 suitability criteria.

Criterion	Description	Weighting
C1	Slope	0.166
C2	Access by air & land	0.088
C3	Access by sea	0.122
C4	Proximity to infrastructure	0.038
C5	Risk of flooding	0.373
C6	Proximity to creeks	0.035
C7	Pond size/contiguity	0.039
C8	Distance to coast	0.077
C9	Soil depth	0.047
C10	Groundwater availability	0.015

3.2.4 Capture of knowledge in membership functions

Once criteria weightings are finalised, membership functions for each criterion are calculated. First, experts decide how many classes need to be defined for each criterion. All criteria are then normalised and rescaled so that all values for all criteria are between 0 and 1. Finally, membership function coordinates suggested for set numbers of classes (Malczewski,1999: p. 133) are used to translate the range of values of each criterion into membership functions defined in Table 3.9.

Malczewski relies on predefined linguistic terms that correspond to a set range of values on a normalised scale of 0 to 1 for all variables. The result is a set of commensurate maps where the range of values across all maps is constant regardless of the variable considered. Once experts decide the specific role played by different ranges of values, the segmentation of each variable dataset follows and the number of membership functions required, their name (e.g. High, Medium …etc) and membership function coordinates are unambiguously implied.

Table 3.9 shows classes of suitability for each criterion expressed in set linguistic terms. Each criterion is first normalised by dividing it by its maximum value, then rescaled to end up with 10 commensurate criteria with values defined on the interval [0,1]. The range of values on the interval [0,1] is predetermined for each class. Informants choose the number of classes corresponding to the terms of suitability they need to segment each criterion. “Low” does not appear in Table 3.8 for criteria C1 and C4 to C9 as corresponding values are unsuitable and corresponding areas are clipped out of the suitability map. In Figure 3.8 and 3.9 they are represented as grey areas to be avoided for prawn farming, as they fail to meet at least one of the minimum requirements for one of the criteria C1, C4, C5, C6, C7, C8 or C9.

Table 3.9: Classes of suitability of each criterion. The classes are expressed as standardised linguistic terms used by informants to define classes of suitability from the range of values taken by each of the suitability criteria C1 to C10.

Criterion	Description	Classes	Linguistic terms of suitability
C1	Slope	2	Medium, High
C2	Access by air & land	3	Very low, Low, Medium
C3	Access by sea	5	Very Low, Low, Medium, High, Very High
C4	Proximity to infrastructure	2	Medium, High
C5	Risk of flooding	2	Medium, High
C6	Proximity to creeks	2	Medium, High
C7	Pond size/contiguity	2	Medium, High
C8	Distance to coast	2	Medium, High
C9	Soil depth	2	Medium, High
C10	Groundwater availability	3	Low, Medium, High

Table 3.10 lists fuzzy numbers TFN1 to TFN5 of the trapezoidal membership functions corresponding to the linguistic terms in Table 3.9. The first, second, third and fourth fuzzy coordinates are named a, b, c, d respectively. Following the terminology introduced in Figure 2.7, corresponding maps are named A, B, C and D.

Map A therefore represents the lowest range of values covered by a linguistic term, D the highest and B and C low to medium and medium to high values.

Table 3.10: Fuzzy numbers of the Trapezoidal membership functions corresponding to the linguistic terms of suitability listed in Table 3.8.

Grid	TFN 1	TFN 2	TFN 3	TFN 4	TFN 5
C1	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C2	(0, 0, 0.1, 0.2)	(0, 0.25, 0.25, 0.4)	(0.3, 0.5, 0.5, 0.7)		
C3	(0, 0, 0.1, 0.2)	(0, 0.25, 0.25, 0.4)	(0.3, 0.5, 0.5, 0.7)	(0.6, 0.75, 0.75, 0.9)	(0.8, 0.9, 1, 1)
C4	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C5	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C6	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C7	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C8	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C9	(0.4, 0.5, 0.5, 0.8)	(0.5, 0.8, 0.8, 1)			
C10	(0, 0, 0.2, 0.4)	(0.2, 0.5, 0.5, 0.8)	(0.6, 0.8, 1, 1)		

3.2.5 Building the model

All 10 criteria can now be processed as 10 commensurate maps where 0 is the minimum and 1 the maximum. Trapezoidal membership functions derived from these values are similar to those in Figure 2.6 of Chapter 2. The model relies on membership functions defined in Table 3.10 and on weightings in Table 3.8.

Building the model starts by assigning, with the help of stakeholders, a linguistic suitability to all values for each variable as demonstrated in Figure 2.7. Next, the weighting of each criterion is evaluated through a series of pair wise comparisons as shown in Tables 3.4, 3.5 and 3.6. These two initial steps are repeated for all cells of the 4 grids corresponding to the 4 possible interpretations "a", "b", "c" and "d" of each linguistic term as depicted in Figure 2.7. The effects of all 10 criteria across the whole region of interest are combined by adding all corresponding grids. Ultimately, all "a" grids are summed into a final map A, all "b" grids into a final map B and so on. These are displayed in Figure 3.2.

ArcView 3.2 (Lee and Wong, 2001) and its extensions Spatial Analyst and Model Builder were used to facilitate the completion of all tasks required in step 4 above. The graphic grid algebra interface of Model Builder is particularly well suited to these tasks.

3.3 Results

The output of the AAGIS model comprises 4 separate grids displayed in Figure 3.2 and Figure 3.3. Map A corresponds to the lowest values in the range of possible interpretations of the results. Map B displays intermediate to low values. Map C corresponds to intermediate to high values. Finally, map D shows the highest values.
Map A corresponds therefore to the most pessimistic assessment of site suitability while map D is the most optimistic. Map B and C represent more balanced intermediate suitability assessments.

Only the most suitable areas are considered as worthwhile targets for a detailed on the ground investigation. The classification used is well suited to this task as it clearly identifies locations of prime interest displayed in red on Figure 3.2 and Figure 3.3. Grey areas are identified by DAC aquaculture experts as clearly unsuitable for a number of reasons detailed in Appendix 2. They include for instance unacceptable proximity to infrastructure, sacred sites or mangrove.

Maps A, B, C and D look deceptively identical in Figure 3.2. Figure 3.3 reveals however subtle variations between maps. As the four maps represent different interpretations of the linguistic terms used to define suitability, only suitable areas common to all 4 maps should be considered in the first interpretation of the results.
Cox (1999: p.31) states "…the technique of defuzzification is not supported by axiomatic principles derived from foundation principles of fuzzy theory itself." One needs however to keep in mind that fuzzy logic is strongly bedded in engineering pragmatism. The defuzzification in Figure 3.4 was therefore implemented in close collaboration with DAC staff to produce the most informative final map.

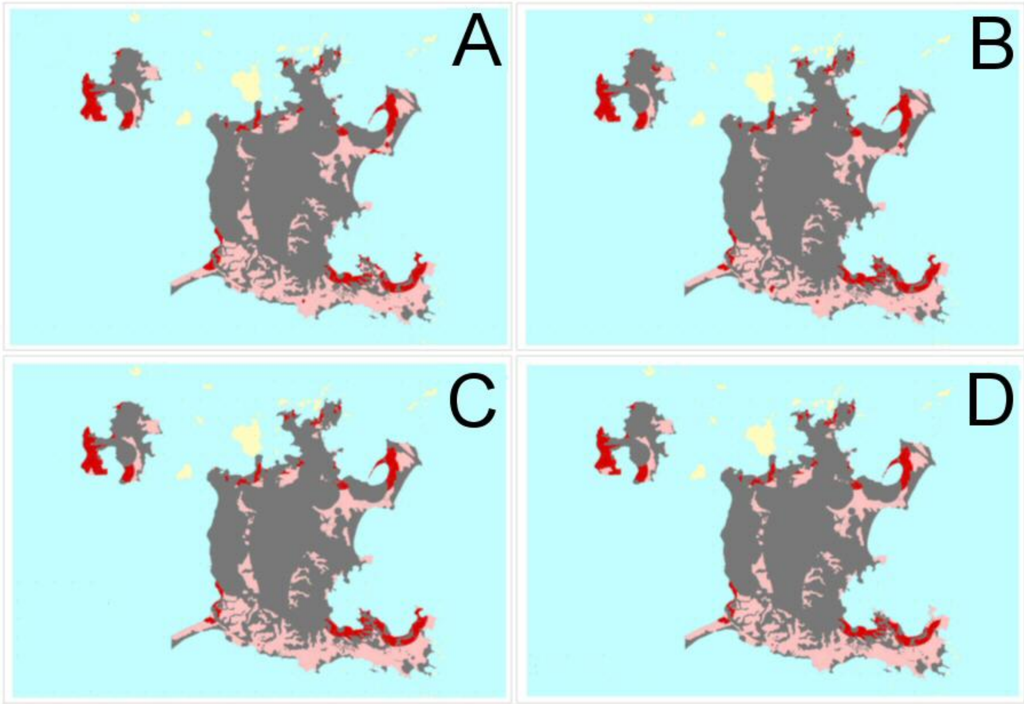

Figure 3.2: Suitability maps A, B, C and D representing the 4 possible interpretations of the linguistic terms used to describe the suitability of environmental variables to aquaculture: A is the most pessimistic interpretation (leftmost coordinate of the trapezoidal membership functions), D the most optimistic (rightmost coordinates) and B and C are intermediate interpretations. Standard deviation (Upton and Cook, 2008) classification, a semi automatic visualisation option in ArcView3.x used here, is available in most GIS software. Areas of below average suitability for prawn farming are grey in these four maps. Areas of very high suitability (more than three standard deviations above average) are red. Areas of suitability between average and 3 standard deviations above average are pink.

The decision was made to take advantage of the relative freedom condoned by what Cox describes as “the somewhat ad-hoc nature of defuzzification” (1999: p. 30). Defuzzification was customised in order to better serve the purpose of the study. The defuzzification process arbitrarily selected by the aquaculture scientists was clearly driven by two considerations. Their prime concern was to minimise the number of sites warranting further investigation. Their second focus was to set such high standards for all selection criteria considered that only sites with the very best potential would be retained.

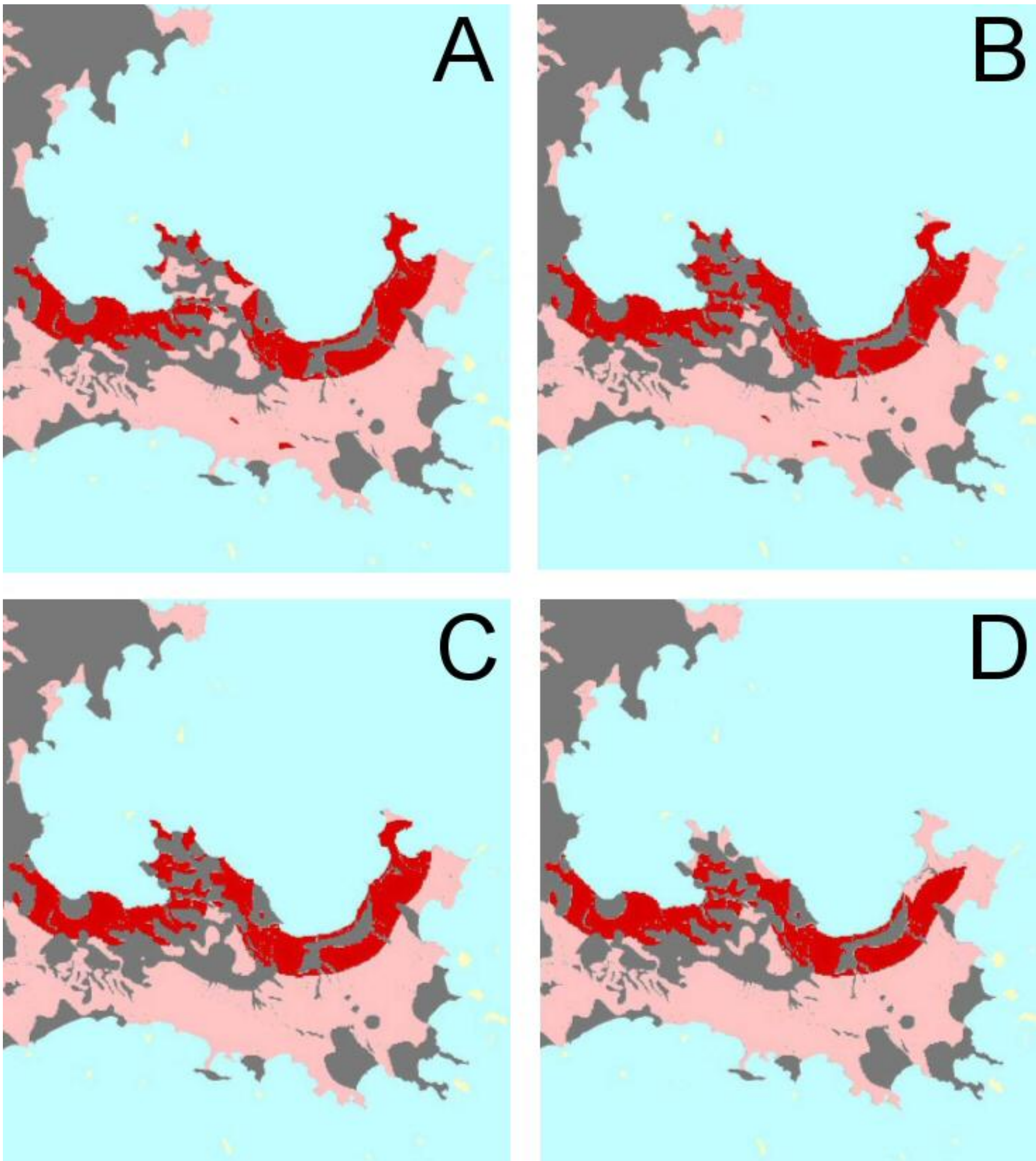

Figure 3.3: This enlarged view of the South Eastern tip of Groote Eylandt is displays details of the suitability maps shown in Figure 3.2.

Results displayed in Figure 3.4 show sites of no less than 1 ha of contiguous high suitability surrounded by a buffer of 1 km of equally high suitability terrain. This filtering process, easily implemented in the GIS to produce the map displayed in Figure 3.4, highlights the great flexibility of the method.

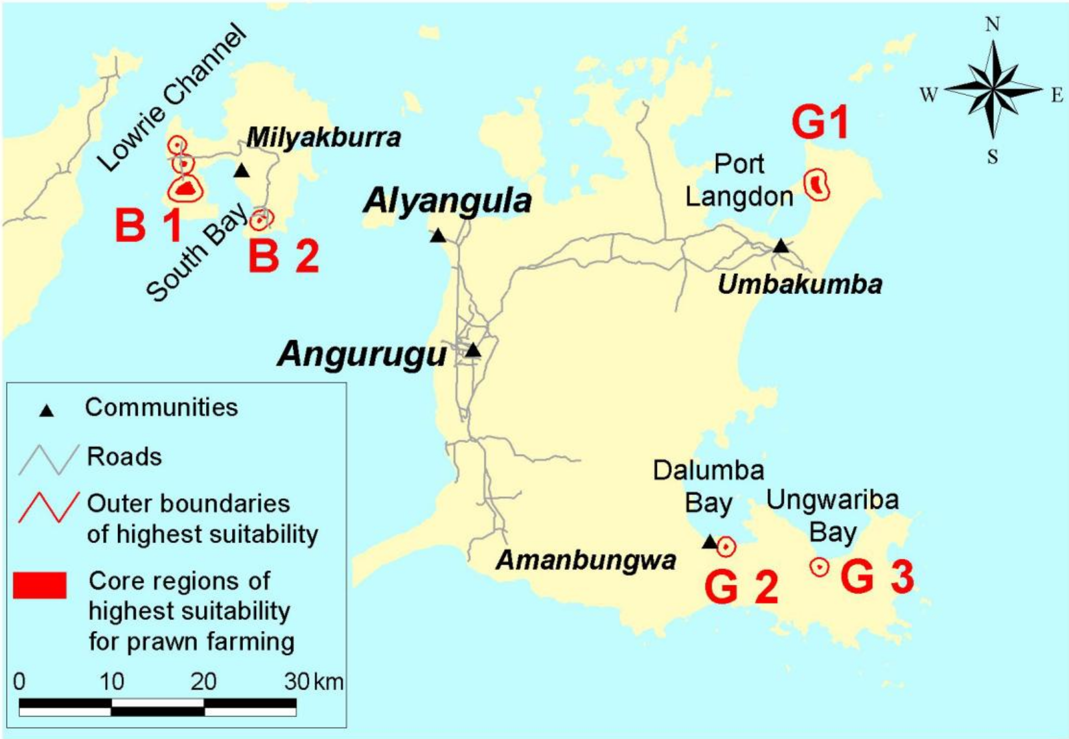

Figure 3.4: Final map showing location of areas suitable for prawn aquaculture. Core regions of higher prawn aquaculture suitability in red show areas of no less than 1 ha of land of highest suitability to prawn farming surrounded by a further 1km buffer of highly suitable ground.

3.3.3 Validation of the model

Final validation can only be performed by field work. A visual investigation of sites, however, provides experts with visual clues sufficient to confirm initial indications of the model. This visual assessment was performed from oblique aerial photography acquired by the NT Government during a qualitative survey of the North East coastline of the Northern Territory in 1999. Plate 3.1 below reveals the type of environment deemed suitable by the model described for the establishment of a prawn farm. Although an aquaculture expert cannot visually confirm the suitability of all sites identified by the model from the incomplete aerial photographic coverage of the Groote Eylandt coast line, photos such as Plate 3.1 reflect, in that location, the validity of the model output.

Figure 3.5: Oblique aerial photograph of site B2. The site is located east of the entrance of South Bay on Bickerton Island.

3.4 Discussion

Malczewski (1999: p.130) writes "Here we limit our discussion to the trapezoidal numbers" although he admits that triangular membership functions fall in the same category of most often used membership functions. He does not explain why, in the context of MCDA he prefers them to triangular membership functions. Malczewski (1999: p. 186) recognises two drawbacks of pair wise comparisons to assign criterion weightings: questionable meaningfulness and rapidly escalating demand put on decision makers when the number of criteria exceeds 10. However, Malcewski (1999: p.187) stresses that, in support of pair wise comparisons for criterion weightings, the method has been tested for spatial decision making and built into IDRISI GIS (Eastman, 2009) decision-making module. Although trapezoidal membership functions and pair wise comparisons are not used elsewhere in this thesis, they stand as a reminder of the variety of techniques not considered in this thesis as they do not lead to simpler GIS modelling procedures.

Reiterating caveats in section 3.1, parallels can be drawn between fuzzy multicriteria decision analysis described by Malczewski (1999) and other similarly non mainstream spatial applications of fuzzy logic (Burrough *et al.*, 1992, Costa Fonte and Lodwick, 2005, Lagacherie *et al.*, 1996). All are well suited to a specific domain of application. Their scope, however, is rather limited. In this instance, Malczewski's (1999) spatial fuzzy multi criteria decision analysis was selected because of its broad range of NRM applications from marine, to mine site rehabilitation and weed control.

Ultimately, AAGIS was well received by the NT Government and other NRM specialists (Puig, 2005; Puig, 2008).

The implementation of fuzzy logic described in this chapter shares similarities with the work of Burrough (1998) on fuzzy boundaries. They are sufficiently visually explicit to be easily understood, unfortunately, their range of applications is rather limited. They do not link to fuzzy rule-based modelling, unquestionably the most prolific application of fuzzy logic. The approach adopted was initially prompted by the need for a methodology able to facilitate the inclusion of Aboriginal knowledge in the GIS model. Giving the local community a sense of ownership of this land management tool was another desirable aspect of the solution adopted. Surveys, similar to that detailed in section 5.3, were to be carried out, in collaboration with anthropologists and linguists, to capture an oral traditional knowledge reliant on terms which generally meet the criteria of the "sorites" paradox outlined in section 1.1. Fuzzy logic, widely recognised as best suited to the capture of human knowledge, a view strongly supported by Chapter 5, was consequently well adapted to the task. Unfortunately, contrary to the initial scope of the project, the intended capture of traditional human knowledge, in the context of this survey, turned out to be impossible for two completely independent reasons. The budget of this project was limited and did not allow for an anthropologist to spend on Groote Eylandt the time necessary to speak to traditional experts. In addition, prawns do not appear to have played an important role in the diet of Aboriginal cultures of the Northern Territory. Little traditional knowledge of prawns is therefore likely to exist on Groote Eylandt. Other traditional knowledge may, however, be highly relevant particularly in relation to seasonal bad weather such as rough seas and storms which may affect coastal prawn farms. However, owing to a limited budget, no capture of traditional knowledge of relevant local weather patterns was attempted.

Advantages of this fuzzy suitability analysis are noteworthy. Various ranges of possible values taken by all environmental variables selected are defined in linguistic terms. Those are less likely to disenfranchise the broad spectrum of stakeholders often associated with NRM projects. The model can be described in non technical terms thus facilitating cross cultural dialogues as the linguistic terms used are readily translated in any local language. The original output of this model consists of 4 maps instead of one as would be normally expected. Users are therefore visually reminded that the conclusion reached by such a model is not absolute. The extreme possible interpretations of the linguistic terms of suitability impose upper and lower limits on the final result. In this instance the intermediate interpretation, as well as the upper and lower limits, are parts of the model output. A corollary of the previous statement is the need to provide as well the single and easily readable output generally requested by end users. The approach adopted here directly involves them in designing their defuzzification procedure. Consequently the model output matches very closely the user's needs.

A different choice of membership function could result in an improvement of the strategy described here. If instead of trapezoidal membership functions recommended by Malczewski (1999), triangular membership functions defined in Chapter 2 are selected, the whole procedure remains unchanged and 3 maps A, B and C instead of 4 are generated. The central map B is then in sharper contrast with the two extreme maps A and C. Map B could then be the single output of the model. Maps A and C would represent the limits of the suitability displayed in B. Advantages of this adaptation of Malczewski's method include simpler membership functions and the elimination of the duplication of information in central maps B and C. Although not a path-breaking improvement, the adoption of triangular membership functions instead of trapezoidal membership functions is consistent with the approach to membership functions design adopted throughout this thesis and removes the plateau of the membership function which carries no information and plays no role in that context.

The close involvement of aquaculture specialists and other stakeholders in the modelling process is a key advantage of this strategy. Although only two DAC experts contributed their knowledge to this project, the methodology is clearly scalable. Linguistic and anthropological support would make it very well suited to predictive modelling based on a combination of Aboriginal and Western knowledge. Although Aboriginal knowledge has been recorded in Northern Australia for more than 20 years, Smith (2008) deplores a lack of effective implementation in environmental models where it would matter most.

Summary

The Anindilyakwa Aquaculture GIS relies on fuzzy multicriteria suitability analysis to identify the best locations for prawn farming on the coast of Groote Eylandt and Bickerton Island in the remote Gulf of Carpentaria. Raster GIS's flexibility facilitates the creation of a model of site suitability comprised of 10 layers of environmental data. Fuzzy logic, through linguistic terms and their equivalent membership functions incorporates in the model the knowledge of two aquaculture experts. The modelling framework described in this chapter enables a number of specialists to merge their respective expertise. Their knowledge is expressed in two components of this model: membership functions and weightings. The former are derived from linguistic terms of suitability of the different ranges of values of the environmental variables considered. The latter reflect the relative importance of the respective environmental variables and their associated membership functions. Trapezoidal membership functions of each of the 10 environmental variables are represented by their 4 coordinates from which 4 maps are derived for each variable. Once merged, the matching maps of the 10 variables scan the range of possible interpretations of the different levels of suitability of the coastline for prawn farming. Although the method described relies on trapezoidal membership functions, triangular membership functions may be preferable as they would eliminate some duplication of visual information.

The final product is a single map of suitability for prawn farming that summarises all aquaculture expertise and environmental data available at the time. This map of suitability for aquaculture prawn farming is defuzzified, to meet the end user's wish, by merging all available information to extract the 5 most suitable areas. The aerial photography of one of the five areas identified by this desktop GIS analysis confirms its suitability to prawn farming.

This case study highlights two advantages of this approach to site suitability analysis. The highly visual nature of the solution, to be expected from a GIS analysis, greatly facilitates communications between the modeling team and all stakeholders. The process of inclusion of experts' knowledge is well suited to the development of a decision making tool easily adaptable to a wide range of technical requirements and cultural backgrounds. DAC experts found the process of weightings evaluation by pair wise comparison challenging. Although both highly qualified in their domain, one systematically assigned more importance to economical considerations while the other was driven by environmental concerns. In the end their complementary views were all merged in the model. Nowhere else in this thesis is fuzzy logic so integrated within a GIS modelling methodology. Fuzzy logic, however, does not modify any fundamental GIS functionality. Instead, fuzzy logic considerably enhances the information content of the graphical solution displayed in the final map. Figure 3.4 captures the consensus reached by two experts despite somewhat diverging views on site suitability. Figure 3.4 does not suggest where to carry out field surveys on the basis of a blunt Boolean classification of the natural environment. Instead, our innate tendency to incorporate moderated beliefs in our decision making process is implemented in a series of 4 maps representing the range of possible interpretations of all grades of suitability considered. The final map of suitability is therefore an information rich document well adapted to different levels of use calling for different depths of interpretation. A parallel can be drawn with the role played by statistics in GIS modeling. Beyond the graphical output of the GIS, statistics allow one to question the reliability of the solutions emerging from a map. The number of samples and their distributions in the different regions of the model will help users to develop a better understanding of the underlying reliability of the visual output of the GIS.

The case study explored in this chapter aims at producing an information enriched GIS model. Statistics do so by incorporating in the model an in depth understanding of the variability of the data. Fuzzy logic, in the context of this chapter, strives to emulate humans' natural ability to constantly generate simple models, based on readily available information, to make sense of their surrounding. This case study is an example of the synergy resulting from the combined use of GIS and fuzzy logic to improve the management of natural resources. The product is an information rich yet simple map of site suitability.

CHAPTER 4

DATA DRIVEN FUZZY RULE-BASED MODELLING

Overview

This chapter focuses on objective fuzzy rule-based modelling. In this chapter, principles introduced in Chapter 2 are applied to three practical examples of data driven modelling. They illustrate how fuzzy rule-based modelling addresses two common tasks of GIS modelling: classification and prediction. Small datasets of high dimensionality, in the case studies considered, are of particular relevance to GIS modelling. The simple fuzzy rule-based approach to predictions from high dimensionality datasets, proposed in this thesis, is first tested on a popular dataset then evaluated against a more sophisticated fuzzy rule-based method. A complex multivariate NRM case study finally provides an opportunity to compare the same fuzzy rule-based modelling strategy with statistical techniques adopted in advanced ecological modelling.

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Principles of fuzzy rule-based classification are introduced in a case study based on Fisher's iris dataset downloaded from the Monash University web site (http://www.csse.monash.edu.au/~lloyd/tildeFP/). In this dataset, containing 150 records, each iris flower, described by the length and width of its petals and sepals, belongs to one of three varieties. A fuzzy rule-based model is derived from this dataset. Its performance with weighted and non weighted rules is evaluated.

Fuzzy rule-based predictions from high dimensionality datasets are demonstrated on two case studies. The first case study, based on Nakanishi's paper (Nakanishi *et al.*, 1993) describes a sophisticated technique for the objective identification of fuzzy rule-based models. A simplified method is applied to data provided by Nakanishi (Nakanishi *et al.*, 1993, p. 279). The dataset comprises 70 records of five input and one output variables from the operation of a chemical plant. The simplified method proposed is compared with Nakanishi's. In the second case study, the simplified fuzzy rule-based modelling strategy previously tested is used to revisit a study of the influence of environmental variables on foraging patterns of elephant seals. The small dataset of 50 records and 14 variables is well suited to a demonstration of the contribution of fuzzy rule-based modelling to NRM studies where advanced statistical techniques, such as GAM and GLM in this case, often prevail.

4.1 Application of fuzzy rule-based modelling to classification

Fisher's iris dataset (Fisher, 1936) lists widths and lengths of petals and sepals of varieties of iris flowers. Fifty records of petal and sepal widths and lengths are listed for each of the three following varieties: setosa, virginica or versicolor. Fisher used this dataset to teach his students multivariate analysis. Popular in pattern recognition and artificial intelligence circles to test algorithms performance, these data are well suited to demonstrate how to build a fuzzy rule-based model. The data can be obtained from websites listed in Appendix 3. A number of similar versions of this dataset exist. They differ in their spelling of iris varieties and in the units used to measure the lengths and widths of petals and sepals. The dataset used here was downloaded from the Monash University website. The dataset is reproduced in Appendix 4.

The model described below is predictive in the sense that it predicts the iris variety from measurements of length and width of petals and sepals of a flower. At the same time it can be considered as an example of fuzzy classification (Chen and Fang, 2005; Chiu, 1997). Fuzzy rule-based modelling can clearly serve a variety of purposes. However, instead of focusing on the purpose of the model, this chapter demonstrates how fuzzy models cope with different type of data. In this case study the output is categorical (variety of flower) and inputs are continuous ratio variables (measurements of length and width). A randomly selected sample of 10 out of a total of 150 records is displayed below.

Table 4.1: Subset of Fisher's iris dataset. The 3 varieties of iris flowers setosa, versicolor and virginica are identified on the basis of flower metrics: petal and sepal width and length.

ID	Sepal length (cm)	Sepal width (cm)	Petal length (cm)	Petal width (cm)	Class code	Class
122	5.6	2.8	4.9	2	3	Iris-virginica
33	5.2	4.1	1.5	0.1	1	Iris-setosa
139	6	3	4.8	1.8	3	Iris-virginica
95	5.6	2.7	4.2	1.3	2	Iris-versicolor
118	7.7	3.8	6.7	2.2	3	Iris-virginica
90	5.5	2.5	4	1.3	2	Iris-versicolor
11	5.4	3.7	1.5	0.2	1	Iris-setosa

The approximation of a linear function in section 2.6.1 is a relatively simple univariate problem. Many readily available data fitting algorithms could be used instead of a fuzzy rule-based model to provide good predictions of y from values of x. The iris dataset belongs to the multivariate category which typically requires more sophisticated approaches. The model described below relies on the same strategy described in section 2.6. This generic, scaleable, approach to quantitative as well as qualitative predictions is one of the advantages of fuzzy-rule based models. To create a fuzzy rule-based model capable of predicting the flower variety from flower metrics listed in this table, we must first identify all input and output membership functions, as well as the rules they define, along with their weightings if necessary.

4.1.1 Identification of the parameters of a fuzzy rule-based model

This phase of development of the model is generally referred to as "identification". Plotting all input variables, one by one, against the output variable often reveals interesting properties of a dataset.

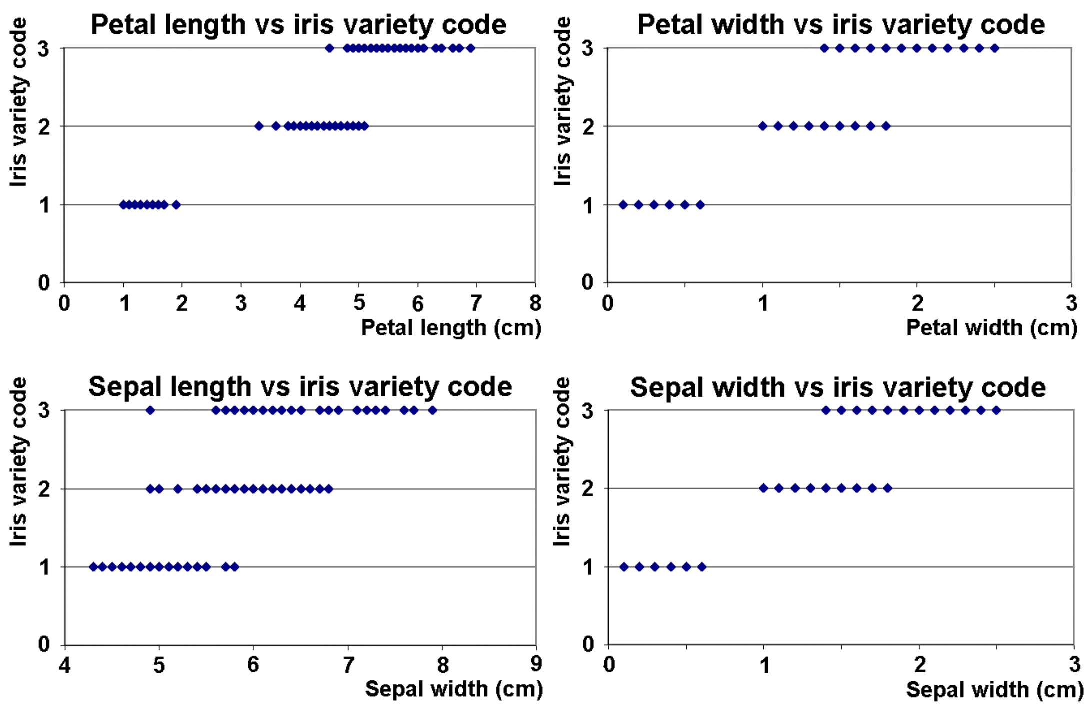


Figure 4.1: Plots of iris varieties versus flower metrics. Setosa, versicolor and virginica varieties correspond to codes 1, 2 and 3 respectively.

Figure 4.1 shows that out of the 4 flower metrics considered, sepal length is the least representative of a single iris variety. Sepal length shows a substantial overlap of the three classes and should therefore have lower weightings. The first step in fuzzy rule-based modelling consists of translating the initial dataset into membership functions. Two dimensional fuzzy patches are used in the first model explored as both variables are numerically continuous. Categorical outputs in this model are coded below. This code was selected for its simplicity. Any three equal consecutive intervals are suitable. Corresponding code numbers assigned to the three categories are then the centre of the corresponding interval. Encoding these categories with non contiguous numbers could result, for instance, in flowers not being assigned to any existing class rather than being misclassified.

setosa	$\rightarrow$	range [0,1]	$\rightarrow$	class code = 1
versicolor	$\rightarrow$	range [1,2]	$\rightarrow$	class code = 2
virginica	$\rightarrow$	range [2,3]	$\rightarrow$	class code = 3

Fuzzy patches are one-dimensional in this model. Measurements of length and widths of petals and sepals in Figure 4.1 and 4.2 are plotted in the middle of the corresponding output range. The model associates setosa with all output values between 0 and 1, versicolor with all values between 1 and 2 and virginica with values between 2 and 3. For practical purpose all categorical output values of the training dataset are assigned to the middle of their corresponding range: 0.5 for setosa, 1.5 for versicolor and 2.5 for virginica. A subset of 120 randomly selected flowers is extracted from the original dataset to train the model. The remaining 30 records will be used to assess its performance. Figure 4.2 and 4.3 as well as Table 4.2, 4.3 and 4.4 refer to this randomly selected subset, not to the complete dataset. As the sample is randomly selected we have a slightly different number of records of each iris variety: 40 setosa, 37 vertosa, 43 virginica. Membership functions can now be derived from the experimental dataset.

Many flowers have identical measurements and consequently a number of records are plotted in the same location in Figure 4.1. A flower cannot belong to two different varieties at once: the vertical axis is consequently Boolean. Two flowers of different varieties may have the same petal or sepal width or length: the horizontal axis is therefore fuzzy. The resulting fuzzy patches only have one fuzzy dimension (on the horizontal axis) and are no longer represented by rectangles but by lines

(Figures 4.2 and 4.3). Fuzzy membership functions, drawn on the vertical axis, would have no height. They are flattened rectangles corresponding to the orange, blue and red thick lines on the vertical axis. They are trapezoidal membership functions with no overlap defined below by their trapezoidal fuzzy number.

setosa	→	(0,0,1,1)
versicolor	→	(1,1,2,2)
virginica	→	(2,2,3,3)

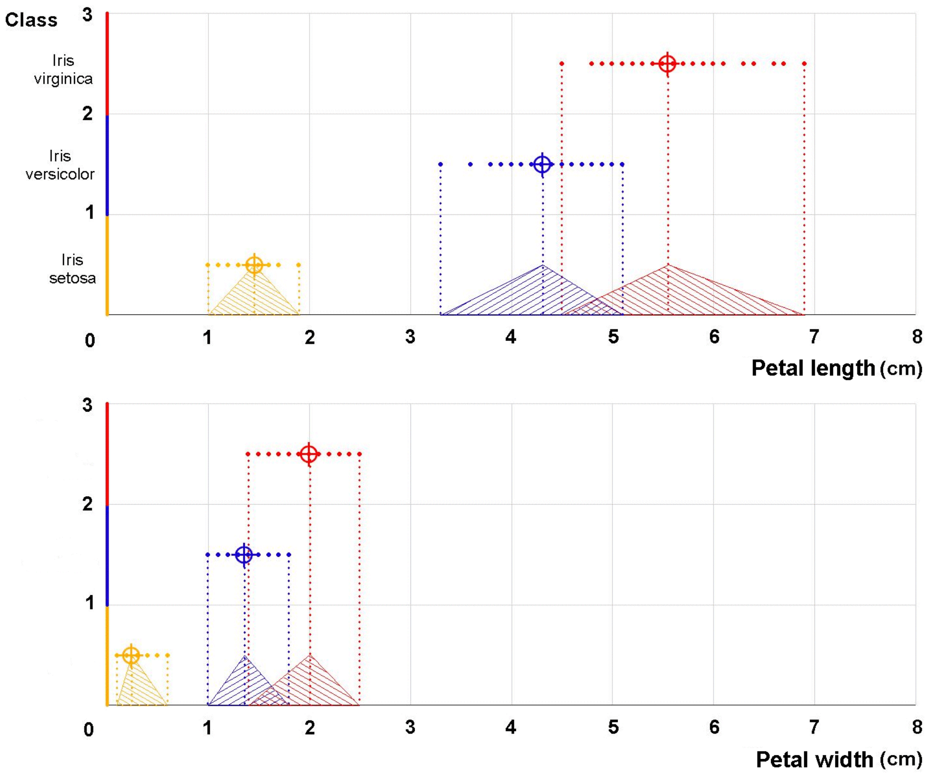


Figure 4.2: Membership functions of petal length and petal width. Iris variety setosa, versicolor and virginica are plotted on the horizontal axis in orange, blue and red, respectively. Y values are the centre of the range of the corresponding flower class. X values are measurement in cm of the metric displayed. Circles with a cross are centroids of metric measurements: they define the apex of the respective membership functions.

Here we have a practical design for fuzzy rule-based models predicting categories from fuzzy input variables. In the training dataset all output will be coded as 0.5 for setosa, 1.5 for versicolor, 2.5 virginica: that is the centre of the range of possible values for the corresponding Iris variety. Figure 4.2 and 4.3 allow us to make a number of observations. Owing to different amount of overlap between membership functions, the twelve membership functions and therefore the twelve corresponding rules of the resulting predictive model do not have the same discriminating power. Petals will be more useful to identify species than sepals as sepal membership functions overlap a lot more. Iris setosa is uniquely identified by small petals, smaller than both versicolor and virginica. The least useful variable is sepal width as the three membership functions overlap so much that only some iris setosa (light grey triangle in the lower panel of Figure 4.2) have sepals distinctively wide. Sepal widths are particularly unreliable as all versicolor sepal widths could be identified as setosa or virginica instead. Petal length is best at separating the three varieties as the percentage overlap between successive membership functions is lowest.

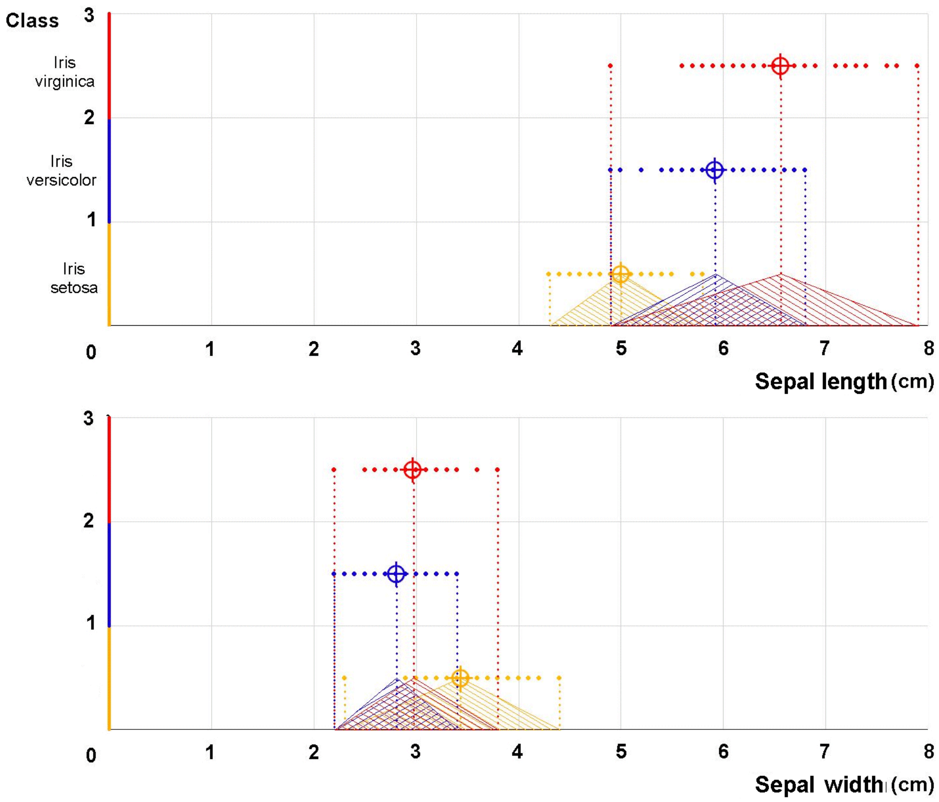


Figure 4.3: Membership functions of sepal length and sepal width.

The previous qualitative description of the role the different variables play in the model is important. It provides a clear understanding of what drives the classification of these three species without having to rely on mathematical expressions, whose significance is rarely equally understood by all members of a multidisciplinary research team. Comments above need to be reflected in the model. Independent variables poorly related to the dependent variable have a low correlation coefficient.

The assumption is of course that the type of relationship between the two variables is known. This relationship is generally considered to be linear. If the relationship is not linear it should be made linear by applying a suitable expression to the data. This is not always feasible and, consequently, weightings are often ignored in this thesis particularly when dealing with small noisy datasets. Here however they are calculated to demonstrate that they can be effective with some datasets.

The more records in a membership function the more representative and reliable its contribution to the final model. The density of records is the metric used here to capture this property. More membership function metrics could be explored to calculate weightings. However, simplifying calculations is one of the most important objectives of fuzzy rule-based modelling. One has therefore to restrain from introducing a level of sophistication which would contradict the initial intent of this dissertation.

Table 4.2: Minimum, maximum, number of values (N Points), density, correlation coefficient, weighting and normalized weighting of the 4 flower metrics for the 3 iris varieties.

Petal Length

Fuzzy patch	Min	Max	N Points	Density	Cor. Coef.	Weighting	N. W.
Setosa	1	1.9	40	44.46	0.95	42.24	0.55
Versicolor	3.3	5.1	37	20.56	0.95	19.53	0.26
Virginica	4.5	6.9	43	17.92	0.95	17.02	0.22

Petal Width

Fuzzy patch	Min	Max	N Points	Density	Cor. Coef.	Weighting	N. W.
Setosa	0.1	0.6	40	80.00	0.95	76.24	1.00
Versicolor	1	1.8	37	46.25	0.95	44.08	0.58
Virginica	1.4	2.5	43	39.09	0.95	37.25	0.49

Sepal Length

Fuzzy patch	Min	Max	N Points	Density	Cor. Coef.	Weighting	N. W.
Setosa	4.3	5.8	40	26.67	0.78	20.86	0.27
Versicolor	4.9	6.8	37	19.47	0.78	15.23	0.20
Virginica	4.9	7.9	43	14.33	0.78	11.21	0.15

Sepal Width

Fuzzy patch	Min	Max	N Points	Density	Cor. Coef.	Weighting	N. W.
Setosa	2.3	4.4	40	19.05	0.44	8.31	0.11
Versicolor	2.2	3.4	37	30.83	0.44	13.44	0.18
Virginica	2.2	3.8	43	26.88	0.44	11.72	0.15

All information relevant to a fuzzy rule-based model that can be derived from Figures 4.2 and 4.3 is captured in Table 4.2. Density is the number of values divided by the range of values in the membership function. This corresponds to the number of points divided by the difference between the maximum and minimum. The correlation coefficient is directly derived from the input data. Weightings are the product of density and correlation coefficient. The normalised weighting is obtained by dividing the weighting of each membership function by the highest weighting which here is 76.24.

Table 4.3 translates the information in Table 4.2 into the coordinates a, b and c of the triangular membership functions that make up the fuzzy rule-based model. All normalised weightings and membership function names are listed. Table 4.3 completely defines the input component of the model. Parameters of the output component are in Table 4.4. The main outcomes of the identification of the fuzzy rule based-model of Fisher's Iris flower variety prediction based on measurements of petal and sepal width and length are summarised in Tables 4.3 and 4.4. They can be described as follows.

"Flower Code" is the output variable comprised of three trapezoidal membership functions. The four input variables are 'Sepal Length', 'Sepal Width', 'Petal Length', 'Petal Width'. Each of the four input variables is made of three triangular membership functions. Twelve rules are derived from the twelve input triangular membership functions (3 for each of the 4 input variables). All rules are assigned a normalised weighting.

Table 4.3: Input membership function coordinates a, b, c, normalised weightings and membership function names.

Petal Length

Fuzzy coordinates	a	b	c	N. W.	MF name
Setosa	1.00	1.46	1.90	0.55	Se_PL
Versicolor	3.30	4.31	5.10	0.26	Ve_PL
Virginica	4.50	5.55	6.90	0.22	Vi_PL

Petal Width

Fuzzy coordinates	a	b	c	N. W.	MF name
Setosa	0.10	0.24	0.60	1.00	Se_PW
Versicolor	1.00	1.36	1.80	0.58	Ve_PW
Virginica	1.40	2.00	2.50	0.49	Vi_PW

Sepal Length

Fuzzy coordinates	a	b	c	N. W.	MF name
Setosa	4.30	5.01	5.80	0.27	Se_SL
Versicolor	4.90	5.92	6.80	0.20	Ve_SL
Virginica	4.90	6.57	7.90	0.15	Vi_SL

Sepal Width

Fuzzy coordinates	a	b	c	N. W.	MF name
Setosa	2.30	3.44	4.40	0.11	Se_SW
Versicolor	2.20	2.81	3.40	0.18	Ve_SW
Virginica	2.20	2.97	3.80	0.15	Vi_SW

Output memberships are defined as the three non overlapping trapezoidal membership functions in Table 4.4. They are typical of rule-based models with fuzzy input and Boolean output.

Table 4.4: Coordinates of the 3 non overlapping trapezoidal output membership functions corresponding to the 3 iris varieties setosa, versicolor and virginica.

Fuzzy coordinates	a	b	c	d
Setosa	0	0	1	1
Versicolor	1	1	2	2
Virginica	2	2	3	3

Previous observations of the relative lack of relevance of the flower metric sepal width are confirmed by its very low weightings in Table 4.3. This flower metric is therefore discarded as Figure 4.3 shows a near complete overlap of all 3 membership functions for this metric. The final model comprises therefore 9 rules. From Table 4.3 and 4.4 we can write:

Rule 1 IF Input MF is Se_PL THEN Output MF is Setosa NW= 0.55
Rule 2 IF Input MF is Ve_PL THEN Output MF is Versicolor NW= 0.26
Rule 3 IF Input MF is Vi_PL THEN Output MF is Virginica NW= 0.22
Rule 4 IF Input MF is Se_PW THEN Output MF is Setosa NW= 1.00
Rule 5 IF Input MF is Ve_PW THEN Output MF is Versicolor NW= 0.58
Rule 6 IF Input MF is Vi_PW THEN Output MF is Virginica NW= 0.49
Rule 7 IF Input MF is Se_SL THEN Output MF is Setosa NW= 0.27
Rule 8 IF Input MF is Ve_SL THEN Output MF is Versicolor NW= 0.20
Rule 9 IF Input MF is Vi_SL THEN Output MF is Virginica NW= 0.15

All rules in this case study have single conditions. Indeed multiple conditions concatenated by AND, OR, XOR, NOT operators described in section 2.7.4 can replace single conditions. However, complex conditional combinations, frequent in control systems, are less common in fuzzy rule-based models of natural systems. The complexity of actual interactions between input and output variables in natural systems is better described by multiple simple rules linking a single antecedent to a single consequence. This view is reinforced by the two fuzzy rule-based models presented in Chapter 5.

4.1.2 Building the fuzzy rule-based model

The fuzzy rule-based model is implemented in Matlab (MathWorks, 1999) with weightings, and in Scilab (Campbell *et al.*, 2006) without weightings. The Scilab fuzzy logic toolbox (Urzua, 2004), in version 0.2 used here, does not implement weightings.

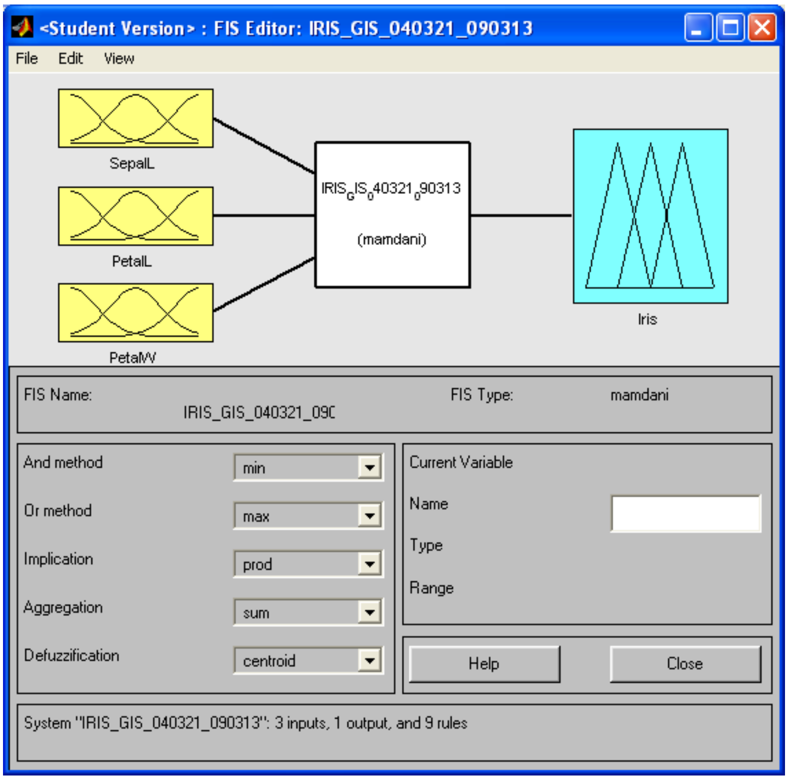


Figure 4.4: Screenshot of the Matlab Fuzzy Logic Toolbox (FLT). FLT provides a clear diagrammatic description of the structure of a fuzzy rule-based model.

Once all the parameters of the model defined during the identification phase completed in section 4.1.1 are entered, the model can be run to classify iris flowers from the length and width of petals and length of sepals. The parameters selected for the Matlab model are displayed in Figure 4.4. The Matlab rule viewer in Figure 4.5 shows how each variable (yellow) contributes, through sepal and petal measurements displayed in the Input window, to the iris flower classification. The process leading to the calculation of the output by centroid defuzzification is easy to follow. The Matlab graphical representation of the contribution (blue) of each rule to the classification output helps to develop a clear understanding of the model.

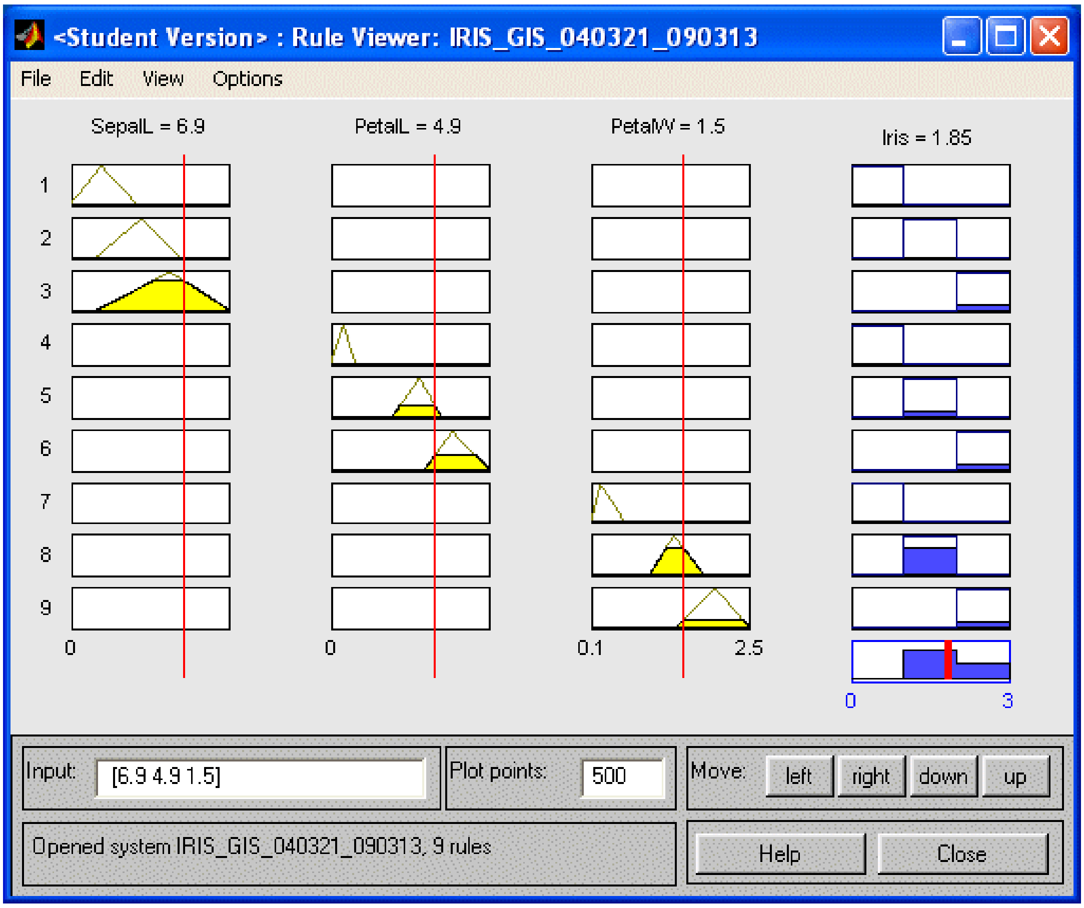


Figure 4.5: Screenshot of the Matlab Fuzzy Logic Toolbox (FLT) rule definition window.

4.1.3 Assessing the fuzzy model performance

The performance of the models with and without weightings is assessed on the ability to correctly classify 30 flowers defined by the three first rows of flower metrics displayed in Table 4.5. These 30 records are not part of the 120 records used to train the model in Chapter 4.1.1. We are therefore assessing the ability of the model to correctly process unknown information.

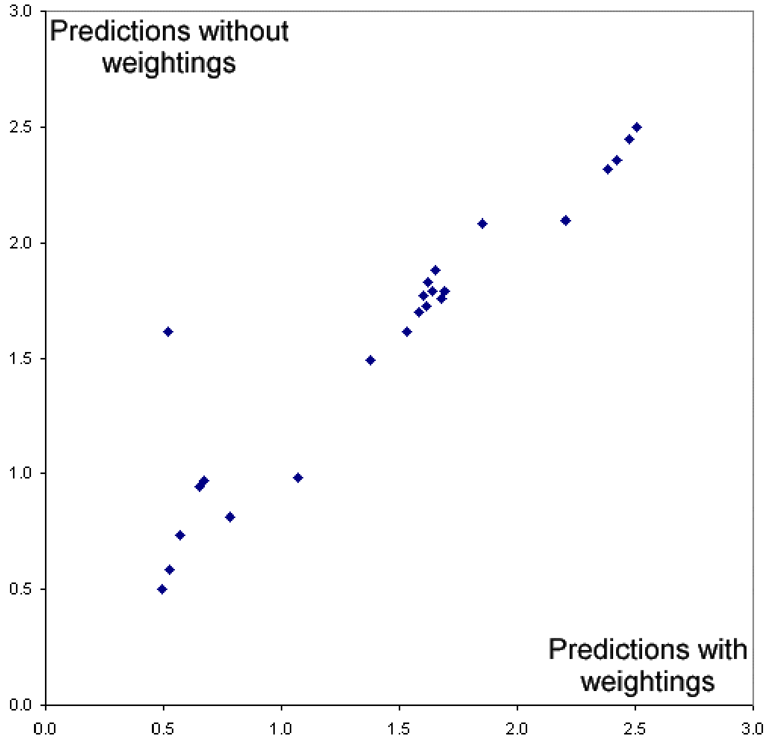
Table 4.5 shows that the weighted classifier made only one error out of thirty predictions while the non weighted classifier failed to correctly classify four flowers. The weighted classifier performs best. The comparison between the predictions of the two models, however, shows that in only one instance their predictions are substantially different. The 0.96 correlation coefficient between outputs of the weighted and non weighted models displayed in Figure 4.6 confirms that their predictions are very similar. However, the classification based on weighted rules, as displayed in Table 4.5, performs better.

Table 4.5: Performance of the model with and without weightings. Predicted values in red indicate misclassified flowers. The classification with weightings performs best with an accuracy of 29/30 = 96.67%.

Sepal length (cm)	Petal length (cm)	Petal width (cm)	Iris variety	Range	With weightings	Without weightings
5	1.3	0.3	Setosa	0 to 1	0.53	0.58
5.8	4	1.2	Versicolor	1 to 2	1.59	1.70
4.8	1.4	0.3	Setosa	0 to 1	0.50	0.50
5.7	4.2	1.3	Versicolor	1 to 2	1.53	1.61
5	1.4	0.2	Setosa	0 to 1	0.52	1.61
6.1	4.7	1.4	Versicolor	1 to 2	1.64	1.79
6	4.5	1.5	Versicolor	1 to 2	1.68	1.76
5	3.5	1	Versicolor	1 to 2	0.78	0.81
5	1.6	0.4	Setosa	0 to 1	0.52	0.59
4.8	1.4	0.1	Setosa	0 to 1	0.50	0.50
6.4	5.3	2.3	Virginica	2 to 3	2.39	2.32
6.9	5.1	2.3	Virginica	2 to 3	2.51	2.50
7.7	6.7	2	Virginica	2 to 3	2.51	2.50
6	4	1	Versicolor	1 to 2	1.69	1.79
5.1	3	1.1	Versicolor	1 to 2	1.07	0.98
6.9	4.9	1.5	Versicolor	1 to 2	1.85	2.08
5.4	1.7	0.4	Setosa	0 to 1	0.67	0.97
5.5	3.7	1	Versicolor	1 to 2	1.38	1.49
6.6	4.4	1.4	Versicolor	1 to 2	1.62	1.83
5.8	5.1	2.4	Virginica	2 to 3	2.21	2.10
5.4	1.7	0.2	Setosa	0 to 1	0.66	0.94
5.2	1.4	0.2	Setosa	0 to 1	0.57	0.73
6.4	5.6	2.1	Virginica	2 to 3	2.42	2.35
6.3	4.4	1.3	Versicolor	1 to 2	1.60	1.77
7.2	6	1.8	Virginica	2 to 3	2.51	2.50
4.8	1.6	0.2	Setosa	0 to 1	0.50	0.50
5.7	3.5	1	Versicolor	1 to 2	1.62	1.72
4.7	1.3	0.2	Setosa	0 to 1	0.50	0.50
7	4.7	1.4	Versicolor	1 to 2	1.65	1.88
6.7	5.2	2.3	Virginica	2 to 3	2.47	2.44

The iris dataset in this case study, initially used by Fisher (1936) to demonstrate the principles of discriminant analysis (Kachigan, 1991), has become a standard test data set for a wide range of classification methods (Chiu, 1997; Halgamuge, 1997; Ishibuchi and Nakashima, 2000; Kumar and Sirohi, 2010; Lee et *al.*, 2006; Lee; 2009; Ling, 2009; Nakashima et al., 2002; Qiu et *al.*, 2007). Chen and Fang (2005: p. 47) show that the 6 fuzzy rule-based methods they compare, on Fisher's (1936) dataset, achieve classification accuracies between 94.67% and 96.67% while their own improved method reaches 97.33% . Lee (2009: p. 85) lists six additional fuzzy based methods, tested on the same dataset with similar classification accuracies between 96.00% and 97.12%. Table 4.5 shows that the method proposed in this thesis, particularly with weighted rules, has a classification accuracy of 96.67% on par with other method based on fuzzy logic.

Figure 4.6: Correlation between outputs of the weighted and non weighted models.



4.1.5 Discussion

Figure 4.6 shows that the two models respond very differently only in the point (0.5,1.6) defined by the fifth record from the top, in Table 4.5. The corresponding setosa flower is characterised by a sepal length of 5. Figure 4.3 shows that all three sepal length rules are triggered by this value. Table 4.2 shows that the setosa rule carries a higher weighting of 0.27. This rule will therefore have a stronger influence in the weighted model only. Table 4.3 shows that the point of coordinate 1.4 and 0.2, in ‘Petal Length’ and ‘Petal Width’ dimensions respectively, only belongs to setosa membership functions. This discrepancy between the weighted and non weighted model outputs can therefore be attributed mainly to Rules 7, 8 and 9 at the end of section 4.1.1. We can now try to understand why the weighted model performs much better than the non weighted model in this case.

Setosa rules, displayed in the top three panels of Table 4.3, carry higher weightings than versicolor and virginica rules. Their membership functions, however, are smaller than those of versicolor and virginica varieties. They tend therefore to be less influential during the COG defuzzification as bigger membership functions pull the centroid more towards them. For the same membership value, during the aggregation process, the answer will be more strongly influenced by the bigger membership functions. Only weightings can counteract this effect which is particularly relevant in that case as 'Sepal Length' triggers all three membership functions at once. Two larger non setosa membership functions influence the answer. Their effect can only be countered effectively by weightings.

In all 3 remaining cases of flowers misclassified by the non weighted model, the discrepancy between the outputs of both models is generally small. This observation supports a general impression conveyed by this thesis, and reinforced in Chapter 5, that Mamdani type fuzzy rule-based models with ratio valued inputs and output rarely benefit much from weightings. In the case of models with a categorical output, a small variation in output can result in a different category and consequently a very serious error. In that case weighted rules may be advantageous when the COG defuzzification is used.

4.2 Multivariate predictive modelling on the basis of variables of unknown influence on the outcome

Generalised linear models (GLM) have grown in popularity among ecologists during the last three decades (Guisan *et al.*, 2002). The sophistication and capabilities of advanced statistical modelling tools are not without impediments. Experiments often need to be carefully designed to meet underlying requirements (Stern *et al.*, 2004). These conditions are rarely met by NRM datasets. Within this context additional effort and expertise are not justified as they are unlikely to translate into substantially better predictions. The reason is simple: predictive capability is limited by the nature and quality of the data. This chapter proposes a less onerous methodology well suited to NRM datasets.

Section 4.2.1 introduces a generic semi automatic data driven fuzzy rule-based modelling methodology to tackle multivariate predictive models where both input and output variables are numerical. Section 4.2.2 applies this modelling strategy to real experimental data on elephant seal wanderings in the Southern Ocean. Predictions of foraging patterns of elephant seals obtained by this method are compared with GLM results (Bradshaw *et al.*, 2004).

4.2.1 A generic semi automatic data driven fuzzy rule-based methodology to tackle multivariate predictive models

This case study has three objectives. Firstly, Nakanishi *et al.*'s strategy (1993) of semi automatic data driven fuzzy rule-based modeling is presented. Secondly, a simplified approach to Nakanishi's strategy is proposed. Thirdly, the performance of the two methods is compared.

4.2.1.1 Nakanishi's identification method

Nakanishi *et al.* (1993) offer an elegant and practical identification method summarised in 8 steps:

1/ split the initial dataset in 2 subsets containing an equal number of records: one is used to train the model, the other to assess it;

2/ split in two the training subset: these two subsets are used to identify initial variables to retain in the model;

3/ a fuzzy clustering algorithm is used to segment the training datasets;

4/ one model is created from each of the two training subsets with fuzzy membership values generated by fuzzy clustering;

5/ each of these two models is evaluated with data generated from the other model;

6/ predictions from both models are evaluated as all rules are progressively incorporated, one variable at a time;

7/ variables that produce incompatible predictions are eliminated;

8/ the model comprised of the remaining variables is assessed on the evaluation dataset.

Nakanishi *et al.*'s (1993) article is particularly useful as it provides a practical technique to design membership functions and a sensible method to pick variables to include in the model. This 8 step strategy, however, is involved and time consuming and tends to defeat the purpose of fuzzy logic.

In steps 1 to 3 Nakanishi *et al.*'s (1993) method produces trapezoidal membership functions that often provide a better representation of reality than triangular membership functions as they allow more than one value to perfectly represent a class. The equations of the two sloping sides are provided by the regression lines that interpolate, on each side, all experimental membership values between 0 and 1. The intersection of these two lines with $\mu(x) = 0$ and $\mu(x) = 1$ provides the four vertices of the trapezoidal membership function. The membership function $\mu(x)$ represents the membership of a record to a class created by fuzzy clustering in Step 3. Calculating the equation of the regression line can be avoided by identifying visually, from a plot of records versus their membership value, which records should be the vertices of each membership function. The visual approach is advantageous as it does not require writing a script that will decide which points to regress. This decision is difficult to embed in an algorithm as the leftmost and rightmost records of each membership function do not necessarily correspond to records with a null membership.

In steps 4 to 8 Nakanishi *et al.* (1993) propose a very elegant solution to the problem of deciding which variables to include in the model. They do not rely on any statistical method to choose variables that are good predictors of the output. The role of non statistical models is important where two fundamental statistical premises are ignored: independence of data and undefined distribution. Independence of data rarely occurs when dealing with georeferenced field records, a common problem in NRM surveys. In this context field records are frequently either auto correlated or spatially correlated. Both instances contravene the assumption of independence of data. The statistical distribution of NRM data is often unknown. This is inherent to the nature of fieldwork. For reasons of prohibitive cost of acquisition and practicality, datasets are often too small (less than 50 records) to allow field records to be meaningfully fitted to any statistical law of distribution. Geostatistics address the issue of spatial correlation, however a major intrinsic limitation (Houlding, 1999) remains. Records need to be normally distributed. As mentioned previously this condition is often difficult to meet as the dataset cannot be normalised if the initial distribution cannot be unambiguously identified because the dataset is too small. The simplified fuzzy rule-based modelling method described in the next section ignores statistical tests to provide GIS modellers stand-alone investigative tools.

4.2.1.2 A rationale for simplifying Nakanishi *et al.*'s (1993) fuzzy rule-based modelling strategy

Nakanishi *et al.*'s (1993) approach to fuzzy rule-based modelling is very comprehensive but time consuming. It provides the material required to demonstrate the simplified fuzzy rule-based modelling strategy advocated in this thesis. GIS specialists are often requested to predict properties across a landscape. They have to rapidly ascertain the predictive capability of available multivariate datasets. The first step generally consists in checking the correlation coefficient between the output and all potential input variables. Although very low correlation coefficients immediately identify input variables that can be discarded, those with intermediate correlation coefficients are more difficult to handle. A fundamental question thus remains: does the dataset allow the prediction of values of output variables? The strategy proposed intends to unambiguously answer this question in the most efficient manner.

Let us first review Nakanishi's eight step approach to only retain steps which are crucial to assess the predictive capability of the dataset. The intention is not to dismiss Nakanishi et al.'s (1993) excellent method but to simplify it in order to provide a faster first pass approach capable of suggesting whether or not the predictive capability of the dataset warrants the additional time and effort required by Nakanishi et al.'s (1993) technique. Steps 1 and 2 are eliminated as the whole dataset is often required to estimate its predictive capability. Step 3 is retained because a fuzzy clustering algorithm will rapidly process a vast volume of data with minimum human intervention. Steps 4, 5 and 6 are eliminated because the priority is to make sure that predictions are possible, not to refine the model. Step 7 is retained as variables without predictive power need to be eliminated as soon as possible. Finally, step 8 is retained. Compared with Nakanishi's method, the predictive capability estimated will be optimistic because it relies on the same dataset for the identification and evaluation of the model. If the correlation coefficients between predicted and observed outputs are low we can therefore be sure that no predictive model can be created.

The simplified fuzzy rule-based modelling strategy proposed is a three step process. Firstly, a fuzzy clustering algorithm derives all identification parameters from the whole dataset. Secondly all variables that produce unacceptably erratic membership functions are eliminated. Thirdly, the model created from the remaining variables is evaluated on the whole dataset. If it can be established that a predictive model is feasible, additional time may be allocated to refine the predictions. A GLM or other sophisticated statistical model may then be preferred. If the prediction capability of the model is poor there is little chance that additional effort will result in substantially better predictions. The relevance of the dataset to the problem investigated needs to be reconsidered before additional resources are committed to modelling.

4.2.1.3 Simplified semi automatic segmentation of Nakanishi's dataset

One of three datasets in Nakanishi *et al.*'s (1993, p.279-280) paper is reproduced in Table 4.6 below. Table 4.6 contains seventy records of five input and one output variables defining a process in a chemical plant. These variables are listed below.

X1 = monomer concentration
X2 = change of monomer concentration
X3 = monomer flow rate
X4 = local temperature 1 inside the plant
X5 = local temperature 2 inside the plant
Y = set point for monomer flow rate

To implement the first step of the simplified strategy outlined in the previous section, all 3 subsets in Table 4.6 are merged into a single dataset. This dataset is segmented with Fuzme (Minasny and McBratney, 2002) which is a freely available clustering software created at the University of Sydney. Fuzme performs a semi automatic segmentation as a good deal of human intervention is required. By comparison, however, the manual segmentation performed in section 2.1 and leading to the identification of membership functions in Table 2.2 is subjective. It relies more on the skills of the modeler.

Table 4.6: Nakanishi's dataset. The five input and one output variables define a process in a chemical plant. X1, X2, X3, X4 and X5 are input variables monomer concentration, change of monomer concentration, monomer flow rate, local temperature 1 inside plant and local temperature inside plant 2, respectively. Y is the output variable set point for monomer flow rate.

ID	X1	X2	X3	X4	X5	Y
1	6.59	-0.21	464.00	-0.10	0.10	700.00
2	6.59	0.00	703.00	-0.10	0.10	900.00
3	5.51	-0.29	1782.00	-0.10	0.00	1900.00
4	5.62	0.11	3562.00	-0.40	0.10	3700.00
5	5.79	-0.03	3895.00	0.20	-0.10	3900.00
6	5.65	-0.14	3887.00	-0.10	0.00	3900.00
7	4.81	-0.23	4462.00	0.00	-0.10	4900.00
8	4.72	0.01	5668.00	0.00	-0.10	6000.00
9	4.70	0.05	6368.00	-0.10	0.00	6400.00
10	4.59	0.04	6250.00	-0.20	-0.10	6400.00
11	4.77	0.00	6569.00	0.00	-0.10	6600.00
12	4.77	0.03	6779.00	0.00	-0.10	6800.00
13	4.57	-0.04	6832.00	0.00	0.10	6800.00
14	4.56	-0.01	6832.00	-0.10	0.10	6900.00
15	4.56	0.00	7022.00	0.00	0.00	7000.00
16	4.51	-0.03	6958.00	0.10	-0.10	7000.00
17	4.50	0.02	7006.00	0.00	0.10	7000.00

ID	X1	X2	X3	X4	X5	Y
18	6.50	-0.09	797.00	0.10	0.10	700.00
19	6.45	-0.09	784.00	0.00	0.10	800.00
20	6.02	-0.18	1211.00	0.00	0.10	1400.00
21	5.44	0.01	2404.00	-0.10	-0.10	2500.00
22	5.94	0.17	3701.00	-0.20	0.10	3800.00
23	5.99	-0.03	3896.00	0.20	-0.10	3900.00
24	5.24	-0.24	4048.00	0.10	0.00	4400.00
25	4.61	-0.01	5284.00	-0.10	0.20	5400.00
26	4.58	-0.14	5844.00	-0.20	0.10	6100.00
27	4.84	0.03	6412.00	-0.10	-0.10	6400.00
28	4.77	0.01	6587.00	-0.10	0.10	6600.00
29	4.77	0.00	6559.00	0.00	0.00	6700.00
30	4.73	0.00	6844.00	-0.10	0.00	6800.00
31	4.71	-0.06	6783.00	0.00	0.00	6800.00
32	4.48	-0.02	7032.00	0.00	0.00	7000.00
33	4.48	0.00	6973.00	0.00	0.00	7000.00
34	4.56	-0.01	7009.00	-0.10	0.10	7000.00
35	4.47	0.00	6986.00	-0.10	0.10	7000.00

ID	X1	X2	X3	X4	X5	Y
36	6.80	-0.05	401.00	-0.20	-0.10	500.00
37	6.48	-0.02	717.00	-0.10	0.10	700.00
38	6.45	0.00	794.00	-0.20	0.10	800.00
39	6.54	0.06	706.00	-0.20	0.10	800.00
40	6.20	-0.25	792.00	0.00	0.00	1000.00
41	5.80	-0.22	1557.00	-0.20	0.00	1600.00
42	5.43	-0.08	2206.00	-0.10	0.10	2300.00
43	5.51	0.07	2685.00	0.10	0.00	2800.00
44	5.97	0.03	3775.00	-0.10	0.00	3800.00
45	5.77	0.15	3629.00	-0.10	0.00	3800.00
46	6.02	0.05	3829.00	-0.10	-0.10	3900.00
47	5.82	-0.17	3920.00	0.20	-0.10	3900.00
48	5.48	-1.70	3930.00	0.20	0.00	4000.00
49	5.04	-0.20	4448.00	0.00	0.00	4700.00
50	4.62	-0.19	5078.00	-0.30	0.30	5200.00
51	4.54	-0.07	5225.00	-0.30	0.10	5600.00
52	4.71	0.17	5391.00	-0.10	0.00	6000.00
53	4.55	-0.03	6068.00	-0.20	0.00	6400.00
54	4.65	0.06	6358.00	-0.10	-0.10	6400.00
55	4.81	0.11	6379.00	-0.30	0.00	6400.00
56	4.83	-0.01	6416.00	0.10	-0.10	6500.00
57	4.76	-0.07	6514.00	0.00	0.00	6600.00
58	4.73	-0.04	6672.00	0.00	0.00	6700.00
59	4.74	0.01	6775.00	-0.20	0.00	6800.00
60	4.63	-0.07	6849.00	0.00	0.00	6800.00
61	4.66	-0.05	6816.00	0.00	0.00	6800.00
62	4.61	-0.02	6803.00	0.00	0.00	6800.00
63	4.70	0.04	6812.00	0.00	0.00	6800.00
64	4.57	0.01	6998.00	-0.10	0.00	7000.00
65	4.50	0.00	7027.00	0.00	0.00	7000.00
66	4.54	-0.02	6862.00	-0.10	-0.10	7000.00
67	4.54	0.06	6995.00	0.00	0.00	7000.00
68	4.57	0.03	6986.00	0.10	-0.10	7000.00
69	4.48	0.01	6975.00	0.00	0.00	7000.00
70	4.47	-0.04	6998.00	0.00	0.10	7000.00

Much research went into data driven fuzzy rule-based modelling by semi automatic clustering in the 1980s and 1990s. In depth comparisons (Babuska, 1996) of clustering algorithms are available in Chapter 2. The Gustafson Kessel algorithm (Babuska, 1996, p.63) derived from the fuzzy c-means clustering algorithm, can detect clusters of different shapes and orientation in n dimensional space where n is the number of variables considered in the model. Fuzme supports the Gustafson Kessel algorithm used to segment the dataset in Table 4.6. For practical reasons, such as number of rules and easy assignment of linguistic labels to membership functions, the maximum number of classes is generally set to nine.

Table 4.7:Effect of the number of clusters on class size disparity. The number of classes in the first column shows that as the number of classes increases the ratio of the maximum to minimum number of records per class a to l increases from 2 to5.

Class	a	b	c	d	e	f	g	h	I
2	43	27							
3	14	15	41						
4	8	13	36	13					
5	6	13	26	12	13				
6	12	3	3	9	36	7			
7	9	11	13	3	26	3	5		
8	5	3	14	15	11	10	9	3	
9	10	3	10	3	10	11	15	3	5

The more classes, the better the chance to capture in each class one single facet of the process reflected by the dataset. Modelling one single aspect of a process is easier and therefore more reliable. However, classes that contain a small number of elements are likely to be less reliable as they may not contain enough values for a trend to emerge from the background noise.

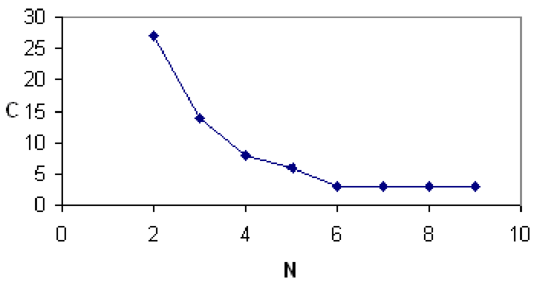


Figure 4.7: Effect of minimum number of records per class (N) on number of classes (C).

The influence of a few unreliable records on class parameters may be unacceptable. There is consequently a balance to maintain between the number of clusters generated and the number of elements per cluster. Performance indices are calculated by the clustering. These performance indices may help to choose the optimum number of classes. From a membership function design point of view, it remains preferable to maximise the number of clusters while avoiding wide size disparity between clusters evident in Table 4.7. The effect of numbers of classes on their size is visualised in Figure 4.7 which shows that, when the number of classes exceeds five, clusters of only three elements occur. Five is the number of classes selected as it appears to be the best compromise between number of clusters and cluster reliability.

4.2.1.4 Designing output membership functions

During the semi automatic clustering process, the dataset is segmented into classes called membership functions. Within each class, membership values of all variables are sorted by the actual values of the output variable. Variables which explain the output variable have a membership to the same class that is related to that of the output variable. Membership values of explanatory variables therefore vary smoothly with gradual changes in membership value of the output variable. Chaotic variations of membership of a variable to a class reflect the absence of correlation between changes of this variable and those of the output variable. Consequently, non explanatory variables have irregular membership functions. This section relies therefore on the visual aspect of plots of membership values versus record value to provide a quick assessment of the predictive capability of the corresponding independent variable.

To derive the coordinates of all trapezoidal membership functions, Nakanishi *et al.*'s (1993) first calculate the parameters of the regression lines that interpolate values on the slanted sides of the trapezium. The coordinates of the four apices of each membership function are the coordinates of the intersection of these two lines with the 0 and 1 horizontal lines. This methodology is straightforward but its implementation is time consuming. Visual estimation of points to regress relies on deciding which points close to 0 and 1 should be rejected. Considering the importance of visual control in this process and the empirical nature of selecting points to be regressed in Nakanishi *et al.*'s (1993) method, it was decided to simplify Nakanishi *et al.*'s (1993) technique.

This simplification concerns the numerical values and plots of experimental records versus class membership previously mentioned (Figure 4.8). Four important records described by reference to the centre of the membership function, must be identified. On the left, the highest and lowest values which should be assigned a membership of 0 and 1 respectively must be defined. Similarly, on the right, the highest and lowest values which should have a membership of 0 and 1 respectively need to be identified. The coordinates of these 4 points become the coordinates of the corresponding output trapezoidal membership functions displayed in Table 4.8. This approach, apparently less rigorous than Nakanishi *et al.*'s (1993), is simpler and acknowledges the visual/empirical nature of the process of selecting records from which membership functions are derived.

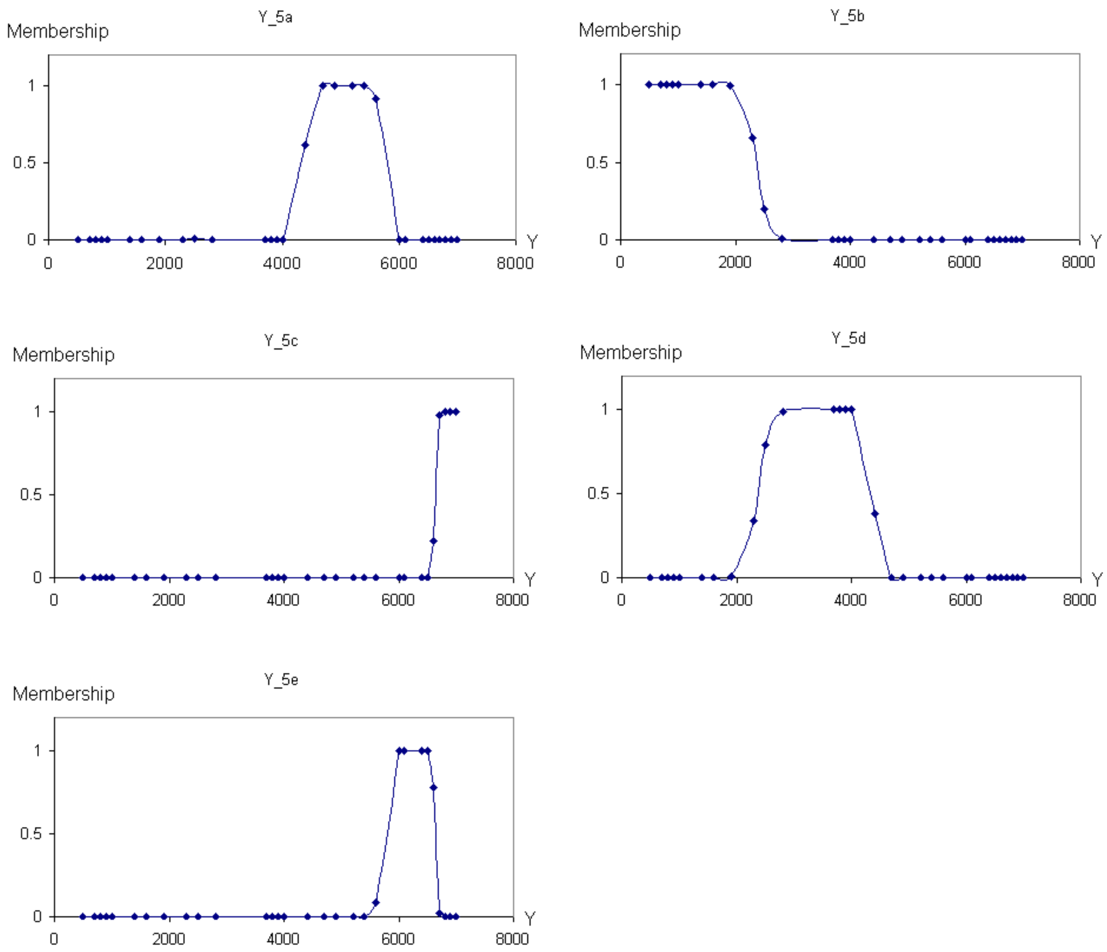


Figure 4.8: Plots of all membership values of the output variable Y produce smooth envelopes.

Figure 4.8 shows the five membership functions derived from the five graphs Y_5a, Y_5b, Y_5c, Y_5d, Y_5e corresponding to the five classes 5a, 5b, 5c, 5d and 5e respectively. These five classes are defined by fuzzy clustering of output membership values.

Table 4.8: Vertex coordinates of the output trapezoidal membership functions.

	Mu_Ya	Mu_Yb	Mu_Yc	Mu_Yd	Mu_Ye
a	4000	500	6500	1900	5400
b	4700	500	6700	2800	6000
c	5400	1900	7000	4000	6500
d	6000	2800	7000	4700	6700

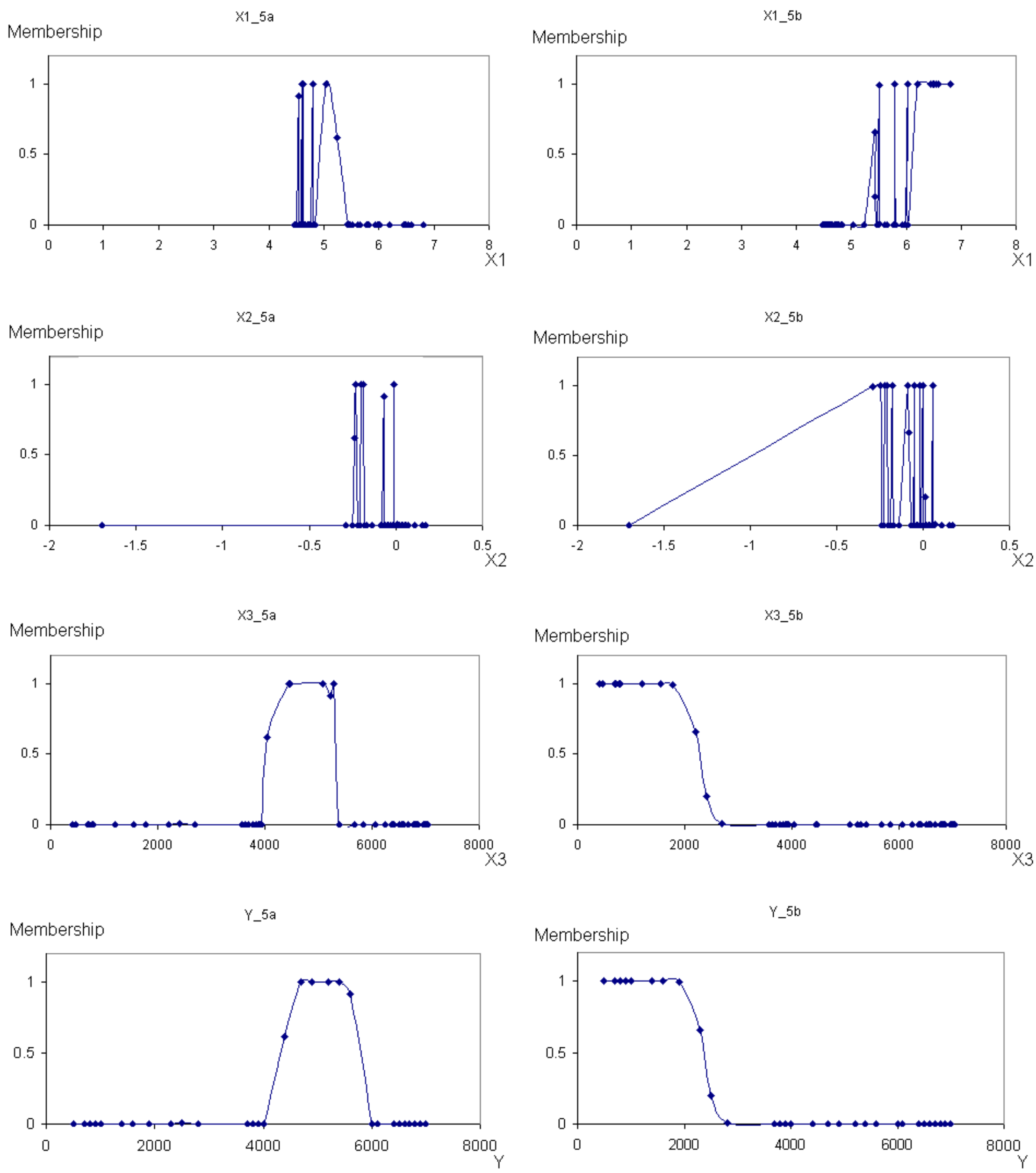


Figure 4.9: Plots of membership values of input variables X1, X2 and X3 and output variable Y display a clear contrast between these variables. The envelopes of membership values of classes 5a and 5b of variables X3 and Y are much smoother.

Classifying all membership values in all classes of all variables by Y imposes the segmentation of Y to all input variables. A degradation of smoothness of the envelopes of membership values (Figure 4.9) results from a decrease in dependence between output and input variables. Although these graphs correspond to clusters 5a and 5b only, clear differences already emerge. Only variables correlated with the output Y have a smooth envelope.

The technique described before is applied to derive membership functions from membership values in each of the 5 classes from 5a and 5e for all 5 input variables X1, X2, X3, X4 and X5 in Table 4.6. Visually deriving membership functions from Figure 4.8 is straightforward. The situation changes rapidly with the ability of the input variable to predict the output variable. Figure 4.9 clearly demonstrates this situation. Plots of membership values (Figure 4.9) readily allow to define the coordinates of membership functions Y_5a, Y_5b, and X3_ 5b as well as X3_5b which are still reasonably well behaved. However, membership functions X1_5a, X1_5b, X2_5a and X2_5b show that these two variables are characterized by extreme variations in membership of ordered values. The association of values of these two input variables with the output is extremely erratic. This graph therefore casts serious doubts on the ability of these two variables to have any ability to predict the output.

The latest observation has important consequences equally applicable to predictive modelling either fuzzy or statistical: X1 and X2 should be discarded as they do not display any ability to reliably predict values of Y. One can draw a parallel with the statistical concept of correlation. This approach has one major advantage: the nature of the relation between output and input does not need to be defined. A correlation coefficient can only provide a useful estimate of the ability of one variable to explain the other only if the general mathematical expression of one of the two variables as a function of the other is known. This frequently overlooked limitation of the correlation coefficient, highlighted in section 4.3, frequently applies to natural systems.

4.2.1.5 Selecting input variables

Figure 4.9 reflects the interdependence between output and input variables. Membership functions Y_5a and Y_5b as well as X3_5a and X3_5b display progressive variations between successive values resulting in smooth envelopes. Although membership functions X1_5a and X1_5b can still be drawn, variations within these membership functions are erratic and the amplitude of most variations is maximum. Finally, membership functions can no longer be identified in X2_5a and X2_5b as variations between output and input values are too inconsistent. The interpretation of these observations is that X3 and, to a lesser extent, X1 explain the output variable Y. On the contrary, X2 does not explain Y at all. The same reasoning is applied to input variables X4 and X5 displayed in Figure 4.10. The fuzzy rule-based model can consequently make predictions of Y values only from records of X1 and particularly X3.

The above approach serves three purposes. Firstly, it highlights relations between input and output variables without relying on any statistical measure such as the correlation coefficient. Secondly, the strength of the relation between input and output variable is reflected by the joint behaviour of their corresponding value. This second statement reflects the fact that when successive values within an input membership function appear to vary widely relatively to the sorted output, the ability of the corresponding erratic input variable to predict a comparatively smooth output, is obviously poor. Thirdly, all variables that need not be considered in the fuzzy predictive model can be easily identified as their membership functions cannot be sketched from plots of experimental records versus membership value, as shown in Figure 4.9.

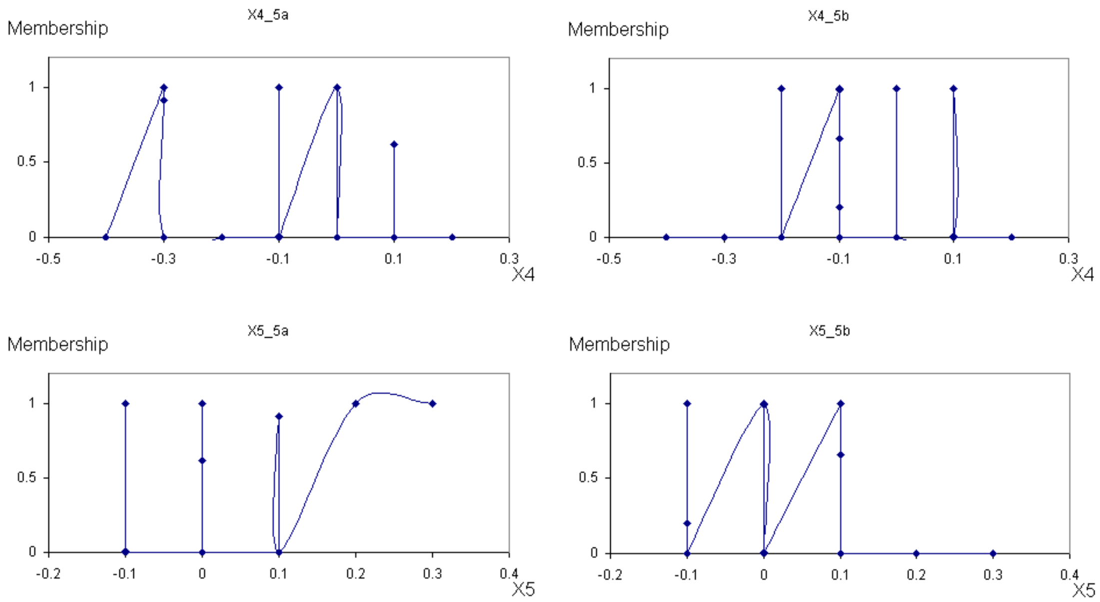


Figure 4.10: Plots of experimental records versus membership values for variables X4 and X5.

Comparing the monotonicity of membership of sorted values of input variables casts some light on their contribution to the predictive power of the model. A metric could be derived by calculating the average variation in membership between successive records in a given class/cluster. However, this path is not followed as the emphasis is to simplify the method described by Nakanishi *et al.* (1993). Visual examination is generally sufficient to identify input variables which do not help predict the output.

Table 4.9: Membership function coordinates of variables X1 and X3 derived from a detailed visual examination of plots in Appendix 3.

	Mu_X1a	Mu_X1b	Mu_X1c	Mu_X1d	Mu_X1e
a	4.51	5.24	4.47	5.04	4.57
b	4.61	6.20	4.47	5.48	4.58
c	5.04	6.80	4.77	6.02	4.84
d	5.43	6.80	4.81	6.20	5.04

	Mu_X3a	Mu_X3b	Mu_X3c	Mu_X3d	Mu_X3e
a	3930	401	6416	1557	5078
b	4448	401	6775	2685	5391
c	5284	1782	7032	3930	6416
d	5391	2685	7032	4448	6672

From previous discussions of patterns in Figure 4.9 and 4.10 we can draw two conclusions. Firstly, input variables X2, X4 and X5 can be removed from the model as sketching their membership functions from membership values imposed by the fuzzy clustering of Y is simply not feasible. Secondly, predictions of Y rely therefore on values of X1 and X3. Membership functions of the latter are much smoother than those of X1. X3 is therefore a more reliable predictor of Y than X1.

The method detailed in section 4.2.1.2 to derive the coordinates of the five membership functions of Y from plots in Figure 4.9 is used to evaluate corresponding parameters for all remaining membership functions of independent variables X1 and X3. All corresponding plots are available in Appendix 3. Results are listed in Table 4.9. A fuzzy rule-based model is built from Table 4.8 and Table 4.9 to predict values of Y from observations of X1 and X3. Rules are not weighted to make the model as simple as possible.

4.2.1.6 Evaluation

Techniques described in section 4.1 are used to build the Mamdani type fuzzy rule-based system derived from Table 4.8 and 4.9 and further described in Appendix 3.

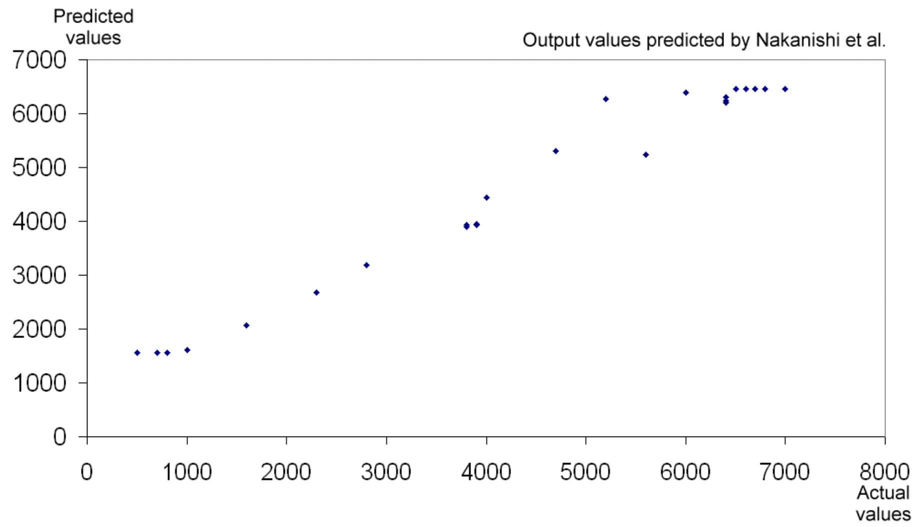


Figure 4.11: Predicted versus actual values of the Mamdani type inference system based on the methodology detailed by Nakanishi et al. The correlation coefficient is 0.99.

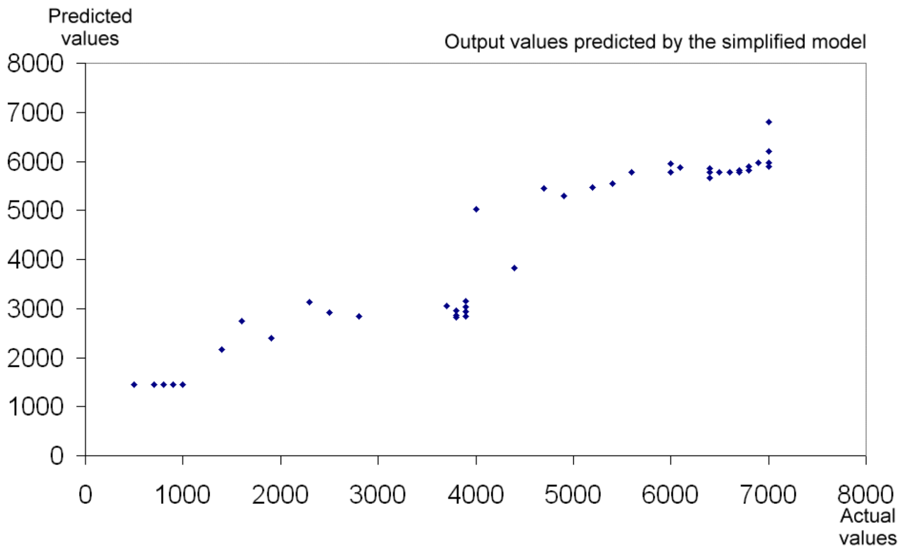


Figure 4.12: Predicted versus actual values of the inference system based on the simplified modelling approach outlined in this article. The correlation coefficient is 0.97.

Identical (predicted, actual) pairs in Figure 4.11 create the illusion of a larger number of points in Figure 4.12 where fewer points coincide.

The performance of the model is evaluated by plotting predicted values against observed values. This representation allows both a rapid visual comparison of models. If several models are tested they can easily be ranked on the basis of their correlation coefficients. This approach is used to compare Mamdani type predictive models with identical parameters derived from data in Appendix 3. Results displayed in Figure 4.11 and 4.12 show that the model based on the method of Nakanishi *et al.* (1993) produces a smoother pattern of predictions. Nakanishi *et al.*'s (1993) model in Figure 4.11 performs better than the simplified model in Figure 4.12. Nakanishi *et al.*'s (1993) model, built from a subset of the whole dataset, predicts values of the whole dataset with a correlation coefficient of 0.99. By comparison, although the simplified model uses the whole dataset to predict the values it was derived from, its correlation coefficient is 0.97 which is lower than that of Nakanishi *et al.*'s (1993) model.

4.2.2 Discussion

Nakanishi *et al.*'s (1993) paper provides an excellent opportunity to evaluate the return on additional sophistication in the design of a fuzzy rule based model. The simplified model previously explored in section 4.2.1 implements three simplifications. Firstly the identification and evaluation of the simplified model are carried out on the same whole dataset. Secondly, although rule weightings were implemented in section 4.1, where they substantially improved the performance of the model, they are ignored in this simplified model. Thirdly, the identification is performed semi automatically by the fuzzy clustering software Fuzme (Minasny and McBratney, 2002) while it was done manually in Fisher's iris classification. Accounting for advantages and disadvantages of the shortcuts in the simplified model is necessary to assess its value.

A model can be expected to perform better when evaluated on the training dataset, thus giving an inflated correlation coefficient by comparison with a model tested on an evaluation dataset different to the training dataset. The simplified model, however may give better predictions if rules are weighted as demonstrated in section 4.1. The effect of these two shortcuts on the correlation coefficient between observations and predictions of the simplified model tend to compensate each other. In any case they do not have a compounding effect and are therefore unlikely to lead to unreasonable expectations of predictive capability. The simplified model offers a fast development strategy well adapted to an initial investigation. Once it has been established that a predictive model can actually be derived from the available dataset, applying Nakanishi *et al.*'s (1993) method can eventually be considered.

GIS modelling can benefit from the fuzzy rule-based modelling approach previously outlined as predictive models can be rapidly derived from large multivariate datasets to assess the contribution of all available input variables. Variables with little predictive power can be rapidly eliminated. Variables eliminated by this process can be compared with those discarded through more traditional exploratory data analysis techniques (EDA) such as draftsman displays. Discrepancies could point at non linear relationships between input and output worth investigating. The next section demonstrates how this simplified strategy can benefit applications of spatial predictive modeling to NRM.

4.3 What drives elephant seals' foraging patterns?

Bradshaw *et al.* (2004) explore the impact of environmental conditions on the foraging patterns of elephant seals. Local conditions are evaluated in terms of changing surrogates such as sea surface temperatures and ocean colour measured by remote sensing. Others like bathymetry are constants of a location. Generalised Linear Models (GLM) and Generalised Additive Models (GAM) were developed to predict the time elephant seals spent at sea within 300 km x 300 km grid cells. The processed dataset used in his article (Bradshaw *et al.,* 2004) was kindly provided by Dr Bradshaw. Bradshaw *et al.* (2004) conclude that, in this instance, GLM and GAM did not lead to models with good predictive capability. Despite much time and effort committed to this study, the predictions of Bradshaw *et al.*'s (2004) models appear to be foiled by the complexity of poorly known underlying processes and by the compounding effect of heterogeneous scales of initial datasets of varied origins. This interesting case study deserves to be revisited to further explain its uncertain conclusion.

The simplified fuzzy rule-based methodology detailed in section 4.2, is an ideal candidate to revisit Bradshaw *et al.*'s (2004) interpretation for three reasons. Firstly, the simplified fuzzy rule-based methodology can be easily and rapidly implemented. Secondly the method proposed is non statistical and therefore independent of Bradshaw's underlying assumptions attached to GLM and GAM models, including those related to the spatial nature of the data. Thirdly, much of the data is affected by a high level of uncertainty of unknown origin.

4.3.1 The dataset

Environmental variables describe various physical properties of the oceanic environment where a population of elephant seals from Macquarie Island was monitored between 1999 and 2001. The following study is based on 50 foraging trips of these elephant seals. A total of 14 environmental variables are investigated to cast some light on what drives their foraging patterns. Field data describing environmental conditions prevailing in the area while elephant seals were monitored are complex and will not be discussed here as a detailed description can be found in Bradshaw *et al.*'s (2004) paper. Information was generally obtained by remote sensing over large areas. Results were then merged within grid cells 300 km x 300 km. Variables in the dataset in Appendix 3 are listed below.

BATGRAD = bathymetry gradient

BATMEAN = bathymetry mean

COLGRAD = ocean colour gradient

COLMEAN = ocean colour mean

ICEGRAD = ice gradient

ICEMEAN = ice mean

LAT = latitude

LON = longitude

TIME = time spent in grid cell

PCTIME = percentage time in grid cell

PFGRAD = productivity gradient

PFMEAN = productivity mean

SLAGRAD = sea level anomaly gradient

SLAMEAN = sea level anomaly mean

DIST = distance covered

PCTIME is simply TIME spent in a specific grid cell expressed as a percentage of the overall time spent at sea. These two variables are displayed in Figure 4.13 to validate the identification process. Environmental factors BAT, COL, ICE, PF, SLA are each represented by variables GRAD and MEAN. The former is obtained by a Sobel filter which calculates the gradient within a 3 x 3 matrix while the latter is simply the average value across the whole 300 km x 300 km grid cell. The relatively small size of this dataset and the sophistication and variety of the techniques used to acquire and process information makes this dataset particularly relevant to the problems of GIS modellers of natural processes.

4.3.2 Identification of a fuzzy rule based predictive model of elephant seals' foraging pattern

The approach adopted here is the simplified methodology described in section 4.2. The output variable is arbitrarily segmented in 5 classes. If this segmentation leads to encouraging results, a larger number of classes can be considered to refine the model. The first membership function (suffix a) across all variables is displayed to identify membership functions which appear to show an acceptable level of association with the output variable PCTIME. Membership functions of PCTIME and TIME, two variables closely related by a linear function, are displayed in Figure 4.13. The striking similarity between corresponding membership functions of these two variables is a reminder of what can be expected from two highly correlated variables. All 5 membership functions a, b, c, d and e of the output PCTIME and TIME are displayed in Figure 4.13 while in Figure 4.14 only membership function a is displayed for all variables. All 13 membership functions displayed, with the exception of the top left PCTIME, are completely erratic. None of the changing membership values in these 13 ordered variables follows the smooth variations observed in the PCTIME membership function in the top left corner. None of these 13 variables can therefore be a reliable predictor of PCTIME. To make the matter worse, unpredictable fluctuations in membership occur across most of the range of each variable therefore ruling out the predictive usefulness of any membership function which could be derived. Indeed a single membership function stretching across all values of a variable displays extreme fuzziness: a highly undesirable property. These 13 variables cannot be used to predict values of PCTIME. They do not appear therefore to influence the time spent by elephant seals in any of the 300 km x 300 km grid cells.

The semi automatic segmentation of the dataset, as previously described, relies on Fuzme. Babuska (1996) compares clustering algorithms to conclude that the Gustaffson-Kessel (GK) has a number of advantages on alternative algorithms: it can detect clusters of different size and orientation and is less sensitive to initialization parameters. GK, one of the algorithms available in Fuzme, was therefore selected to segment the elephant seals dataset. Inconsistencies in GK implementation by Fuzme, highlighted by yellow outlines in Figure 4.13 were initially identified by Dubois (personal communication 4/01/07) during a meeting at Paul Sabatier University in Toulouse (France). These do not however affect the coordinates of the trapezoidal membership functions derived from these graphics. The 4 coordinates of all trapezoidal membership functions can still be derived from the 4 major breaks in slope which can all be clearly identified in Figure 4.13. Except for the previously mentioned glitch, PCTIME and TIME share near identical shapes. This is to be expected as PCTIME is simply the time spent foraging in a specific area expressed as a percentage of the overall time spent at sea by each elephant seal. Figure 4.13 provides therefore a visual reference of what can be expected when input and output are related by a linear function.

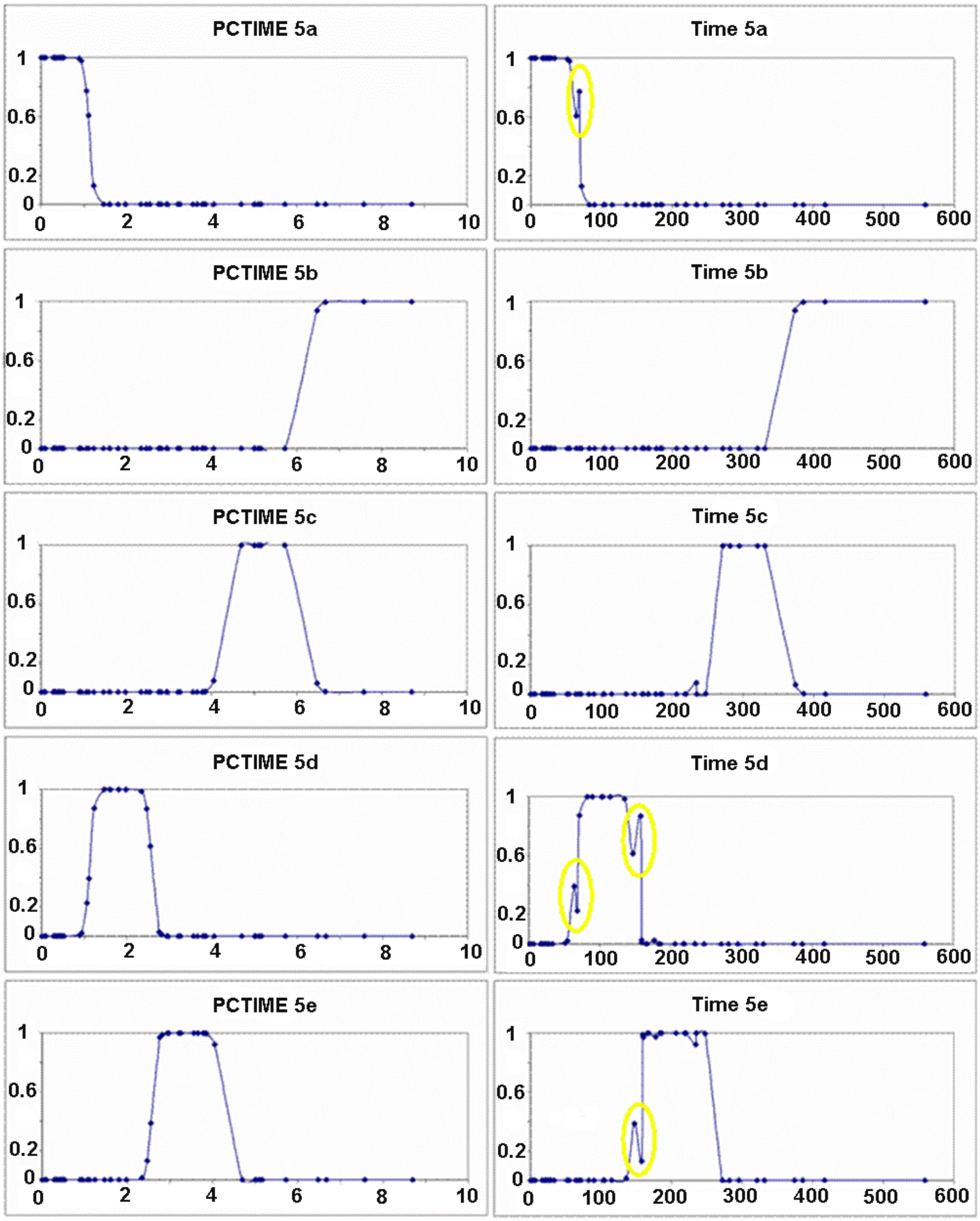


Figure 4.13: Fuzzy membership values of PCTIME and TIME. Inconsistencies are circled in yellow.

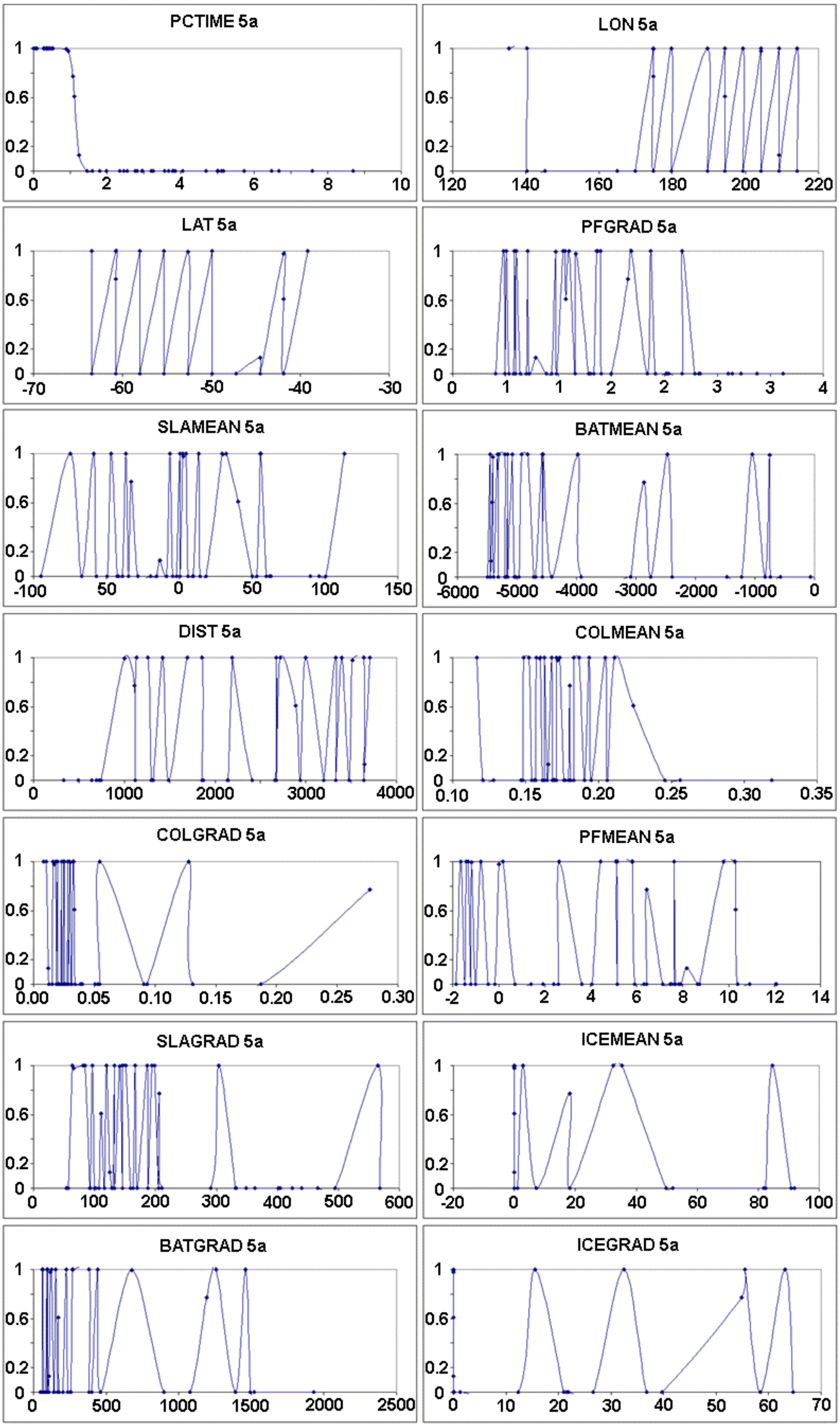


Figure 4.14: Fuzzy membership values of all input variables (except TIME) for class 5a. None allows to derive a membership function similar to PCTIME 5a.

Clusters of remaining variables plotted for the first of the 5 memberships considered here are displayed in Figure 4.14. Compared with PCTIME, these 13 plots are very chaotic. They display inconsistent memberships across the whole range of values.

Results displayed in Figure 4.14 for the first membership function of all variables do not warrant further efforts.

4.3.3 Discussion

The interpretation of Figure 4.13 and 4.14 leads to a simple conclusion: predicting how much time an elephant seal spends in one 300 km x 300 km is impossible on the basis of the 13 environmental predictors considered. Bradshaw *et al.* (2004) conclude "In contrast to other studies …, our results suggest that even more complex, non-linear models still fail to provide a strong predictive framework for apex predator foraging at coarse spatial scales" (Bradshaw *et al.*, 2004; p. 1021). A detailed analysis of this statement is outside the scope of this thesis, yet some aspects of this statement deserve further consideration.

Bradshaw *et al.* (2004) spent a great deal of time and effort processing a very diverse dataset to investigate relationships between oceanographic variables and the behaviour of elephant seals. They relied on Generalised Linear models (GLM) and Generalised Additive models (GAM) to identify which of the variables considered could drive elephant seals foraging patterns. The approach they adopted is supported by Guisan *et al.* (2002) who researched the roles of GLM and GAM in ecological modelling. Guisan notes however that GLM and GAM "…implicitly incorporate biotic interactions and negative stochastic effects … that can change from one region to another. This can make models fitted for the same species, but in different areas and/or at different resolutions, difficult to compare ... Hence, the predictive capability of such models is frequently low…" (Guisan *et al.*, 2002; p. 91). These are serious limitations as the interpretation of Bradshaw *et al.* (2004) relies on oceanographic data averaged within grid cells varying in size between 9 km x 9km (ocean colour/chlorophyll α) and 25 km x 25 km (sea-ice concentration). They statistically determine the ideal grid cell size for their interpretation to be 300 km and consequently resampled all their data to that scale. Defining an ideal spatial aggregation of measurements of these variables in relation to the problem investigated is difficult. Their 300 km oceanic grid cells, although statistically the best compromise, may still be too coarse. As a result of this considerable resampling, interpretation of the data probably suffers from the modifiable areal unit problem (MAUP) caused by scale and zoning effects (Wong and Lee, 2005). Once averaged across 300 km grid cells, one can easily imagine that characteristic signatures of preferred elephant seals feeding grounds will have a negligible influence on the average value of all variables in the corresponding cell. In addition, as stated by Bradshaw (personal communication), dealing with a small sample of intelligent mammals adds an elusive variable: their “personality”. The latter is probably impossible to model when dealing with wild animals. This element alone has the potential to make any kind of predictive modelling of their foraging pattern very difficult. Ultimately, modelling results obtained by Bradshaw *et al.* (2004) prove inconclusive.

So, what is the contribution of fuzzy rule-based modelling to Bradshaw *et al.*’s (2004) study? On the basis of a completely different approach, fuzzy rule-based modelling supports Bradshaw *et al.*’s (2004) finding. The foraging patterns of the elephant seals considered in this study cannot be predicted from the available dataset. This lack of predictive capability does not therefore appear to be related to the modelling methodology adopted by Bradshaw but to the dataset itself. No statistical assumption or simplification underpins the fuzzy rule-based model. Compared with GLM and GAM, fuzzy rule-based modelling appears to be a blunt tool. This may be precisely its greatest quality in GIS/spatial modelling of ecological data. A large dataset can be rapidly explored to decide if a detailed statistical investigation may be warranted. If during the identification phase of a fuzzy rule-based model no input variable appears capable of explaining the output variable there is little chance that a statistical predictive model can be created. A “sentinel” variable such as TIME in this study reminds the user of what can be expected when one an input variable is highly correlated the output.

Fuzzy rule-based modelling can clearly help investigate the suitability of large and complex datasets to the development of statistical predictive models. This represents a considerable contribution to GIS modelling both in terms of better allocating time spent on advanced statistical techniques and in casting some light on otherwise inconclusive outcomes.

Summary

Two important applications of fuzzy logic to predictive modelling in GIS are reviewed in this chapter. The first application deals with the classification of categorical data described by ratio variables. The second application focuses on the rapid development of predictive models from small datasets of high dimensionality.

The classification model is demonstrated through the classification of Fisher's iris dataset. Four flower metrics are used to differentiate between three varieties of iris flower: setosa, versicolor and virginica. These metrics are petal length, petal width, sepal length and sepal width. The identification of the model carried out on 120 of a total of 150 records shows that sepal width is independent of iris flower variety. This variable is therefore discarded. For each of the 3 remaining iris metrics, all records of each variety are represented by one triangular membership function. The resulting fuzzy rule-based model comprises nine rules. Normalised weightings are calculated for each rule on the basis of its width and number of associated records. Two models are implemented: one with rule weightings in Matlab (MathWorks, 1999), the other without rule weightings in Scilab. Both models are evaluated on the remaining 30 records not used during the identification process. The model with weighted rules performs best and misclassifies only one flower out of 30.

The rapid development of predictive models from small datasets of high dimensionality relies on a simplified fuzzy rule-based modelling strategy. This strategy is implemented on a dataset used by Nakanishi *et al.* (1993) to introduce a sophisticated identification technique (Nakanishi *et al.*, 1993). The simplified identification technique relies on the whole dataset to create a single model. Segmentation is performed semi automatically by projecting output membership

functions on input variables. Some input variables have membership functions where records follow a smooth envelope. Erratic envelopes reflect the inability of the corresponding input variable to follow variations in the output variable. The simplified strategy concludes that three of the initial five input variables fall in that category and are therefore discarded. Nakanishi *et al.* (1993) come to the same conclusion but his approach is more demanding. Correlation coefficients between observations and predictions by the two models are compared. Nakanishi *et al.*'s (1993) performs best with a correlation coefficient of 0.99 while the simplified method scores 0.97.

The simplified fuzzy rule-based modelling method, well suited to the rapid evaluation of the predictive capability of large multivariate datasets is tested on a case study of fifty records of foraging patterns of elephant seals in the Southern Ocean (Bradshaw *et al.*, 2004). Bradshaw *et al.* (2004) rely on fourteen environmental variables from varied sources to predict the time spent by elephant seals in 300km x 300km grid cells. Bradshaw *et al.*'s (2004) predictions based on GLM and GAM models are inconclusive. The identification of the simplified fuzzy rule-based model shows that none of the environmental variables, on its own, has any predictive power. Combinations of variables such as flat sea floor in shallow water or steep slopes in deep water could be considered. Results obtained by Bradshaw *et al.* (2004) appear to confirm that, owing to the total lack of predictive capability of all variables used in his study, no further investigation is warranted. The stark contrast between the two strategies resides in the simplicity and unambiguous conclusions of fuzzy rule based modelling method advocated.

This chapter shows that fuzzy logic provides a unified strategy capable of building classifiers as well as predictive models from multivariate datasets of high dimensionality. These two typical facets of GIS modelling are well addressed by the approach advocated in this chapter. Techniques used are not constrained by any assumption of size or nature of the dataset. The modelling strategy detailed here can be used on its own or as a precursor to more involved statistical methods, once it has been independently ascertained that input variables do explain the output variable(s).

CHAPTER 5

KNOWLEDGE DRIVEN FUZZY RULE-BASED MODELLING

Overview

Concepts of fuzzy logic exposed in Chapter 2 and principles of data driven fuzzy rule-based modelling established in Chapter 4 provide the foundation required to introduce the fundamental concepts of knowledge driven fuzzy rule-based modelling. Knowledge capture is arguably the most important phase in the development of knowledge driven fuzzy rule-based models. Often called expert systems, these fuzzy rule-based models have important applications to GIS models developed to improve the management of fisheries. Expert systems belong to the broader context of Artificial intelligence (AI). AI (Dubois and Prade, 1998) is mainly concerned with knowledge-based systems (KBS) and knowledge engineering (KE). KE grew out of the need to apply sound engineering principles to unreliable early KBSs. KE research (Chandrasekaran and Josephson, 1997) concentrates now on sharing knowledge and problem solving methods, or ontologies (Van Heijst *et al.*, 1995; Van Harmelen, 1995), across KBSs. KE is therefore of little relevance to this thesis since it is not concerned with software development but with practical implementations of knowledge based predictive models, or expert systems, to address generic needs (Lehner and Hartmann, 2007). Within this context both knowledge capture and expert system development related through two case studies.

The first case study is an attempt to model fishing power, an elusive variable that accounts for the fish catching efficiency of a fishing vessel. Fishing power underpins the accurate estimation of the productivity of a fishery. Based on the experience of Mackinson (1999), the focus is on the capture of fishers' expert knowledge of fishing power. Questionnaires on fishing power completed by fishers, their processing and interpretation are carefully reviewed. An expert system is derived from the data collected. The limitations of this model and its implication for fishing power modelling are noteworthy. The second case study is articulated around Cheung *et al.*'s (2005) expert system. Derived from experts' knowledge published in the scientific literature, this expert system provides an insight in the status of two key commercial species of a fishery in the Northern Territory. Discrepancies between results obtained and published information demonstrate the relevance of local NRM fuzzy rule-based expert systems to fishery management.

Other potential applications of expert systems are briefly discussed. Although rarely explicitly mentioned, GIS models are omnipresent in this chapter. Their interactions with fuzzy rule-based expert systems are intricate. The resulting modelling synergy is well suited to environmental systems characterised by a web of spatial and non spatial interacting processes.

5.1 Knowledge versus data driven fuzzy rule-based modelling

Knowledge and data driven (Dubois *et al*., 2000) fuzzy rule-based models share the same rule-based structure and rely on the same principles. The difficulty in data driven modelling is more in the identification of the model. In knowledge driven models, often called expert systems, the challenge is in knowledge acquisition.

5.1.1 Expert systems and fuzzy rule-based modelling

What are expert systems? “Expert systems are computer programs that emulate the reasoning process of a human expert or perform in an expert manner in a domain for which no human expert exists” (Hall and Kandel, 1992; p.4). Hall and Kandel offer a useful summary of fundamental aspects of expert systems. Four main structures have been developed to represent knowledge: rules, semantic networks, frames and Bayesian networks (Mello and Brown, 1999). Rules adopt the familiar structure below.

IF premise THEN conclusion

MYCIN (Shortliffe, 1976) was a medical diagnosis system initially applied to the detection and treatment of bacteremia and meningitis (Duda and Shortliffe, 1983). Semantic networks are made up of arcs and nodes where nodes represent objects and concepts while arcs are relations between different types of nodes. CASNET (Weiss et al., 1978) is an example of a semantic network (Hall and Kandel, 1992: p. 17), was initially applied to the diagnosis and treatment of glaucomas. Frames describe specific situations. They may contain data, procedures or pointers to other frames. PROSPECTOR (Gaschnig, 1982) was a mineral exploration expert system based on frames. Bayesian networks have been increasingly used to develop knowledge based predictive models (De Campos and Qiang Ji, 2009; Schubert *et al.*, 2006; Zaarour *et al.*, 2003). However, applications to real-world problems such as Schubert *et al.*'s (2006) GIS integrated Bayesian network avalanche risk assessment system remain laborious (Wang, 2004).

The first three expert systems mentioned above are products of the 1970s, a time when fuzzy logic was still explored to assess what practical applications, if any, it could have. Imprecision needs to be handled with care in an expert system as queries from users as well as knowledge provided by experts are uncertain. Uncertainty was initially translated as probabilities. Experts, however, do not think in probabilistic terms and this unnatural method of recording vagueness can affect expert contributions. Early expert systems predate Zadeh's seminal paper (Zadeh, 1965). Expert systems can therefore be based on crisp logic. Hall and Kandel (1992), however, consider that fuzzy logic improves the performance of an expert system by better managing imprecision in two domains.

The first domain relates to the relative importance assigned to a piece of information. Knowledge is traditionally recorded in a probabilistic manner and a statement will be weighted according to its probability of being correct. The reliability of this weighting depends on the size of the dataset which in turn decides how representative the source is. Large datasets are generally rare and weightings are a common source of imprecision. Fuzzy inference systems, although not immune to imprecision, address it better than probabilistic systems. Dealing with linguistic vagueness is the second domain where fuzzy logic is advantageous. Although alternatives have been used to tackle the inherent vagueness of human language, fuzzy logic provides an intuitive solution less likely to hinder the capture of human language.

Fuzzy rule-based expert systems, in their structure and functions, are similar to previously explored fuzzy rule-based systems. They are however knowledge driven instead of data driven. Knowledge can be generally treated as data in the sense that both Mendel (1995, p: 315) and Salski (2006, p: 12) see no difference in the way numerical data and linguistic statements are processed in fuzzy modelling. When knowledge represents constraints, instead of positive knowledge or data, neither Mamdani nor Sugeno-type are suitable. Implicative gradual rules (Ughetto *et al.*, 1999; Dubois *et al.*, 2003; Jones *et al.*, 2005; Jones *et al.*, 2009) must be used instead. Implicative rules lead to a different type of inference system which, like the Sugeno-type inference system, is not considered in this thesis. With the exception of constraints, there is little difference, conceptually, between data and knowledge driven fuzzy rule-based models. Practically, knowledge driven models are more demanding than data driven models as they generally require time consuming, and therefore expensive, interactions with knowledge providers. There is however, one substantial difference between them. While data driven fuzzy rule based-models can be either of Mamdani or Takagi-Sugeno (TS) type, knowledge driven rule-based models can only be Mamdani type. In a TS model, the output is a mathematical function of the input (Babuska, 1997). Better suited to engineering applications, TS type fuzzy rule-based models are incompatible with human knowledge modelling as their output is a mathematical equation. Only Mamdani type fuzzy inference systems are discussed in this thesis as they offer a unified approach to predictive modelling in a raster GIS environment. There is however, no doubt that for specific problems, involving for instance biochemical systems, TS type fuzzy rule-based models can perform better. The PhD thesis of Babuska (1996) provides an excellent comparison of Mamdani and TS type fuzzy rule-based models.

5.1.2 Examples of spatial NRM fuzzy expert system from the fishery industry

Mackinson (1999: p.1) starts with a statement particularly relevant to this thesis "Since the precise factors that determine changes in structure, dynamics and meso scale distribution of herring shoals are not well understood, multiple sources of knowledge are integrated in the framework of a fuzzy logic expert system. Such work is necessary to develop spatially explicit predictive models needed for management." Although he focuses on herring fisheries, his comment can be readily extrapolated to most NRM domains: fuzzy logic and knowledge are needed for spatial predictions of natural systems behaviour. Mackinson (1999) developed Clupex, an expert system built on rules summarising all available relevant knowledge and scientific data to predict herring shoals properties. Clupex is characterised by 35 potential inputs and 23 outputs, some of them spatial. Fishers can view maps of herring shoals along the Canadian coast. Not all rules are fuzzy, but heuristics that capture knowledge expressed in linguistic expressions play a fundamental role in this expert system. Clupex was created with Exsys (http://www.exsys.com), a commercial software mainly aimed at the business world. The software selected is not necessarily the simplest approach to a typical problem of natural resources management. Solutions adopted are not transparent and may implement technical choices better suited to business than to fisheries. However, three key aspects of this expert system are directly relevant to this dissertation. Firstly, the development of the knowledge base raises issues common to many expert systems. Secondly, the role of fuzzy logic in the development of heuristics is a generic aspect of predictive modelling. Thirdly, the close association between expert system and mapping can substantially benefit GIS modelling. The development of the knowledge base is particularly interesting as Mackinson provides revealing figures. Thirty persons were interviewed: eight fishery scientists, seven fishery managers, nine fishers and six First Nations informants. Interviews lasted two hours on average and included open discussions as well as questionnaires. The interview strategy is articulated around four components. A peer reviewed selection of experts is the first step. A questionnaire is then devised to combine free and directed inquiries. The inclusion of “sentinel” questions targeting the truthfulness and depth of knowledge of interviewees is a crucial safety aspect of this questionnaire. The review process ensures that all interviewees are satisfied with the integrity of the information provided once recorded. This thorough, successful yet time consuming and therefore expensive expert system design methodology needs to be contrasted with the modest attempt to capture NT fishers knowledge described in this chapter. The limited success of the latter, developed with minimum resources, should not therefore be considered as a reflection of the potential of the method.

Cheung *et al.* (2005) build an expert system of IF-THEN clauses from published literature on ecological characteristics of marine fishes related to their vulnerability to extinction under fishing pressure. Predictions of this system match observed declines. They are an improvement on previous models. Useful both for fishery management and marine conservation planning, this tool is relevant to tropical countries where conventional assessment of species extinction vulnerability is difficult for reasons including lack of data on local population dynamics and high species diversity. Traditional knowledge of life histories and ecological characteristics as well as existing databases can provide useful surrogates. One readily accessible source of information is FishBase, a professional reference online database of multilingual information on more than 30,900 species of fish edited by Froese and Pauli (2008). Vagueness and uncertainty, however, are inherent to much information available on fish biology and ecology as demonstrated later in this chapter. Fuzzy rule-based systems are well suited to the interpretation of this data. Cheung's expert system was validated on data from the North Sea, Fiji and the International Union for Conservation of Nature (IUCN) list of threatened species.

Both Mackinson and Cheung developed their fuzzy expert system at the University of British Columbia (UBC) currently considered by many as the leader in fishery research. UBC's ongoing interest in the application of fuzzy logic to fisheries management is a strong indication of its potential in a highly spatial domain where the need for improved management strategies is particularly urgent if dwindling fish stocks are to be preserved.

5.2 The need to capture human knowledge

This section provides some background on the rationale underlying the first case study: the development of a fuzzy rule-based expert system of fishing power.

5.2.1 The example of fishing power in the NT

Fisheries rely on a large number of biological, geographical and economical variables. Fishery scientists are increasingly aware of the benefits of fuzzy logic for a number of reasons. They are increasingly concerned by the growing evidence that traditional statistical methods may not be best suited to generate alarm signals susceptible to protect fish stocks. The demise of the Atlantic cod fishery is a well known example of a number of cases which fuel their concern. Fishery scientists are aware of the need to translate unrecorded traditional knowledge into mathematical models that will improve natural resource management. They need as well, the flexibility to incorporate particularly elusive variables such as fishing power. The rest of this chapter gives an account of a study stemming directly from these three considerations.

$$\text{Catch}_{\text{recorded}} = \text{Catch}_{\text{potential}} \times \text{Fishing Effort} \times \text{Fishing Power} \times \varepsilon \qquad \text{Equation 5.1}$$

Let us now focus on fishing power. The catch of a fisher or a fishing vessel, and ultimately the production of a whole fishery, needs be adjusted to allow comparisons across a fishery. The expression of the adjusted catch needs to take into account all parameters that explain systematic discrepancies between catch recorded by boats fishing in the same location, at the same time, the same species. Mathematically the problem can be defined by Equation 5.1 above. The five variables in this equation are defined as follows. The amount of fish caught by the fishers is represented by $\text{Catch}_{\text{recorded}}$ expressed in kg or T of fish. The suitability of the marine environment to harvesting the species considered is captured by $\text{Catch}_{\text{potential}}$. Fishing Effort is the product of the time spent fishing by the number of units of fishing gear (trap, hook, line). Fishing Power incorporates a number of loosely defined parameters which put together explain why two different fishing vessels targeting the same species under the same conditions will not catch the same quantity of fish. An environmental constant ε is defined locally to account for variations in catch records due to weather as well as seasonal and climatic factors including El Niño/La Niña cycles.

The definition of Fishing Power suggests that this variable is difficult to evaluate. Fishery scientists are still grappling with this concept. Marchal *et al.* (2006) use a statistical approach based on the GLM. Fishing power, being so difficult to define, is generally included in fishing effort. Fishing effort thus becomes unpredictably variable. Marchal's (2006) paper suggests that even sophisticated statistics cannot circumvent a lack of crucial information and that some of the apparent stochastic variations observed may have a deterministic cause. Fishing power is a typical product of human language: an accurate definition of a vague concept. The relevance of this variable cannot be ignored because without effectively accounting for fishing power, information important to fishery management is unavailable. For instance, effect of changing a mix of new and traditional technologies in a fishery cannot be predicted. Discrepancies between observed and predicted productivity, without knowledge of fishing power, is difficult to interpret. Australian fisheries appear to be progressively moving away from prohibitively expensive independent records. They need a reliable assessment of fishing power to meaningfully compare catch records provided by fishers. The Timor Reef case study presented here is particularly relevant to the Australian context as well as the European situation reflected by Marchal (2006).

The Timor Reef Fishery (TRF) displayed in Figure 5.1, located on the edge of the continental shelf, benefits from a unique combination of drowned terrestrial topography and seafloor geomorphology characteristic of intense bacterial activity associated with oil seepage. As a consequence this zone is particularly attractive to both the fishing and the oil industry. For these reasons, during the last two decades, it has been the focus of a level of scientific scrutiny without precedent in Northern Australia. Research project Fishery Research Development Corporation (FRDC) 2005/047 focused on improving the management of this fishery. This project, funded by the FRDC, an Australian federal fisheries research organisation, included an initial investigation of fishing power. This study, although not spatial as such, has a direct bearing on the spatial definition of the very restricted high productivity zone of the TRF displayed in Figure 5.2. Fishery productivity evaluation in NT waters at present only relies on catch records provided by fishers divided by fishing effort. Fishing effort is calculated by multiplying the number of units of a specific fishing gear (drop line or fish trap here) by the time spent fishing at the recorded location. Catch records used to create Figure 5.2 are only adjusted for fishing effort. They should as well be compensated for variations in boat, experience of the skipper and the crew all captured in fishing power. Accounting for the latter allows management to map productivity more accurately. This in turn facilitates the investigation of variations in production and helps refine maps of productivity similar to Figure 5.2. Such maps are fundamental to monitor fluctuations in productivity and ultimately the very survival of fisheries.

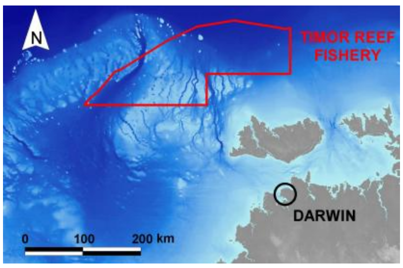


Figure 5.1: The Timor Reef Fishery, in red, is the closest fishery to Darwin (black circle).

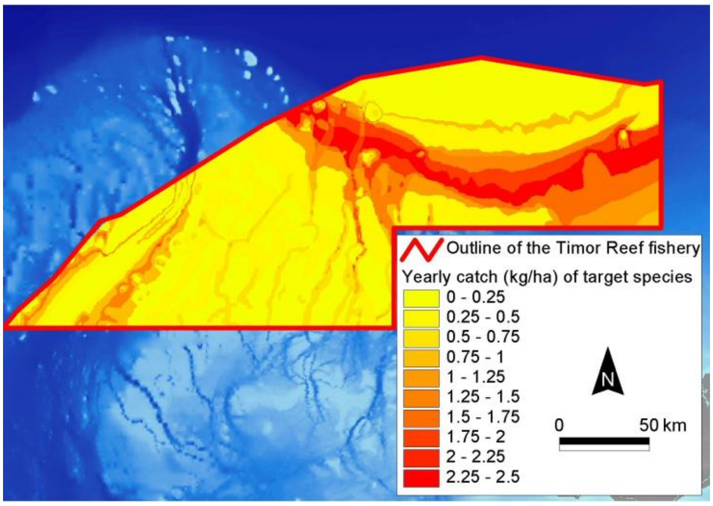


Figure 5.2: Map of the productivity of the TRF. Dark orange areas show the zones of highest commercial value derived from the GIS analysis of catch records plotted on digital maps of geomorphic units and bathymetry. Yellow represents zones of lowest value. This map, based on the interpretation of 10 years of catch records (Lloyd and Puig, 2009) ignores fishing power.

What follows is the first step in establishing a model of fishing power derived from fishers' knowledge. Mackinson's work, previously mentioned, is a useful benchmark. However, this case study relies on a much smaller number of informants. Although undesirable, this situation is more representative of applications outside academia where critical material constraints, often cost related, prevail. Here, an additional difficulty is the small number of experienced fishers.

5.2.2 Capture of human knowledge

Cheung *et al.* (2005) built their fuzzy expert system from peer reviewed scientific literature, a source of captured knowledge. Their model is a useful tool for fishery scientists. There is little doubt that their approach would be equally applicable to other NRM domains. In this instance, however, scientific literature is unlikely to be suitable as local models need to be developed from local knowledge. In many regions of the world there is currently a domain of human knowledge, outside academia, which is of growing interest to scientists: traditional ecological knowledge (TEK) is a subject of much interest in NT environmental research circles (Smith, 2008; Smith, 2009). Unfortunately the adoption of a suitable generic interpretative framework has not received much attention. This case study can be easily adapted to a wide range of purpose specific applications to predictive modelling based on expertise that is independent of the technical or cultural background of the informants.

5.3 Modelling fishing power from fishers' knowledge

The method of recording experts' knowledge used here was derived from a frequently cited study by Chameau and Santamarina (1987). They compared four elicitation methods, described in section 2.5.2, and based their evaluation on questionnaires distributed to 22 professors and graduate students considered either as measurement instruments or repositories of knowledge. The fourth method of expert knowledge capture described, i.e. pair wise comparison, is implemented in Chapter 3, within the AHP, to develop a GIS of prawn farming site suitability. Both experts who participated in this case study concluded that pair wise comparison is effective but tedious. The interpretation of the results is taxing. In contrast, the following case study of capture of fisher's expert knowledge relies on the second elicitation method, interval estimation (Chameau and Santamarina, 1987), considered the best of the four methods listed. Fast and simple, interval estimation has lowest fuzziness. However, the method is only considered to be reliable if a minimum of 5 informants are surveyed, which may be a major limitation when experts are considered.

Chameau and Santamarina (1987) drew three practical conclusions from their study. Firstly, the larger the scale given to informants is, the wider the discrepancies between informants' views and the fuzzier their answers are. Secondly, scales no larger than 10 perform best. Thirdly, informants preferred the interval estimation method.

5.3.1 Fishing power of fishing units of the Timor Reef Fishery

The Timor Reef Fishery is characterised by no more than twelve operating fishing vessels at any given time since its creation in 1989. The number of experienced fishers is even smaller as few of the original fishers are still fishing these waters. Fishers who participated in this survey were very busy and therefore rarely available.

Four experienced fishers found the time to participate in this activity which consisted in a short presentation on the rationale of the study and the subsequent process of filling in the questionnaire. Questions and forms were prepared by fishery research scientists of the Northern Territory Government. The questionnaires reflect their views on what contributes to the power of a fishing unit defined as a vessel. The suitability of the questionnaire to the task is not relevant to the present discussion which focuses on processing the information recorded. There is no doubt, however that the design of the questionnaire itself deserves careful consideration.

The questionnaire relies on the familiarity of the informants with the subject matter. All fishing vessels are known to the informants. Their specifics, however, are detailed to enable these experts to assess the contribution of each element on what they know to be the performance of the overall fishing unit. A fishing unit incorporates crew and equipment. Eleven local vessels were selected and documented in detail. Chameau and Santamarina's (1987) interval estimation was the technique adopted for this study of fishing power. The survey consisted in selecting a range of numbers between 0 and 10 that best described the fishing power of each of seven groups of features for each of eleven vessels operating in the TRF. The lowest power corresponded to 0 and the highest to 10. Fishers were encouraged to select a range of values when no single number appeared appropriate. The seven feature classes considered are listed in Figure 5.3 are dimensions, engines, ice-maker, product storage, electronics, fishing gear and crew. Characteristics of the eleven vessels were detailed, for each of the seven classes above, in five forms. Figure 5.3 shows the form for vessel 4 and 5. Once the fishing power of all seven classes of features were evaluated, fishers had to assign the fishing power they expected the corresponding vessel.

Between five and ten informants were to participate in the survey. Only four actually did. Only two fishers completed their questionnaires correctly. Due to the limited duration of project FRDC 2005/047 and the small pool of experienced TRF fishers, there was no opportunity to approach additional fishers. Despite its limitations, this survey offers a useful insight in four important aspects of knowledge acquisition and processing: evaluation of questionnaires, rescaling answers, translation of answers into membership functions and knowledge driven fuzzy rule-based model development.

	5	6
Vessel	4	5
Dimensions	5	5-6
Vessel Length (m)	17.5	19.6
Vessel Beam (m)	5	5.5
Vessel Draught (m)	1.6	1.6
Vessel Displacement (Tonne)		64
Year Vessel Was Built		1970
Engines	5	4
Main Engine Make	6V92 TTI Detroit	Volvo
Main Engine Power (KW)	432.68	272.29
Auxiliary Engine Make	Perkins	T.A.M.D. 120B
Auxiliary Engine Power (KW)	53.712	25KVA
Auxiliary Engine Date Installed	1997	
Engine Fuel Capacity (LT)	6000	3600
Max. Time Fishing Without Refuiling (Days)	21	16
Aspiration (Natural/Turbo/Other)	Turbo	T.A.M.D. TURBO aftercooled. Marine diesel.
Ice Maker	0	0
Ice Maker Make	Bitzer	
Ice Maker Cap Per Day (Lt)	600	
Ice Maker Type (FW / RSW)	RSW	
Product Storage	5	6
Product Storage		6000kg iced fish, 10000kg cartoned frozen fish
Freezer Capacity (kg)	4000	10000
Ice Boxes Capacity (kg)	4000	nil
Brine Tank Capacity (kg)	700	1500
Electronics	4	5
Sounders Make	Furuno 36 KW	Furuno
Sounders Use		Colour
SONAR Make		nil
SONAR Use		
RADAR Make	KODEN	Furuno
RADAR Use		64 miles
RADIO Make	BARRET	HF VHF
RADIO Use		
GPS Plotter Make	Furuno	nil
GPS Plotter Use		
Plotter Make	Furuno	nil
Plotter Use		
Computer Make		nil
Computer Use		
Software Make		nil
Software Use		
Home Based Computer Type		nil
Home Based Computer Size		
Software Used		nil
Fishing Gear	5	3
Throw Aways (number)		3
Traps (number)	10	nil
Traps Type	D	
Hand Reels (number)		nil
Hand Reels Type		
Hydraulic Reels (number)	4	nil
Hydraulic Reels Type		
Hook Size	12"	8
Hook Type	Tuna Circle	Tuna Circle
Hook Number Line	30	30
Line Type	200 LB	Nylon
Line B/Strain		6mm?
Line Make		Kuralon
Pot Hauler Type		Cray pot winch
Pot Hauler Make		Hamilton
Bait Type	Squid or Scad	Squid
Crew	6	4
Skippers Experience in an Allied Industry	10 yrs fishing WA & Timor Box on the west coast for 5 years before Darwin 1988.	
Crew 1 Experience at Sea (years)		5
Crew 1 Length of Time on Same Boat (years)	3	5
Crew 2 Experience at Sea (years)		1
Crew 2 Length of Time on Same Boat (years)	3	1
Crew 3 Experience at Sea (years)		1
Crew 3 Length of Time on Same Boat (years)	?	1
Crew 4 Experience at Sea (years)		2
Crew 4 Length of Time on Same Boat (years)	?	2
Crew 5 Experience at Sea (years)		
Crew 5 Length of Time on Same Boat (years)		
Crew 6 Experience at Sea (years)		

Figure 5.3: One of 5 similar sheets making up the fishing power questionnaire. Seven classes of features giving their fishing power to TRF fishing vessels are separated by 7 black markers in the left margin. Identification codes of the corresponding vessels are in the top row. Fishing power estimated by informants is hand written next to the corresponding class of features.

5.3.2 Critical evaluation of knowledge data

The following codes are used in Figure 5.4 which displays records directly derived from questionnaire sheets similar to the sample displayed in Figure 5.3.

FP = fishing power of the whole fishing unit
DI = dimensions of vessel
EN = engines
FG = fishing gear
IM = ice-maker;
PS = product storage
EL = electronics;

Average ratings for each category are first calculated to compare the views of these two experts. Results are plotted in Figure 5.4. Estimates of fishing power from Informant 2 are systematically higher. Rescaling the information provided is necessary to avoid unnecessarily widening membership function. As informants are used as measuring instruments to measure the quantity fishing power, this rescaling is equivalent to recalibrating measuring instruments before a survey. The intention is not to modify the views of the experts but merely to make comparisons more meaningful.

One important role of graphs in Figure 5.4 is to verify that variables identified by NT Government fishery scientists to produce the questionnaire displayed in Figure 5.3 are relevant. Although fishers were consulted before completing the questionnaire form, one of the seven input variables supposed to explain the fishing power of each TRF fishing vessel should have been discarded. “Ice maker” recorded nineteen estimates of 0 fishing power out of a total of twenty estimates. The two experts indicated through their estimates that “Ice maker” does not contribute to the overall fishing power of a TRF vessel. Therefore, this variable is removed from the model. Most records reflect a lack of contrast in the dataset.

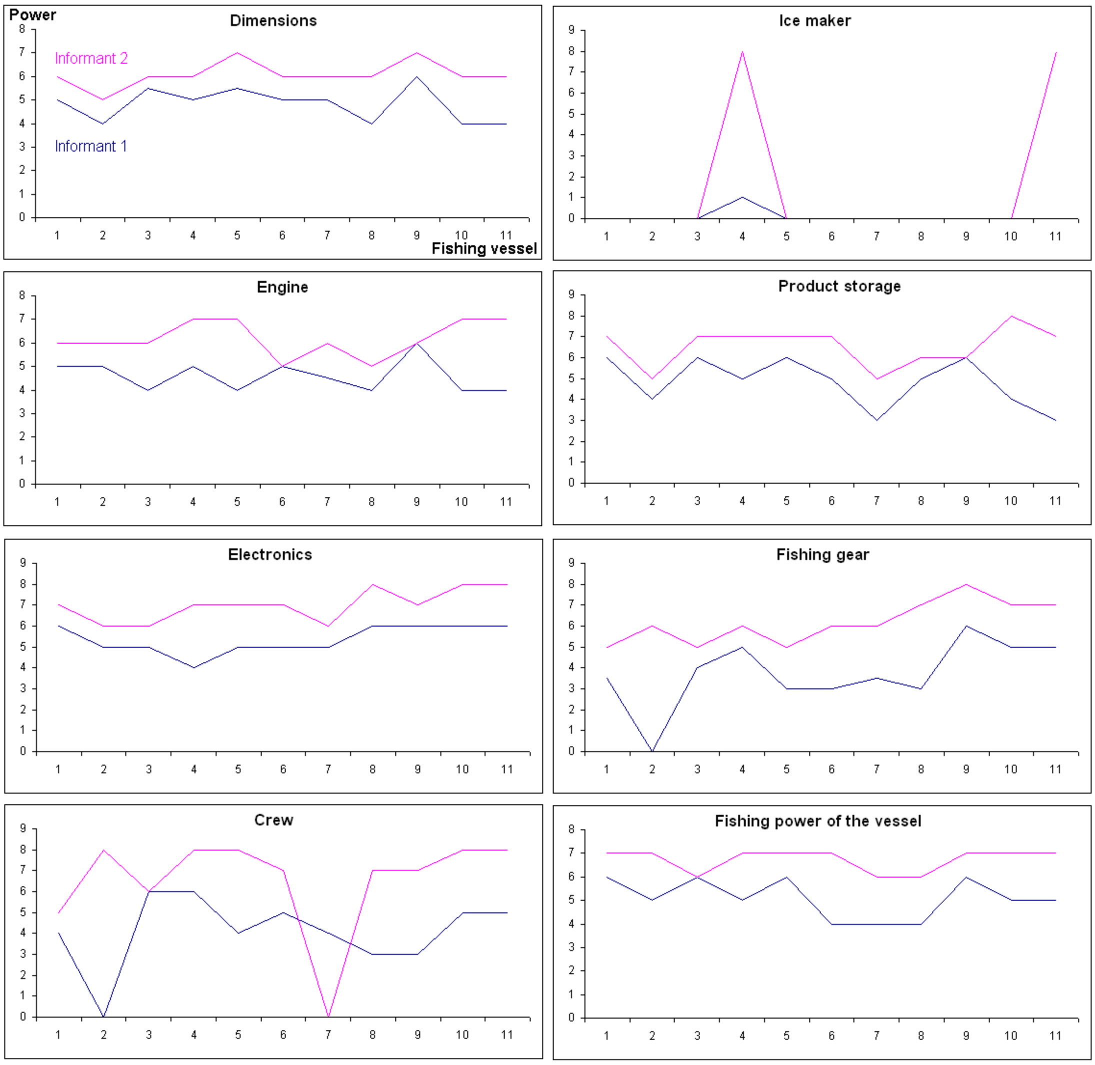


Figure 5.4: Graphical representation of fishing power estimates provided by informants who participated in the survey.

The dataset hardly contains any vessel with features displaying either excellent or very poor fishing power. Clearly such a vessel would not be commercially viable and therefore would not exist if it were fitted with inappropriate equipment. Similarly, a vessel with equipment far superior to that of the rest of the fleet is hard to imagine as it would be too expensive to equip and probably not cost effective. A predictive model derived from this dataset is therefore better suited to rank the fishing power of typical boats but should still be capable to decide if a vessel is substantially better or worse than average.

5.3.3 Rescaling knowledge data

Here, rescaling the data consists in changing the origin only. Modifying the unit of measurement could be considered in principle, however such drastic modification of the original data should only be considered after careful investigation as it may cast doubts on the reliability of the model.

Table 5.1: Fishing power estimates collected with the questionnaires are recalibrated to account for informant's systematic bias.

INFORMANT 1

Fishing Unit	FP	DI	EN	IM	PS	EL	FG	CR
1	6	5	5	0	6	6	3.5	4
2	5	4	5	0	4	5	0	0
3	6	5.5	4	0	6	5	4	6
4	5	5	5	1	5	4	5	6
5	6	5.5	4	0	6	5	3	4
6	4	5	5	0	5	5	3	5
7	4	5	4.5	0	3	5	3.5	4
8	4	4	4	0	5	6	3	3
9	6	6	6	0	6	6	6	3
10	5	4	4	0	4	6	5	5
11	5	4	4	0	3	6	5	5
Average =	5.09	4.82	4.59	0.09	4.82	5.36	3.73	4.09
Informant 1 calibration factor =			0.09					

INFORMANT 2

Fishing Unit	FP	DI	EN	IM	PS	EL	FG	CR
1	7	6	6	0	7	7	5	5
2	7	5	6	0	5	6	6	8
3	6	6	6	0	7	6	5	6
4	7	6	7	8	7	7	6	8
5	7	7	7	0	7	7	5	8
6	7	6	5	0	7	7	6	7
7	6	6	6	0	5	6	6	0
8	6	6	5	0	6	8	7	7
9	7	7	6	0	6	7	8	7
10	7	6	7	0	8	8	7	8
11	7	6	7	8	7	8	7	8
Average =	6.73	6.09	6.18	1.45	6.55	7.00	6.18	6.55
Informant 2 calibration factor =			1.73					

As fishers are more likely to agree on the overall fishing power of vessels than on the power of their parts, Table 5.1 focuses on the average estimated fishing power of the 11 vessels. The first informant's estimates are close to the expected value of 5, while the second informant's estimates are higher. For reasons previously outlined, both datasets will be adjusted to obtain an average fishing power of 5 which is the centre of the scale [0,10]. Both informants rank the "Ice Maker" as the least important contributor to the fishing power of the vessel. This variable is consequently removed. Table 5.2 contains the rescaled fishing power estimates used to derive a fuzzy rule-based model.

Table 5.2: Rescaled fishing power estimates. Values in Table 5.1 (column FP) are adjusted to obtain equal averages of 5. Identical adjustments are added to corresponding arrays in Table 5.1 to obtain all adjusted estimates. The "Ice Maker" IM variable is removed. Grey cells are ignored in calculations as they merely reflect the absence of answer.

INFORMANT1 recalibrated estimates

Fishing Unit	FP	DI	EN	PS	EL	FG	CR
1	5.91	4.91	4.91	5.91	5.91	3.41	3.91
2	4.91	3.91	4.91	3.91	4.91		
3	5.91	5.41	3.91	5.91	4.91	3.91	5.91
4	4.91	4.91	4.91	4.91	3.91	4.91	5.91
5	5.91	5.41	3.91	5.91	4.91	2.91	3.91
6	3.91	4.91	4.91	4.91	4.91	2.91	4.91
7	3.91	4.91	4.41	2.91	4.91	3.41	3.91
8	3.91	3.91	3.91	4.91	5.91	2.91	2.91
9	5.91	5.91	5.91	5.91	5.91	5.91	2.91
10	4.91	3.91	3.91	3.91	5.91	4.91	4.91
11	4.91	3.91	3.91	2.91	5.91	4.91	4.91
AV	**5.00**	4.73	4.50	4.73	5.27	4.01	4.41

INFORMANT 2 recalibrated estimates

Fishing Unit	FP	DI	EN	PS	EL	FG	CR
1	5.27	4.27	4.27	5.27	5.27	3.27	3.27
2	5.27	3.27	4.27	3.27	4.27	4.27	6.27
3	4.27	4.27	4.27	5.27	4.27	3.27	4.27
4	5.27	4.27	5.27	5.27	5.27	4.27	6.27
5	5.27	5.27	5.27	5.27	5.27	3.27	6.27
6	5.27	4.27	3.27	5.27	5.27	4.27	5.27
7	4.27	4.27	4.27	3.27	4.27	4.27	
8	4.27	4.27	3.27	4.27	6.27	5.27	5.27
9	5.27	5.27	4.27	4.27	5.27	6.27	5.27
10	5.27	4.27	5.27	6.27	6.27	5.27	6.27
11	5.27	4.27	5.27	5.27	6.27	5.27	6.27
AV	**5.00**	4.36	4.45	4.82	5.27	4.45	5.47

5.3.4 From estimates to membership functions

Data from Table 5.2 is merged into Table 5.3 to calculate for each variable the minimum, average and maximum estimate fishing power. These statistics, displayed in Table 5.3, become the coordinates of the corresponding triangular membership functions in the fuzzy rule-based model of fishing power. From Table 5.3 we can readily define the following seven triangular membership functions.

fishing power of vessel (FP) → FP-M with coordinates (3.9, 5, 5.9)

fishing power of dimensions (DI) → DI-M with coordinates (3.3, 4.6, 5.9)

fishing power of engine (EN) → EN-M with coordinates (3.3, 4.5, 5.9)

fishing power of product storage (PS) → PS-M with coordinates (2.9, 4.8, 5.1)

fishing power of electronics (EL) → EL-M with coordinates (3.9, 5.3, 5.1)

fishing power of fishing gear (FG) → FG-M with coordinates (2.9, 4.2, 5.1)

fishing power of crew (CR) → CR-M with coordinates (2.9, 4.9, 5.1)

The triangular membership functions above correspond to medium fishing powers. They associate input fishing power estimates for the 6 input variables DI, EN, PS, EL, FG and CR to output fishing power FP.

Table 5.3: Coordinates (a, b, c) of triangular membership functions for medium values of fishing power of all variables. a, b, c correspond to minimum, average and maximum values, respectively. Rows with incomplete information (row 2 yellow and row 7 blue) are ignored.

Fishing Unit	FP	DI	EN	PS	EL	FG	CR
1	5.91	4.91	4.91	5.91	5.91	3.41	3.91
2	4.91	3.91	4.91	3.91	4.91		
3	5.91	5.41	3.91	5.91	4.91	3.91	5.91
4	4.91	4.91	4.91	4.91	3.91	4.91	5.91
5	5.91	5.41	3.91	5.91	4.91	2.91	3.91
6	3.91	4.91	4.91	4.91	4.91	2.91	4.91
7	3.91	4.91	4.41	2.91	4.91	3.41	3.91
8	3.91	3.91	3.91	4.91	5.91	2.91	2.91
9	5.91	5.91	5.91	5.91	5.91	5.91	2.91
10	4.91	3.91	3.91	3.91	5.91	4.91	4.91
11	4.91	3.91	3.91	2.91	5.91	4.91	4.91
1	5.27	4.27	4.27	5.27	5.27	3.27	3.27
2	5.27	3.27	4.27	3.27	4.27	4.27	6.27
3	4.27	4.27	4.27	5.27	4.27	3.27	4.27
4	5.27	4.27	5.27	5.27	5.27	4.27	6.27
5	5.27	5.27	5.27	5.27	5.27	3.27	6.27
6	5.27	4.27	3.27	5.27	5.27	4.27	5.27
7	4.27	4.27	4.27	3.27	4.27	4.27	
8	4.27	4.27	3.27	4.27	6.27	5.27	5.27
9	5.27	5.27	4.27	4.27	5.27	6.27	5.27
10	5.27	4.27	5.27	6.27	6.27	5.27	6.27
11	5.27	4.27	5.27	5.27	6.27	5.27	6.27
Min	3.91	3.27	3.27	2.91	3.91	2.91	2.91
Av	5.00	4.55	4.48	4.77	5.27	4.24	4.94
Max	5.91	5.91	5.91	6.27	6.27	6.27	6.27

Membership functions for Low and High power membership functions can be easily derived from Medium membership functions. The technique, demonstrated in Figure 5.5, stems from a principle established in Chapter 2: membership values should add up to one.

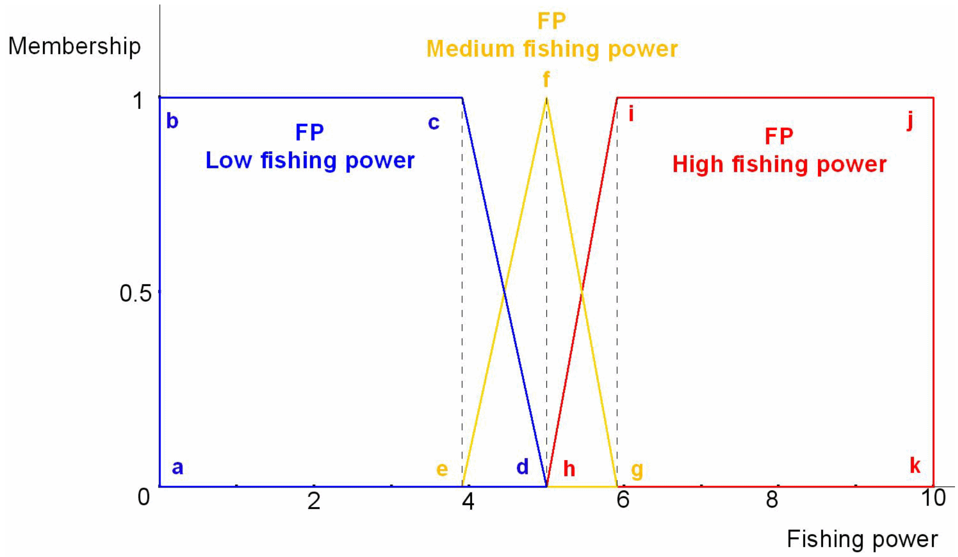


Figure 5.5: Trapezoidal membership functions of low (blue), medium (orange) and high (red) fishing power of fishing units.

Trapezoidal fuzzy numbers TaFN and triangular fuzzy number TiFN define all three membership functions of the fishing power of TRF fishing units. They are listed below.

FP Low fishing power = FP-L ⇒ TaFN (FP-L) = (a, b, c, d) = (0, 0, 3.91, 5)

FP Medium fishing power = FP-M ⇒ TiFN(FP-M) = (e, f, g) = (3.91, 5, 5.91)

FP High fishing power = FP-H ⇒ TaFN = (h, i, j, k) = (5, 5.91, 0, 0)

The same reasoning is extended to the six input variables DI, EN, PS, EL, FG, CR. Trapezoidal and triangular fuzzy numbers of all membership functions are listed in Table 5.4. The information in Table 5.4 is entered into Scilab (Campbell *et al.*, 2006) to develop a fuzzy-rule based model of fishing power using the Scilab settings displayed in Figure 2.14.

Table 5.4: Coordinates of all membership functions necessary to create an initial fuzzy rule-based model of fishing power for the TRF fishery.

Membership function	Low				Medium			High			
Variable	a	b	c	d	e	f	g	h	i	j	k
FP	0	0	3.91	5.00	3.91	5.00	5.91	5.00	5.91	10	10
DI	0	0	3.27	4.55	3.27	4.55	5.91	4.55	5.91	10	10
EN	0	0	3.27	4.48	3.27	4.48	5.91	4.48	5.91	10	10
PS	0	0	2.91	4,77	2.91	4,77	6.27	4,77	6.27	10	10
EL	0	0	3.91	5.27	3.91	5.27	6.27	5.27	6.27	10	10
FG	0	0	2.91	4.24	2.91	4.24	6.27	4.24	6.27	10	10
CR	0	0	2.91	4.94	2.91	4.94	6.27	4.94	6.27	10	10

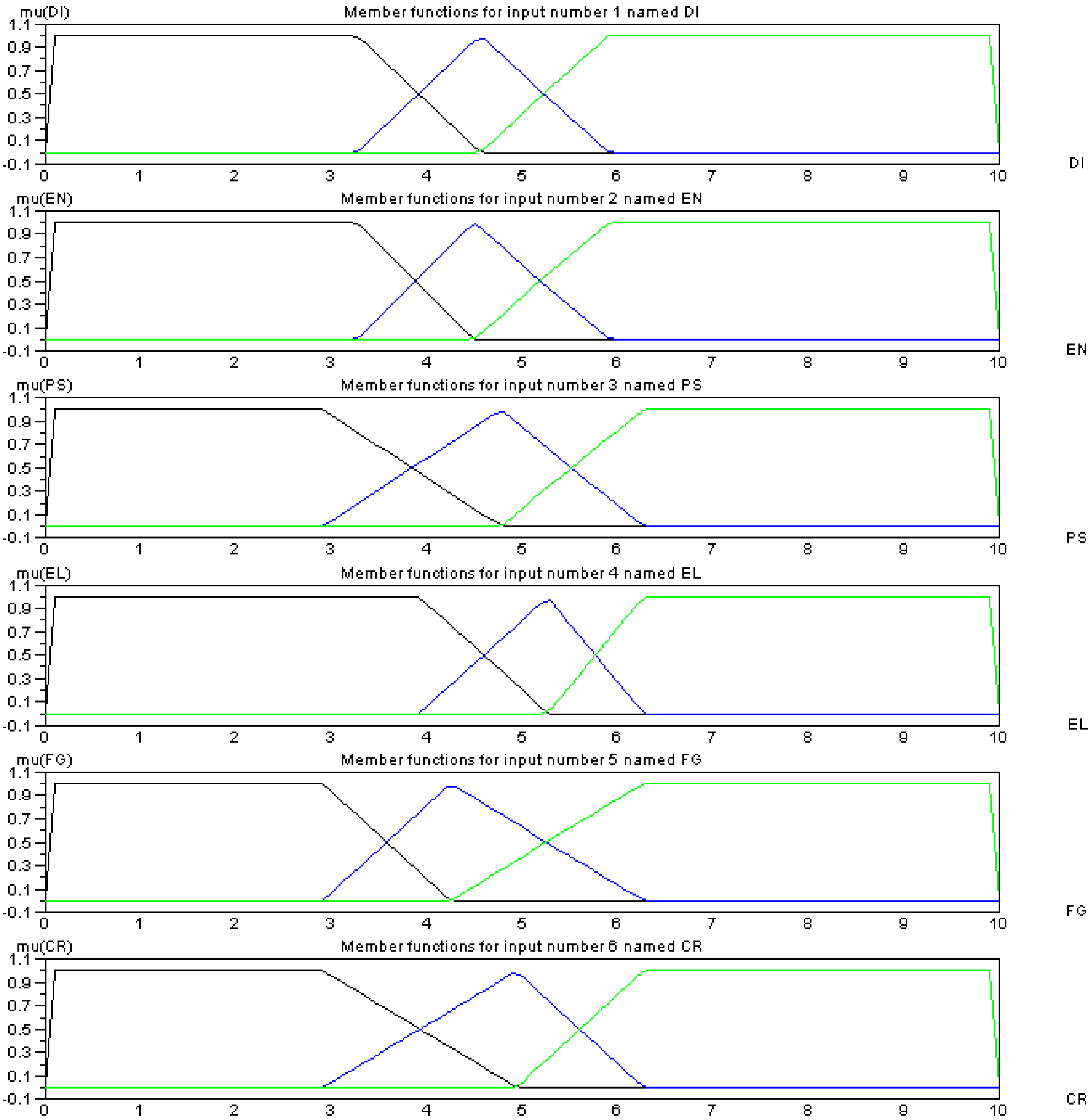


Figure 5.6: Graphical representation in sciFLT of all membership functions of input variables DI, EN, PS, EL, FG, CR. Blue triangular membership functions are derived from questionnaires while black and green trapezoidal membership functions are inferred.

Table 5.5: Rules defining logical associations between estimates of fishing power for all inputs DI, EN, PS, EL, FG, CR and the fishing power FP of the whole fishing unit.

R1:	IF	{DI is DI-L}	THEN	{FP is FP-L}	weight = 1
R2:	IF	{DI is DI-M}	THEN	{FP is FP-M}	weight = 1
R3:	IF	{DI is DI-H}	THEN	{FP is FP-H}	weight = 1
R4:	IF	{EN is EN-L}	THEN	{FP is FP-L}	weight = 1
R5:	IF	{EN is EN-M}	THEN	{FP is FP-M}	weight = 1
R6:	IF	{EN is EN-H}	THEN	{FP is FP-H}	weight = 1
R7:	IF	{PS is PS-L}	THEN	{FP is FP-L}	weight = 1
R8:	IF	{PS is PS-M}	THEN	{FP is FP-M}	weight = 1
R9:	IF	{PS is PS-H}	THEN	{FP is FP-H}	weight = 1
R10:	IF	{EL is EL-L}	THEN	{FP is FP-L}	weight = 1
R11:	IF	{EL is EL-M}	THEN	{FP is FP-M}	weight = 1
R12:	IF	{EL is EL-H}	THEN	{FP is FP-H}	weight = 1
R13:	IF	{FG is FG-L}	THEN	{FP is FP-L}	weight = 1
R14:	IF	{FG is FG-M}	THEN	{FP is FP-M}	weight = 1
R15:	IF	{FG is FG-H}	THEN	{FP is FP-H}	weight = 1
R16:	IF	{CR is CR-L}	THEN	{FP is FP-L}	weight = 1
R17:	IF	{CR is CR-M}	THEN	{FP is FP-M}	weight = 1
R18:	IF	{CR is CR-H}	THEN	{FP is FP-H}	weight = 1

Six triangular membership functions are derived from informant estimates: one for each of the six categories of features responsible for the fishing power of a fishing unit. Twelve additional membership functions are generated. These twelve additional membership functions simply exploit the previously mentioned "complement to 1" property which states that throughout the range of output values of the model, the sum of memberships for all output values is equal to 1. The simplest membership functions capable to achieve this role are the trapezoidal functions that flank each triangular membership function to its left and right (Figure 5.6). Out of a total of twenty one membership functions displayed in Figure 5.5 and 5.6, only one third, the triangular membership functions, rely on fisher's expertise. The predictive model of fishing power comprises eighteen rules, R1 to R18, displayed in Table 5.5. They are generated from these twenty one membership functions by assigning the input membership functions Low, Medium and High fishing power of each feature of a fishing unit to the corresponding output membership function of fishing unit. Although these 18 rules have the same weighting by default, it is clear that all rules based on trapezoidal membership function are less reliable as they are not based on hard evidence. The model is evaluated by comparing the estimates of fishing power by the two experts fishers to the prediction of the model created from the same estimates. Scattered predictions displayed in Figure 5.7, and a low correlation coefficient of 0.54, reflect the poor predictive capability of the model.

Observed	Predicted
5.91	5.60
5.91	5.82
4.91	5.56
5.91	4.44
3.91	4.38
3.91	3.24
3.91	3.54
5.91	6.63
4.91	4.58
4.91	4.22
5.27	3.57
5.27	3.90
4.27	3.45
5.27	6.53
5.27	6.22
5.27	4.37
4.27	5.19
5.27	6.19
5.27	7.24
5.27	7.08
Cor. Coef. =	0.54

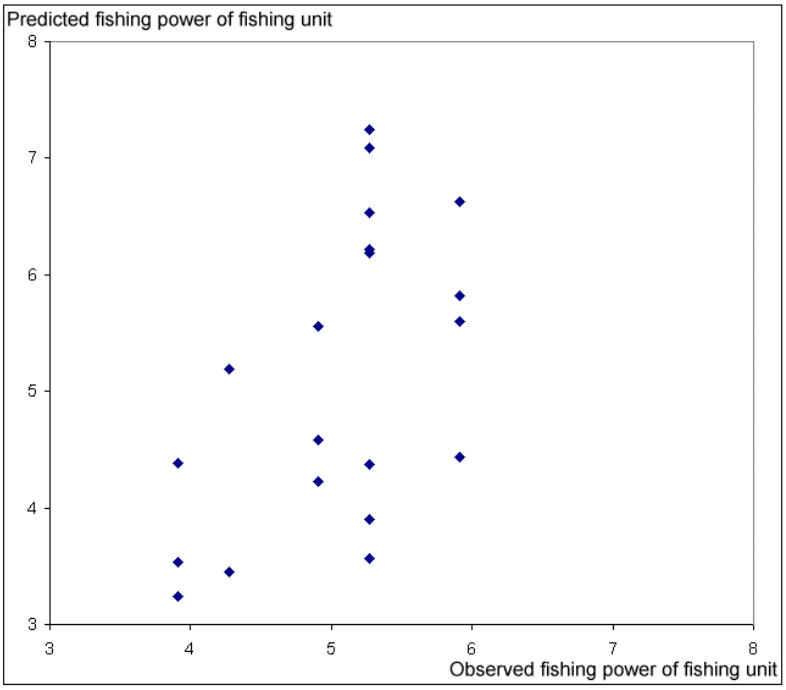


Figure 5.7: Plot of predicted against observed fishing power of fishing units.

5.3.5 Discussion

This study of fishing power is based on only two informants. Chameau and Santamarina (1987) recommend a minimum of five informants. The main limiting factor was the availability of reliable informants. This constraint is likely to be a systematic difficulty of knowledge surveys. Knowledge driven fuzzy rule-based models may initially have to rely on numbers of informants smaller than the prescribed minimum. Information could be acquired through successive surveys leading to an incremental model development process likely to improve the poor predictive capability of the initial model.

The limited predictive capability of this model can be explained by the lack of information in the lower and upper part of the range of values of fishing power considered. Figure 5.6 shows that any input that does not exactly correspond to the apex of a triangular function fires a well defined triangular membership function and a poorly defined trapezoidal membership function. Trapezoidal membership functions in this model do not reflect hard evidence. They are merely derived from the triangular membership functions themselves. The stronger the contribution of trapezoidal functions in this model, the poorer the predictions. A consequence is the presence, in the predicted dataset, of values of fishing power both lower and higher than those observed.

The previously mentioned lack of hard evidence to support the trapezoidal membership functions of this model, results from a training dataset of eleven operating fishing vessels all with average fishing power. This lack of contrast is undesirable from a modelling point of view but understandable within the context of this survey. Operational vessels are unlikely to display either low or high fishing power. In the first instance they would be uneconomical as low fishing power would imply little income. In the second instance they would be too expensive to fit. Fishing power is therefore only likely to show some contrast if vessels from different origins are included in the survey. Australian neighbours such as Indonesia would typically benefit from estimates of fishing power if they intended to merge catch records reported by traditional fishers and vessels similar to those operating in the TRF.

The knowledge elicitation method demonstrated here is well suited to the development of knowledge driven fuzzy rule-based models. The first step of the model identification process consists in minimising the vagueness of the available information through the range of values selected. To do so records are rescaled, if necessary, after checking the consistency of the informants' views. Finally irrelevant variables indirectly identified by the informants are eliminated. Weightings were not implemented in this model as informants had similar views and were sure of their answers. Weightings could play an important role in improving the performance of this fuzzy rule-based by giving more importance to triangular membership functions. However, weightings would thus give more credibility than it deserves to a model which would still be based on a restricted range of data. As it stands there is no doubt that this model is simplistic as it relies only on two informants while five is considered as the minimum. This technique needs therefore to be validated on a larger, more representative dataset.

Reflecting on the purpose of estimating fishing power, TRF management can rely on the map of productivity displayed in Figure 5.2. Fortunately, this map is not distorted by catch records from fishing units with different fishing powers. This situation is likely to prevail in small isolated fisheries characterized by a stable fleet.

5.4 Implementation and applications of a functional fuzzy rule-based expert system

Exploring the development of a knowledge driven fuzzy rule-based expert system in the first part of this chapter provides a good understanding of a number of fundamental issues likely to affect many similar expert systems. Mackinson's (1999) and Cheung's (2005) models, introduced in section 5.2, originated from the rapidly growing needs of fisheries to incorporate human knowledge in their modelling strategies. Clupex, created by Mackinson (1999), relies on fishers' knowledge to develop in Exsys a predictive model of herring shoals. Cheung *et al.* (2005) tapped researchers' knowledge in scientific journals to create an expert system capable of predicting the vulnerability of commercial fishes to fishing pressure on the sole basis of biological parameters. Unfortunately, owing to the proprietary nature of the software used by Mackinson, Clupex cannot be investigated without purchasing Exsis. Cheung *et al.* (2005) on the other hand published all the parameters of his model developed in Excel (Kelly, 2006) using very standard fuzzy rule-based modelling techniques. Cheung *et al.*'s (2005) model was therefore easy to replicate in Scilab.

Cheung *et al.*'s (2005) reliance on Excel is worth noticing. Such ubiquitous and affordable software is well suited to experimental fuzzy rule-based modelling. Appendix 2 describes Exfis (Excel fuzzy inference system) a similar application of Excel functionality. Exfis was an excellent opportunity to experiment with many fuzzy modelling concepts at an early stage of this thesis. The open source freeware Scilab (Campbell *et al.*, 2006), however, was ultimately preferred as models were developed for commercial applications incompatible with the use of a student version of Matlab (MathWorks, 1999). As Scilab (Campbell *et al.*, 2006) emulates Matlab, all knowledge of Matlab is easily transferable into Scilab. The implementation of Cheung's model, described here, is completely software independent. Good graphical representation of all membership functions and clear definitions of all variables and rules are provided. Membership functions coordinates derived from his published figures were easily imported into Scilab. The model was then tested on the two prime target species of the TRF. The sustainability of catches of the first species, the Goldband snapper (*Pristipomoides multidens*), were very controversial. Accessing views of international experts through Cheung's expert system was timely as interest from oil and gas exploration was gathering momentum in the Timor Reef area. Input parameters were emailed to Cheung who confirmed (see Appendix 4) the results described here. Later, the extinction vulnerability of the Red Emperor (*Lutjanus sebae*), second most sought after species of the TRF, was calculated as well.

5.4.1 Description of Cheung's expert system

Cheung *et al.*'s (2005) expert system comprises eight weighted input variables and one output variable. The eight input variables are: maximum length, age at first maturity, longevity, von Bertalanffy growth parameter K, natural mortality rate, fecundity, strength of spatial behaviour and geographic range. The output variable, level of intrinsic extinction vulnerability to fishing, is defined by 4 membership functions. Maximum membership value is 1. Cheung (2005) tested their model on 159 marine fishes with complete records of life history and ecological characteristics extracted from FishBase, a reference online database of multilingual information on more than 30,900 species of fish edited by Froese and Pauli (2008).

Cheung *et al.*'s (2005) evaluation focused on five aspects of the model. The sensitivity of the model to the removal of the various input variables was tested along with the rules' weightings. The validity of vulnerability estimates was compared with known historical abundance trends. The goodness-of-fit of the test statistics reflecting the predictions accuracy was checked. Predictions obtained from two surrogates of extinction risks, maximum length and age, matched broad model outputs. Advantages of the fuzzy rule-based model over an identical Boolean model were demonstrated.

Cheung *et al.* (2005) made a number of observations. The predicted intrinsic vulnerabilities are insensitive to threshold values. Deviations in the output, generally small when individual inputs were eliminated, increase with the number of input variables removed. Intrinsic vulnerabilities predicted by the expert system are significantly better than those from the two surrogates maximum length and age at first maturity. Once fuzzy sets are replaced by classical sets there is no correlation between predicted intrinsic vulnerability and population trends. Information on reef fish aggregation greatly improved the system performance for Fiji's reef species. Eliminating fecundity causes little variation in expert system performance. Intrinsic vulnerability is a lot more dependent on maximum length and age at first maturity.

The considerable contribution of this expert system fishery management is its ability to predict extinction vulnerability for species indirectly targeted by commercial fishing for which no stock assessments or population trends exist. This expert system estimated, from a dataset of 900 species of fish, the intrinsic vulnerability (Morato *et al.*, 2006) to be higher among seamount species than among non seamount species, a result supported by the sudden demise of a number of seamount fisheries. Cheung and his colleagues concede however that additional factors should be integrated with intrinsic vulnerability to provide an overall assessment of risk of extinction.

5.4.2 Implementation of Cheung's expert system in Scilab

The actual implementation of Cheung's *et al.*'s (2005) expert system does not consist in simply recreating an expert system. The original model has to be truncated to remove rules based on variables for which no local data is available. This situation, common in real world resource management applications, demonstrates a substantial advantage of fuzzy rule-based models over equation based models more difficult to adapt to local needs.

Cheung *et al.* (2005) provides clear and complete directives sufficient to build his expert system from figures and explanations provided in his paper. All input and output membership functions in Figures 5.8, 5.9 and 5.10 have been recreated in Scilab from coordinates directly read from figures in his paper.

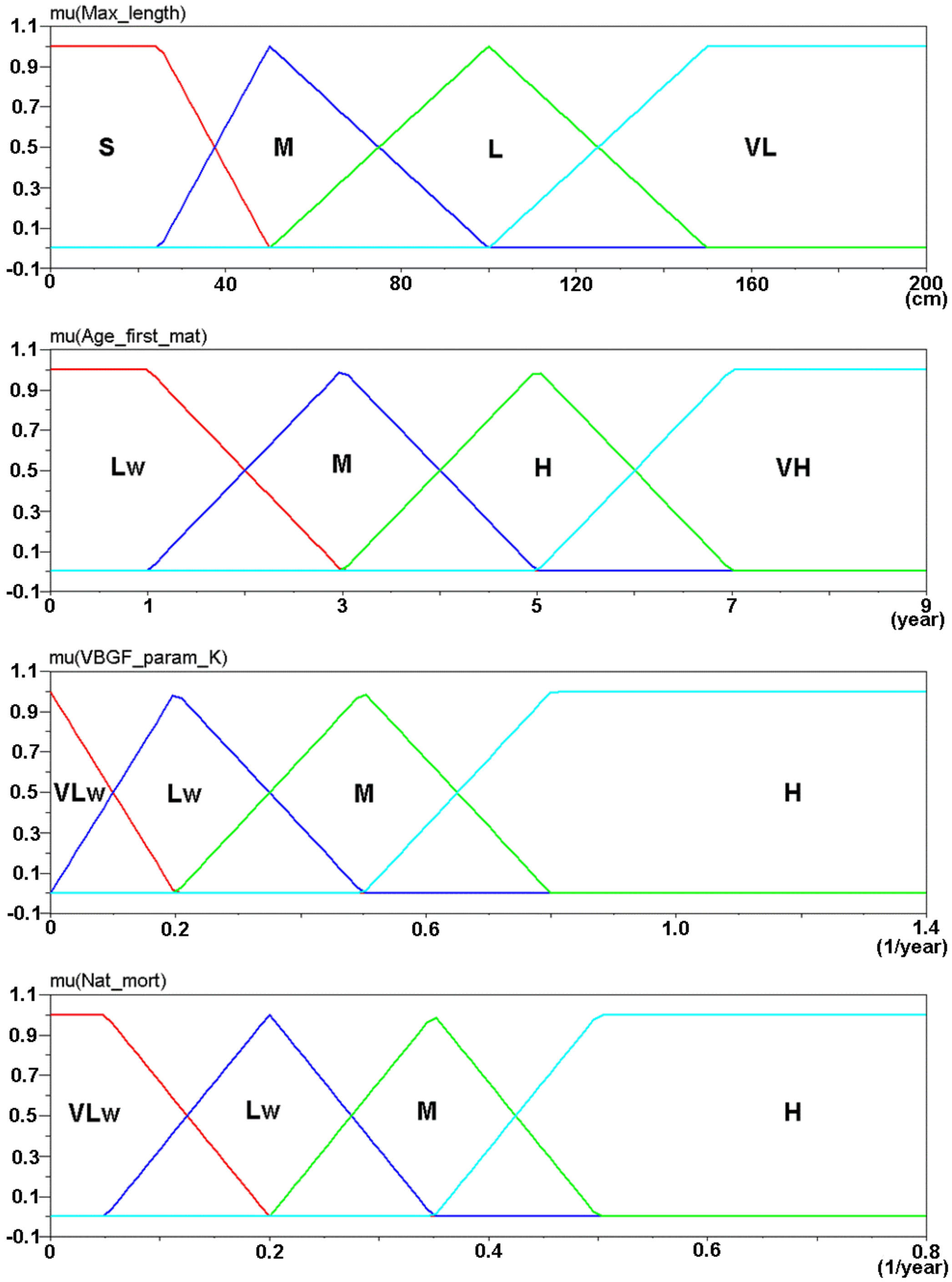


Figure 5.8: First 4 input variables maximum body length, age at first maturity, von Bertalanffy growth parameter K, Natural mortality rate and their corresponding membership functions.

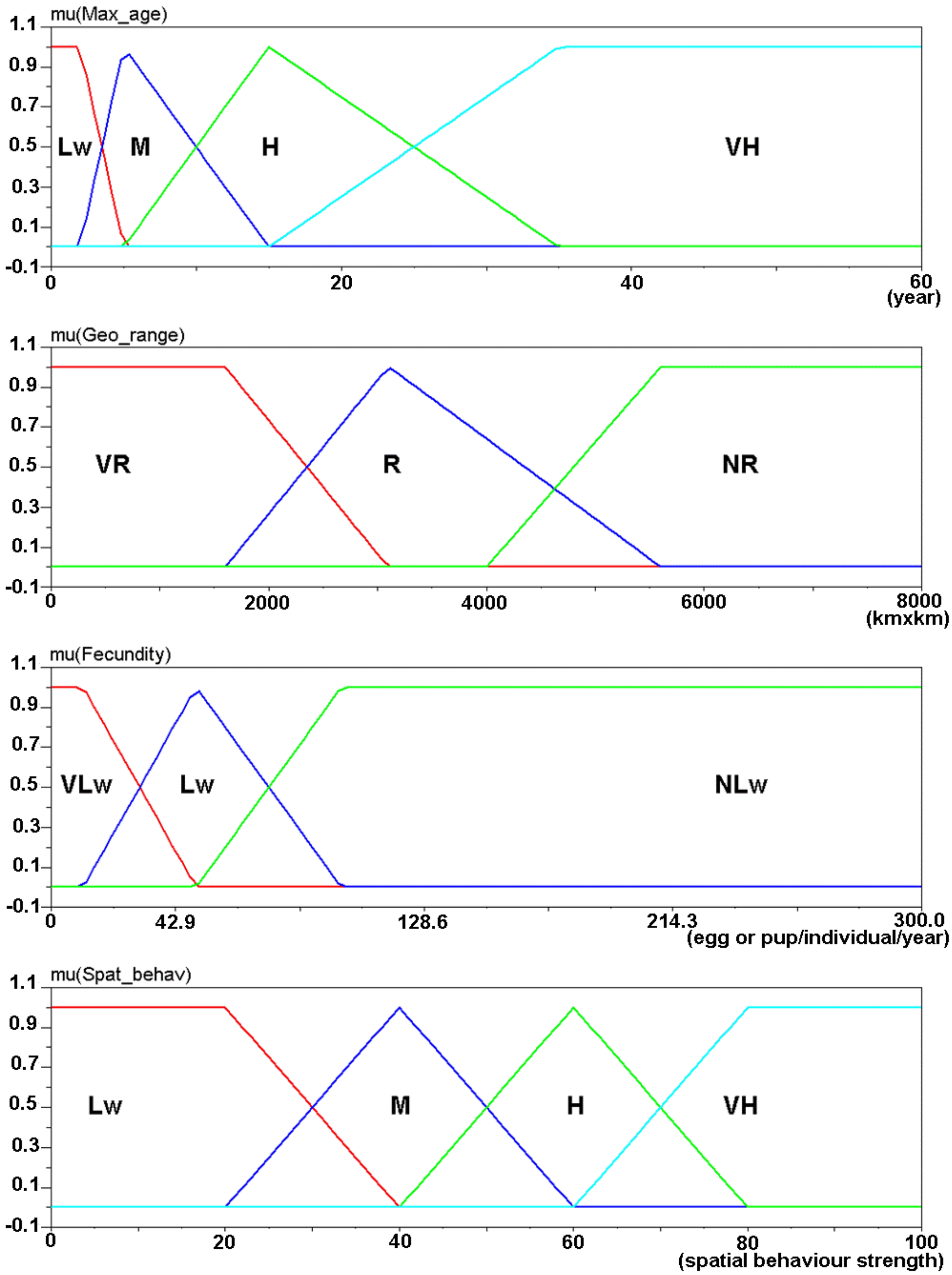


Figure 5.9: Last 4 input variables maximum age, geographic range, annual fecundity, strength of aggregation behaviour and their corresponding membership functions.

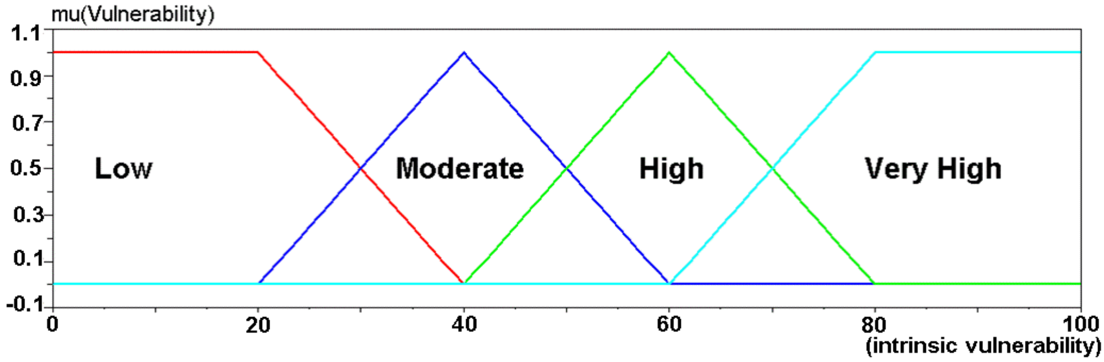


Figure 5.10: Output variable Intrinsic vulnerability of fish species to fishing pressure and its 4 membership functions measured on an arbitrary scale of 1 to 100. The value of highest vulnerability is 100.

Only the first eighteen of the twenty five rules listed in Cheung's paper, written in Scilab, are displayed in Table 5.6. Note that Cheung's original model contains only two rules including fecundity. The third rule, based on membership function NLw displayed in Figure 5.9, does not appear in his model. The influence of this rule on the model is negligible as the fecundity of most species fall in the Not Low membership function. Rules relying on geographic range and spatial behavior do not appear in Table 5.6 as no information on these two variables was available for the two species of the Timor Reef fishery considered here. Rules related to these two variables were therefore removed from the model.

Table 5.6: All rules from Cheung's (2005) expert system retained in the model of fish vulnerability to fishing pressure implemented in this chapter.

R1:	IF	{Max_length is VL}	THEN	{Vulnerability is Very High}	weight = 0.5
R2:	IF	{Max_length is L}	THEN	{Vulnerability is High}	weight = 0.5
R3:	IF	{Max_length is M}	THEN	{Vulnerability is Moderate}	weight = 0.5
R4:	IF	{Max_length is S}	THEN	{Vulnerability is Low}	weight = 0.5
R5:	IF	{Age_first_mat is VH}	THEN	{Vulnerability is Very High}	weight = 0.5
R6:	IF	{Age_first_mat is H}	THEN	{Vulnerability is High}	weight = 0.5
R7:	IF	{Age_first_mat is M}	THEN	{Vulnerability is Moderate}	weight = 0.5
R8:	IF	{Age_first_mat is Lw}	THEN	{Vulnerability is Low}	weight = 0.5
R9:	IF	{Max_age is VH}	THEN	{Vulnerability is Very High}	weight = 0.5
R10:	IF	{Max_age is H}	THEN	{Vulnerability is High}	weight = 0.5
R11:	IF	{Max_age is M}	THEN	{Vulnerability is Moderate}	weight = 0.5
R12:	IF	{Max_age is Lw}	THEN	{Vulnerability is Low}	weight = 0.5
R13:	IF	{VBGF_param_K is VLw} OR {Nat_mort is VLw}	THEN	{Vulnerability is Very High}	weight = 0.5
R14:	IF	{VBGF_param_K is Lw} OR {Nat_mort is Lw}	THEN	{Vulnerability is High}	weight = 0.5
R15:	IF	{VBGF_param_K is M} OR {Nat_mort is M}	THEN	{Vulnerability is Moderate}	weight = 0.5
R16:	IF	{VBGF_param_K is H} OR {Nat_mort is H}	THEN	{Vulnerability is Low}	weight = 0.5
R17:	IF	{Fecundity is Lw}	THEN	{Vulnerability is High}	weight = 0.5
R18:	IF	{Fecundity is VLw}	THEN	{Vulnerability is Very High}	weight = 0.5

Once built in Scilab, using the sciFLT toolbox, Cheung's model is used to calculate the intrinsic vulnerability to fishing pressure of two important commercial species of the Timor Reef fishery. Biological parameters required by the model were provided for Goldband snapper (*Pristipomoides multidens*) and Red Emperor (*Lutjanus sebae*) by Julie Lloyd, then a senior marine biologist with the Fisheries Department of the Northern Territory Government. Although information of this nature can be downloaded from FishBase, local knowledge is fundamental as will be argued in section 5.10.3.

Table 5.7: Vulnerability to fishing pressure of Goldband snapper and male (M) and female (F) Red Emperor.

Species	Max_L	First_Mat	VBGF_K	Nat_Mort	Max_Age	Fecundity	Vulnerability
Goldband snapper	71	5	0.23	0.14	18	165000	61.4
Red Emperor (M)	62.8	6	0.151	0.42	19	NA	40.4
Red Emperor (F)	48.2	4	0.271	0.49	12	Unknown	55.1

The resulting vulnerability values (Table 5.7) indicate that the Goldband snapper vulnerability to fishing pressure is highest. Male and female Red Emperor are characterised by different parameters. The highest of the two values should be retained as it provides a more conservative estimate of the resilience of the Red Emperor to fishing pressure. The intrinsic vulnerability of a species to fishing pressure is an estimate which varies with the geographical source of the information fed into the model. Figure 5.11 is a useful visualisation of the effect of variations in maximum length and age of the Goldband snapper on its intrinsic vulnerability. To generate Figure 5.11 in Scilab, all but 3 variables displayed in Table 5.5 are kept constant. Figure 5.11 shows how at the point in space (First_Mat, VBGF_K, Nat_Mort, Fecundity) defined by values for Goldband snapper in Table 5.7, variations in Max_Age and Max_L affect its intrinsic vulnerability. If older and larger specimens of Goldband snapper were captured in the TRF area, the apparent vulnerability of the species would rise. This observation suggests that FishBase information needs to be considered carefully.

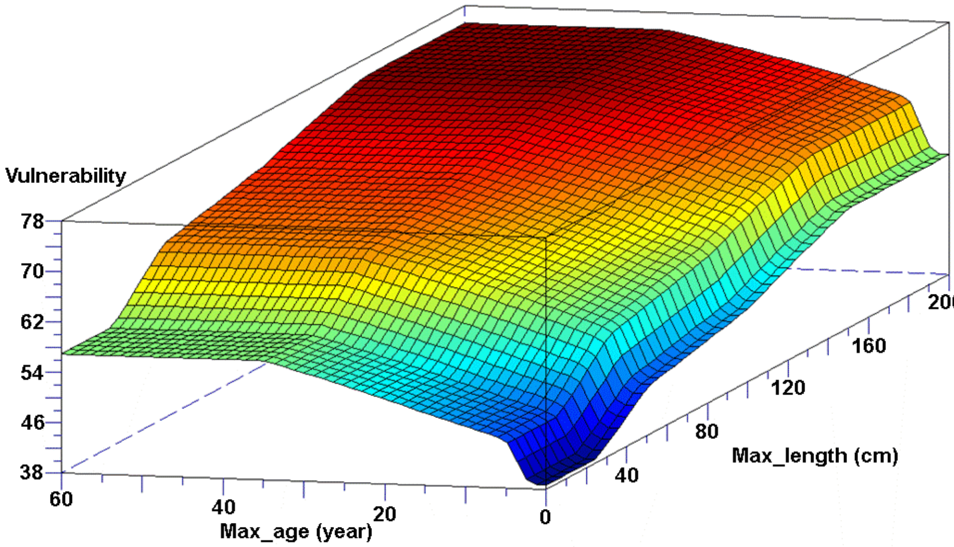


Figure 5.11: 3D plot showing how maximum length (Max_length on Y axis) and age (Max_age on X axis) affect the intrinsic vulnerability of Goldband snapper at point (5, 0.23, 0.14, 165000) in the four dimensional space (First_Mat, VBGF_K, Nat_Mort, Fecundity).

5.4.4 Discussion

Results in Table 5.7 support the views of Cheung *et al.* (2005) that maximum length appears to be a good predictor of intrinsic vulnerability. Goldband snapper is more vulnerable than Red Emperor as the maximum length of the former species is larger. Fecundity plays a minor role and can generally be ignored for one reason at least: most fish produce more than 100 egg/individual/year and belong therefore to the NLw (Not Low) membership function as shown in Figure 5.10. FNLw fecundity is represented by trapezoidal membership function which plateaus for values larger than 100 egg/individual/year. Fecundity will therefore fail to differentiate between intrinsic vulnerabilities of the many fishes with fecundity larger than 100. Fecundity can consequently be ignored in most cases as stated by Cheung (Appendix 4.11). Spatial behaviour and geographic range were not included in the model because no information was available. Two advantages of fuzzy rule-based expert systems are highlighted by this approach. Firstly, their layered structure, where all rules act in parallel, allows to easily simplify models by switching off variables where they have the same constant value across all inputs. Secondly, some rules can generally be removed without completely incapacitating the model. A drop in predictive capability may be observed but the model remains functional. This represents a tremendous advantage over more traditional mathematical or statistical models where even if some variables can be removed from the original equation, numerous adjustments of the original model may be necessary. In addition to its advantages over more conventional models, this model proved to be a very useful complement of FishBase (Froese and Pauli, 2008) to assess the vulnerability of two important commercial fishes of the TRF: the Red Emperor and the Goldband Snapper.

The Red Emperor can be found in the Indo West Pacific, the Red Sea, East Africa and as far North as Japan (Froese and Pauli, 2008). A valuable fish in all Tropical Australian fisheries, this species is characterised by patchy biological information. Its fecundity is not listed in FishBase. The Goldband snapper and Red Emperor share the same geographical range. The vulnerability of the former is high and very high for the latter according to FishBase. These results contradict those in Table 5.7 obtained in Northern Territory waters. Discrepancies between global estimates provided by FishBase and regional or local intrinsic vulnerability assessment obtained by Cheung's *et al'*s (2005) fuzzy rule-based expert system highlight a fundamental role that fuzzy rule-based expert systems can play in most domains of natural resources management. While global models identify variables to incorporate in a model, expert systems can generate locally relevant predictions from local data. Cheung was contacted (see Appendix 4) to confirm the Goldband Snapper vulnerability in Table 5.7. Cheung found 60.2 instead of 61.4. This value 1.2% lower than the result displayed in Table 5.7 was initially attributed to differences in software. Further investigation revealed a flaw in sciFLT (Urzua, 2003) undocumented although known to its author. Cheung used an Excel (Kelly, 2006) based computational environment assigning weightings equal to 0.5 to all rules. Although sciFLT offers the same option to assign weightings to rules, weightings are not reflected in the output. Urzua (jaime_urzua@yahoo.com) was contacted. He explained his intention to implement rule weightings in the sciFLT extension for Scilab 5.x versions. In its current version, however, sciFLT does not support weighted rules. Weightings remain equal to 1 regardless of the value assigned.

Once the minor discrepancy issue is addressed one may wonder what an intrinsic vulnerability of 60 actually means? According to FishBase, a vulnerability of 60 is high. Cheung *and al.* (2005) quoted in their paper that the ill fated Atlantic Cod, a sadly emblematic species for all fishery scientists, has an intrinsic vulnerability of 62. This comparison immediately puts the intrinsic vulnerability of the Goldband snapper in a more meaningful context for any fishery manager. FishBase intrinsic vulnerability values, although useful globally, lack the regional or local context of Cheung's expert system outputs.

The contradiction between FishBase vulnerability indices and Cheung expert system estimates should remind fishery managers that global models, FishBase in that instance, are poor local predictors. Even when the same modelling principles hold locally, global estimates may be incompatible with local observations as they rely on global instead of local statistics. Local observations in absence of historical data should be considered carefully as low intrinsic vulnerability may simply indicate that the species has already suffered from fishing pressure. The outcome would be a decrease in maximum age and length resulting in an apparent decrease in vulnerability. This may explain why in the TRF the Red Emperor appears less vulnerable than the Goldband snapper. This intrinsic vulnerability model is a particularly valuable management tool as it can enable a state like Western Australia, with fisheries ranging from temperate cool in the south to tropical in the north, to rank within each fishery their commercial species on the basis of their sensitivity to fishing pressure. Each fishery could then aim at establishing more realistic quotas by relying on species vulnerabilities which would be fishery specific.

Summary

This chapter is devoted to the inclusion of human knowledge into fuzzy rule-based models often called fuzzy rule-based expert systems. Topics covered here do not all have a cartographic expression. Yet, all can play an important role in the production of maps instrumental in better managing natural resources. The Timor Reef Fishery (TRF) provides a backdrop for two case studies which demonstrate two methodologies relevant to a wide range of NRM contexts. The first methodology focuses on the acquisition of experts' knowledge to build an expert system. The second methodology consists in implementing an existing expert system to compare local predictions with preexisting global predictions.

The acquisition of experts' knowledge was prompted by the need to improve a GIS model of productivity of the TRF, a fishery in the Northern Territory. The current model is based on catch records only compensated for fishing effort. Catch records need as well to be adjusted for variations in fishing power. The latter, however is a notoriously elusive variable, easy for expert fishers to estimate qualitatively but hard to quantify in a systematic and reproducible manner: a typical domain of application for fuzzy expert systems. The first step in the development of a fuzzy expert system consists in recording experts' knowledge. A number of knowledge acquisition methods have been documented (Bilgic and Turksen, 2000). Tests carried out by Chameau and Santamarina (1987) identify the interval estimation method as the most efficient. This technique was used with the collaboration of TRF expert fishers to estimate the fishing power of eleven vessels and seven of their characteristic features. Results from this study reveal that, once rescaled, estimates from informants are highly correlated. The fishing power of all eleven fishing vessels considered is average. The experts surveyed discarded one of the seven variables suspected to affect fishing power. Low, Medium and High fishing power membership functions are inferred for all six input variables endorsed by the two expert fishers. However, as the questionnaires only provide information on medium fishing power, the overall predictive capability of the model is low. This study has four outcomes. Firstly, the knowledge capture methodology adopted is well suited to the task. Secondly, experts need to be presented with a variety of information sufficient to explore the full range of possible values of the output variable which was not possible here. Thirdly, the minimum number of 5 informants required to create a reliable expert system, as suggested by Chameau and Santamarina, is a limitation of this technique. Finally, the current model of productivity of the TRF is more reliable than expected as all fishing vessels have approximately the same medium fishing power. Despite the restricted range of fishing power of the training dataset affects the predictive capability of this model, there is little doubt that this approach is promising. Modelling fishing power is urgently needed wherever management has to rely on catch records to monitor the sustainability of fishing practices.

Cheung *et al.* (2005) describes in detail a fuzzy rule-based expert system developed entirely from expert knowledge embedded in research literature. The structure of their model is strikingly similar to that of the model of fishing power previously described. Cheung's *et al.*'s (2005) model predicts the intrinsic vulnerability of fishes to fishing pressure on the basis of 8 biological variables. Once implemented from the detailed description in Cheung's *et al.*'s (2005) paper, this model is used to predict the vulnerability to fishing pressure of the most important commercial species of the TRF: the Goldband snapper. Its vulnerability of 61 on a scale of 0 to 100 was confirmed by Cheung *et al.* (2005). The Goldband snapper is therefore highly vulnerable, on a par with the Atlantic cod. Discrepancies between vulnerabilities provided by online FishBase and Cheung's *et al.*'s (2005) expert system suggest that local vulnerability of commercial species are inaccurately estimated by FishBase. Fuzzy rule-based expert systems have two major advantages. Firstly, some variables can often be ignored without dramatically affecting the model's output. Secondly, fuzzy rule-based expert systems and data driven fuzzy rule-based models share the same structure detailed in Chapter 4.

Merging fuzzy rule-based expert systems and GIS models into a spatial predictive system produces a new variety of Geographic Information System with much greater capabilities as demonstrated by Mackinson (1999) with Clupex. An additional example is provided by the Timor Reef fishery case studies considered in this chapter. The expert system of fish vulnerability to fishing pressure devised by Cheung *et al.* (2005) has much potential. In a large fishery it could be merged with an existing GIS model to produce a new type of Geographic Information System. Effects of environmental changes, species maps of productivity similar to Figure 5.2, and species vulnerability could all be combined to predict on a yearly basis the ideal mix of species targeted in each zone of the fishery to maximise both sustainability and profit.

CHAPTER 6

CONCLUSION

Overview

Chapters 2 and 5 focus on fuzzy rule-based modelling. Chapter 3 explores a radically different implementation of fuzzy logic. The contrast between Chapter 3 and the remaining chapters is a reminder of the variety of implementations of fuzzy logic which lack the wide range of applications, unified framework and credentials of fuzzy rule-base modelling. Case studies in Chapters 4 and 5 demonstrate that fuzzy rule-based modelling equips GIS modellers with the same strategy capable to build a variety of multivariate predictors from experimental data or human knowledge. This approach leads to directions of research poised to benefit developing countries.

GIS modelling will gain most from combining the sophistication of statistical methods with the simplicity and versatility of fuzzy rule-based modelling. Fuzzy logic has a particular role to play in GIS modelling when uncertainty is not statistical but linguistic, a common occurrence in geography in general and in NRM in particular.

6.1 Material presented in this thesis

Chapters 2 to 5 explore different facets of the role that fuzzy logic can play in GIS modelling. Chapter 2 provides the necessary background knowledge. The concept of membership function is the keystone of fuzzy logic. Fuzzy rule-based modelling, the most successful application of fuzzy logic, relies on membership to establish rules matching values of input and output variables. A fuzzy rule-based model is a list of logical expressions “IF antecedent THEN consequent. Principles of identification of all membership functions and rules are described in detail”. Outputs are derived from inputs through a 4 step process: fuzzification, implication, aggregation and defuzzification. Operators performing these tasks are reviewed. Two types of fuzzy rule-based model exist: Mamdani and Takagi Sugeno. Only Mamdani models are considered in this thesis as they are best suited to environmental problems and knowledge capture. As a demonstration, a fuzzy rule-based model is built from an artificially generated stochastic dataset. The correlation coefficient between input and output is 0.96.

Chapter 3, in contrast with Chapter 2, introduces fuzzy multicriteria decision analysis. This very different modelling approach relies on a graphical interpretation of membership functions to generate 4 maps of suitability from the 4 coordinates of trapezoidal membership function. Well adapted to the GIS visualization of decisions based on uncertain criteria, this strategy is used to map the suitability of a remote island of the Northern Territory to prawn farming. Although very successful in this application, the high specificity of this strategy may distract from the more general fuzzy rule-based modelling. The GIS community may have been similarly distracted by the modelling of fuzzy boundaries between soil types, thus failing to explore more application rich implementations of fuzzy logic in GIS modelling.

Chapter 4 builds on the principles laid out in Chapter 2 to concentrate on data driven fuzzy rule based modelling. The flexibility of this modelling approach is first put to the test by building a fuzzy classifier capable of assigning iris flowers to 1 of 4 varieties on the basis of flower metrics. The 97% accuracy of this classifier is on a par with statistical methods. Well suited to large datasets of high dimensionality, semi automatic objective identification is performed by clustering software. The standard technique is compared with a more sophisticated method: the additional effort is not justified by the marginal gain in accuracy. The construction of this model highlights that designing membership functions by semi automatic clustering is impossible for input variables insufficiently correlated to the output variable. This important observation facilitates the reinterpretation of a small dataset of records obtained by complex manipulations of remotely sensed data to predict the foraging pattern of elephant seals. The published study relies on GLM to conclude that the prediction is poor. No fuzzy rule-based model can be derived using the semi automatic identification strategy previously described thus implying a complete lack of predictive capability of the input variables. This important case study demonstrates the value of using statistical and fuzzy models in parallel.

Chapter 5 introduces knowledge driven fuzzy rule-based modelling. The initial case study consists in translating a fishers' survey into a model of fishing power. Difficulties of using informants as data source are revealed. A fully functional, albeit limited in scope, model of fishing power is created. The second case study consists of implementing a published expert system of fish vulnerability derived from expert knowledge available in peer reviewed scientific literature. Comparison of predictions from this model with globally averaged values indicates the importance of local expert systems. The estimation of fishery sustainability, the development of local erosion model and the prediction of anomalous seasonal weather are three directions of research in applications of expert systems considered in this chapter .

6.2 What the case studies presented in this thesis tell us

Four case studies, all based on fuzzy rule-based modelling, demonstrate that fuzzy logic, through fuzzy rule-based modelling, offers a generic approach to predictive modelling. The first case study shows that fuzzy rule-based modelling can reliably classify iris flowers defined by four flower metrics. The second case study relies on fuzzy rule-based modelling to cast some light on the failure of a sophisticated statistical attempt to predict the foraging patterns of elephant seals from environmental variables. The third case study demonstrates how to build a fuzzy rule-based model of fishing power from fishers' expert knowledge. The fourth case study consists of implementing an existing expert system of fish vulnerability and highlighting its contribution to fishery management.

Although not explicitly dealing with spatial data, the first case study can be extrapolated to a number of geographic problems. The last three case studies explicitly refer to the management of marine natural resources and have direct applications to GIS modelling. The first two models are data driven. They respectively emulate two very different statistical techniques: discriminant analysis and general linear modelling. The second model, aimed at predicting the foraging patterns of elephant seals, is based on a small dataset of environmental records. This model suggests that fuzzy rule-based modelling may be better suited than GLM to process scarce information of uncertain relevance. The last two models are knowledge driven. They are fuzzy expert systems without statistical equivalent. Fuzzy expert systems of fishing power and vulnerability to fishing pressure are readily implemented using the same fuzzy rule-based modelling framework. These four case studies do not rely on statistics, yet their outcomes are predictions. These case studies showcase four substantial contributions of fuzzy logic to GIS modelling. Firstly they provide GIS modelling with the simplicity of a single generic modelling framework. Their second contribution to GIS modelling lies in the transparency they convey to the predictive framework. Thirdly fuzzy logic frees GIS modelling from the reliance on statistics for the identification of explanatory variables. Fourthly, fuzzy logic enables the development of knowledge driven GIS models. These case studies confirm that fuzzy logic offers a simple, unified approach to modelling in a GIS environment. In some instances they highlight capabilities of fuzzy rule-based modelling of particular relevance to GIS modelling.

The prediction of foraging patterns of elephant seals relies on a dataset of 50 records, small by statistical standards. Fuzzy rule-based modelling unambiguously identified the absence of explanatory power of all environmental variables. The statistical approach indicated a poor correlation between input and output variables without excluding the possibility of making predictions. This case study strongly suggests that fuzzy rule-based modelling provides a better approach to GIS modelling of small complex datasets of uncertain quality. The last two case studies describe two very different knowledge driven fuzzy rule-based models. The undisputed supremacy of fuzzy logic in the processing of human knowledge is a substantial contribution to GIS modelling.

Case studies in this thesis focus on applications of fuzzy logic to spatial studies of aquatic NRM. Other researchers (Daunicht *et al.*, 1996; Bock and Salski, 1998; Salski, 1992) applied fuzzy logic to spatial problems of terrestrial ecology and NRM. Salski (1999) describes a particularly interesting knowledge based model of skylark nesting habits in cropped areas of northern Germany. Fuzzy logic provides versatile frameworks for the spatial study of the multitude of complex aspects of both aquatic and terrestrial ecology and their economic extensions to NRM.

In addition to the set duration and clearly defined focus imposed on this research by the nature of a PhD, this study has three limitations. Firstly, all advanced mathematical aspects of fuzzy logic were deliberately ignored. This limitation reflects as much the background of the author as the need to be accessible to the vast majority of potential users in GIS and NRM. Secondly, the aim of this study is to be relevant to the research carried out in Charles Darwin University and to the human and natural environments of the Northern Territory. My prime concern is to improve GIS applications to the management of marine resources, the integration of the expert knowledge of fishers and the interfacing with indigenous Aboriginal ecological knowledge. Many other possible domains of application could not therefore be investigated within the framework of this thesis. Thirdly, the main case studies in this thesis are commercial projects I completed as a practicing professional spatial scientist. This last limitation of my study is therefore one of economic pragmatism, as these case studies reflect the current need of the industry in GIS applications to NRM in Northern Australia.

6.3 Future directions of research in GIS applications of fuzzy logic

While there is clearly a need (Leung, 1999) for fuzzy logic to substantially contribute to improve GIS fundamental conceptual approaches to spatial analysis, little progress has been achieved in that domain during the last decades. Alternatively, one may research how established successful implementations of fuzzy logic can benefit spatial modelling particularly in regions where the paucity of infrastructure and the lack of baseline data lead to an increased reliance on GIS for a wide range of NRM predictive models. The Northern Territory, in the Australian Tropics, is a good example of a region poised to benefit from such research. Three GIS applications of fuzzy logic to Northern Australia are considered. The first application is a direct extension of the expert system of intrinsic vulnerability to fishing pressure described in section 5.4. The second application focuses on the adaptation of erosion models developed in temperate climates to the very different conditions that prevail in the Tropics. The third application addresses the urgent need to capture, in a usable scientific format, rapidly vanishing indigenous traditional ecological knowledge (TEK) wherever it survives. In all instances GIS plays the crucial role of processing and visually summarising complex outputs. Not all variables considered are spatial but the final model is GIS based. In all instances data preprocessing can greatly benefit from the fuzzy rule-based expert systems.

Three domains of research in applications of fuzzy rule-based expert systems are therefore suggested. Firstly, additional effort is needed to improve the estimation of whole fishery sustainability. Secondly, the development of local erosion models, based on remote sensing, could help to better predict the devastating effects of erosion resulting from inappropriate land management in the Tropics. Thirdly, TEK based predictions of seasonal weather in the Northern Territory could provide a framework for the development of other environmental models wherever TEK survives. In all three cases, available human knowledge would replace non existing experimental data and complement surrogate datasets to provide information where there is no affordable alternative at present or in the foreseeable future. An additional benefit of the development of fuzzy rule-based expert systems would be the documentation of endangered human knowledge which in most parts of the world is on the verge of disappearing for ever.

6.3.1 Estimating fishery sustainability

Seamounts are unusual oceanic habitats, generally of volcanic origin. They attract abundant concentrations of fishes which become an easy target for technologically advanced fisheries. Rapid decline and spectacular collapse of some of these fisheries spurred scientific research. The matter became the focus of the public's attention in Australia when large illegal catches of vulnerable Patagonian toothfish (*Dissostichus eleginoides*) were seized in Southern Oceans (Colvin, 2004). Morato *et al.* (2006) used the previous expert system to demonstrate that seamount-aggregating fishes particularly are characterized by a higher intrinsic vulnerability than other commercial species. Fishery management considering commercial fishing on seamounts needs therefore to invest substantially more in catch monitoring to ensure sustainability. A careful cost benefit analysis may then conclude that the cost of extra monitoring combined with the frequent remoteness of these fisheries cast doubts on their profitability. Cheung's *et al.*'s (2005) expert system allows one to evaluate the intrinsic vulnerability of a fishery on the basis of the average yearly catch composition of commercial species, including by catch. The characterisation of fisheries by an index of intrinsic vulnerability offers a country with a very extensive coastline and a great variety of fisheries, like Australia, the possibility to create a nation wide GIS model of fishery vulnerability to fishing pressure. At a regional scale, a GIS of fishery intrinsic vulnerability would help fishery managers to show Government where the risk associated with oil and gas exploration is higher (Puig, 2008). As demonstrated in the previous section, the current reliance on FishBase could have some rather disastrous consequences. Wide ranging species are likely to show local biological parameters substantially different from global average values thus justifying fishery specific calculations of vulnerability.

6.3.2 Developing local erosion models

Natural resource management, particularly in the Australian Tropical North and developing countries, has to rely heavily on merging satellite imagery with preexisting scientific data. GIS offers all the necessary functionality to facilitate the exploitation of information extracted from satellite imagery. Software such as eCognition (2010) improved information extraction from satellite imagery thus opening new doors to Remote Sensing based GIS modelling in countries lacking baseline datasets. Once information extracted from images is in digital format, and readily available through a GIS, a new challenge arises. Environmental variables need to be inferred from remotely sensed data. Although preexisting models can often be adapted to this task, few are applicable to tropical conditions which prevail in many Third World countries (Puig *et al.*, 2000). The Universal Soil Loss Equation or USLE (Wischmeier and Smith, 1978) as well as its improved version, the RUSLE (Revised Universal Soil Loss Equation), are perfect examples. Developed under temperate climatic conditions in the USA, the USLE is notoriously unsuitable to the Wet Dry Tropics. Developing an alternative model is therefore necessary. Existing models define input and output variables and are therefore excellent starting points. Experts can then classify the local landscape in terms of its erodibility on the basis of environmental characteristics (e.g. vegetation, turbidity) and match it with rainfall records, sediments properties, topography and local knowledge of rainfall characteristics. Membership functions for all variables of the standard equation (here the USLE), once created in close collaboration with experts, could allow the creation of rules linking input variables to output. Although this approach may appear rather simplistic it would be a substantial step forward in countries where the most elementary form of the USLE was relied upon in the past.

6.3.3 Predictions of anomalous seasonal weather based on traditional ecological knowledge

Our growing understanding of climate change (Burroughs, 2007) combined with traditional ecological knowledge (Smith, 2008) may help develop strategies to mitigate the effects of anomalous weather. Exceptional events such as drought, unusually high rainfall, large number of high intensity cyclones are not predicted for specific areas of the Northern Territory. Owing to the very low density of population, such predictions are not even considered as any cost benefit analysis would fail to justify the development of local predictive models of exceptional events. To make the matter worse, climatic models are best suited to global forecasting, not to local predictions. Biological expressions of ecosystems responses to precursor climatic signs have probably been used for thousands of years. They are the basis of traditional Aboriginal calendars. The Kunwinjku calendar of Western Arnhem Land is a good example. Detailed observations of nature in the Alligator Rivers Region (AAR) have been transmitted through Aboriginal oral tradition. Much of this knowledge is still available in areas, such as Kakadu National Park, where calendar species are still abundant. A growing scientific interest in indigenous TEK across Tropical Australia suggests that trying to match our limited climatic records with traditional Aboriginal knowledge could allow us to develop local climatic predictive models. Although we cannot eradicate wild weather and effects of climate change we can try to mitigate them. Predicting months in advance the onset of a very active wet season likely to bring torrential rainfalls and increased cyclonic activity would help local authorities to be better prepared when roads are suddenly flooded and remote communities isolated. This type of prediction of local exceptional events can only be achieved where four conditions are met. Firstly, decades of reliable rainfall records are available. Secondly, traditional ecological knowledge still exists. Thirdly, natural diagnostic plants and animals are still abundant. Fourthly, the additional modelling and monitoring effort are justified by the presence of sensitive infrastructure, economic activity or communities.

The East Alligator River Region (AAR) fulfills all 4 requirements. Oenpelli rainfall records started in 1912 and are readily available through the Bureau Of Meteorology website (http:/www.bom.gov.au). Members of the Kunwinjku language group, and other closely related language groups, of Western Arnhem Land (Chaloupka, 1993) are still the custodians of a rich rock painting tradition. Such a detailed visual expression of their TEK reflects the role it can play in the development of local environmental models. Nestled in the heart of Kakadu National Park, Oenpelli is surrounded by a relatively well preserved natural environment. The nearby town of Jabiru plays an important role in the Northern Territory economy as a touristic destination and as a service base for the nearby Ranger uranium mine.

A local predictive model of exceptional events in the AAR could be articulated around a GIS designed to monitor spatial variations in environmental changes. The status of plants and animals is central to the Aboriginal segmentation of the year in six periods across the Kakadu region: Gudjewg, Bang Gerreng, Yegge, Wurrgeng Gurrung, Gunumeleng. These seasons make up the ecologically based Kunwinjku calendar. Traditional ecological knowledge required to read this calendar relies on the careful observation of interconnected floristic, faunistic and meteorological events. Anthropologists, in close collaboration with Aboriginal organisations, can monitor the status of calendar plants and animals to help identify precursor signs of meteorological anomalies. Daily rainfalls of the Oenpelli BOM records can be segmented not by month but by seasons of the Kunwinjku calendar. Bang Gerreng, a short transitional season at the end of the monsoon, is particularly promising as it records dramatic variations in rainfall. Yearly Kunwinjku seasonal averages of historical Oenpelli rainfalls could contribute to the prediction of monsoonal activity and cyclonic intensity of subsequent years. These highly disparate datasets could provide excellent material to develop a fuzzy rule-based expert system merging traditional Aboriginal knowledge, spatial ecological monitoring of Kunwinjku calendar as well as flora, fauna and rainfall records.

6.4 What is the role of fuzzy logic in GIS modelling?

The role of fuzzy logic in GIS modelling is to provide a unified predictive framework. Fuzzy rule-based modelling, researched in this thesis, is well suited to a wide range of typical GIS modelling tasks. Fuzzy rule-based modelling being non statistical is naturally compatible with human knowledge. The contribution of fuzzy logic to GIS modelling can be considered at two different levels.

On a practical level, fuzzy rule-based modelling, well grounded in engineering pragmatism (Babuska, 1996), provides a generic approach to many GIS modelling tasks. Case studies in this thesis demonstrate that fuzzy rule-based modelling equips GIS with a universal approximator (Kosko, 1994) capable of providing estimations based on numerical or human knowledge. Knowledge based models, also called expert systems, show great potential in substantially improving GIS models used in NRM (Mackinson, 2000; Lloyd and Puig, 2009). In addition to niche applications (Malczewski, 1999; Puig, 2003), fuzzy logic equips GIS modelling with a generic predictive modelling methodology which addresses the incapacity of statistical methods to make predictions, when experimental data is scarce, while human knowledge is readily available. Being non statistical, fuzzy rule-based modelling is an ideal independent estimator of the ability of all input variables of high dimensionality datasets to explain the output variable(s).

On a more abstract level, the non statistical representation of vagueness (Zadeh, 1965) inherent to fuzzy logic is a paradigm shift (Klir and Bo Yuan, 1995) addresses the need of many GIS users for an improved approach to uncertainty (Goodchild, 2000). The philosophical paradox that affects probability and statistics (Popper, 1959), and by extension geography (Fisher, 2000) and statistics based GIS modelling, disappears when predictions rely on fuzzy rule-based modelling.

Summary

This chapter recapitulates the case studies presented in this thesis. These case studies showcase a variety of roles that fuzzy rule-based modelling can play. Directly relevant to GIS modelling, disparate tasks typically tackled with statistical methods, can be successfully completed by fuzzy rule-based models. In addition to facilitating the development of GIS models, the unified predictive framework provided by fuzzy logic opens new doors to GIS modelling. Research in applications of fuzzy logic to GIS modelling may lead to better estimate fisheries sustainability, to develop local erosion models in the Tropics and to tap TEK, where it survives, to help the prediction of unusual weather. The six chapters of this thesis reveal substantial contributions of fuzzy logic to GIS modelling.

This thesis demonstrates that the main role of fuzzy logic in GIS modelling is to provide a unified modelling framework that simplifies the development of GIS models. Fuzzy rule-based modelling is this unified modelling framework that can complement statistical predictive techniques presently used in GIS modelling or replace them when readily available human knowledge needs to be substituted to unsuitable experimental data.

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APPENDICES

Appendix 1 Excel Fuzzy Inference System XLFIS

Four sections explore fundamental aspects of early applications of fuzzy rule-based modelling principles in Excel. Section A 1.1 provides a brief introduction to XLFIS while sections A 1.2, A 1.3 and A 1.4 look at the functionality of the various worksheets of an XLFIS workbook.

A 1.1 Introduction to XLFIS

XLFIS implements fundamental fuzzy rule-based modelling principles in Excel. There is no doubt that a practical fuzzy rule-based modelling environment can be created in Excel (Cheung et al., 2005). Computations of large vectors however may be slow.

XLFIS functionality includes:

- emulate some core functionality of sophisticated software such as MATLAB Fuzzy Logic Toolbox. In addition;
- process large datasets (up to a maximum of 65536 records);
- provide a modular computational environment;
- test algorithms without writing codes;
- provide a blue print for applications in Visual Basic.

The code name of the application reflects its functionality:

- XLFIS is designed to create data driven fuzzy rule-based models based on parameters identified graphically. XL_FIS only relies on simple IF …THEN inference blocks without AND, OR, NOT or XOR operators. While suitable for data-driven models, this simple structure is less suited to knowledge driven applications.
- XL_FIS_AI adds automatic training of models from a sample dataset to the XL_FIS core functionality. The automatic training of the model does not rely on neural networks, genetic algorithms or back propagation but on a simple implementation of the graphical concept of fuzzy patch. The model is improved through trial and error weightings adjustments.

The purpose of XLFIS is to provide free access to some easily customisable Fuzzy Inference Systems (FIS) modelling environment.

Software for fuzzy rule-based modelling

- FuzzyTech, MATLAB Fuzzy Logic Toolbox, Cubicalc.
- User friendly, powerful but expensive.
- MATLAB algorithms can be implemented in Excel to create fuzzy rule-based models → XLFIS:
  - up to 19 MFs per variable;
  - up to 252 variables;
  - batch processing of up to 65,534 values or 255 x 255 arrays.

1

Fuzzy rule-based modelling with XLFIS

- XLFIS is an Excel spreadsheet that implements Fuzzy Inference Systems without AND, OR, NOT.
- XLFIS comprises 3 different types of work sheets.
- The MODEL sheet contains all model parameters and user's comments.
- User input is mainly performed in the IO sheet. Model outputs are read from the IO and S_IO sheets.
- V calculation sheets perform all model calculations
- XLFIS components and their role are introduced in the next 9 slides.

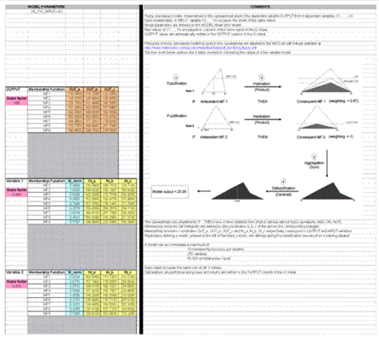
2

XLFIS - MODEL sheet

- The MODEL sheet allows the user to:
  - write comments and paste images to document the model in the pane right of the black column;
  - enter the scale factor used to display all variables with constant range.
- The Model sheet displays all model parameters:
  - all variables are within a black frame with a grey rectangles which visualises the maximum number of membership functions of the corresponding variable;
  - all antecedent (yellow) and consequent (pink) membership function coordinates and their weightings (blue);
  - all scale factors (brighter pink).

3

XLFIS- View of MODEL sheet



4

XLFIS - IO and S_IO sheets

- The IO sheet plays two roles:
  - displays the output of the model in the OUTPUT column;
  - allows the user to input data in the model.
- Data input is ideally copied from an Excel spreadsheet and pasted into columns Variable 1, Variable2, …etc.
- The S_IO sheet is similar to the IO sheet but displays rescaled input and output data. Input and output rescaled values are used to train the model. During training, model parameters identification is an interactive graphical process performed in ArcView.
- **NB**: XLFIS is not designed for semi automatic identification techniques relying.

5

XLFIS - View of IO sheet

OUTPUT	Variable 1	Variable 2
0.83	2807.00	1851.00
0.86	2915.00	1810.00
0.91	3024.00	1811.00
0.96	3126.00	1849.00
1.01	3216.00	1877.00
1.01	3222.00	1977.00
1.01	3226.00	2011.00
1.01	3235.00	2060.00
1.00	3221.00	2110.00
0.99	3219.00	2136.00
0.99	3227.00	2155.00
0.98	3249.00	2176.00
0.97	3308.00	2201.00
0.93	3410.00	2249.00
0.93	3411.00	2254.00
0.93	3416.00	2248.00
0.94	3397.00	2238.00
0.97	3299.00	2212.00
0.97	3222.00	2199.00

6

Figure A1.1: Slides above and in Figure A1.2 are from presentations on fuzzy rule-based modelling given at CDU and at NT Government Fisheries venues in 2004.

XLFIS an Excel workbook, comprises a variable number of worksheets:

- MODEL, displayed in Figure A1.3, contains all model parameters read in calculation worksheets;
- IO is the input/output sheet where the user pastes data entered in the model in columns V1 to Vn for a model with n variables;
- S_IO, displayed in Table A1.2, contains the information of IO multiplied by the scaling factors recorded on MODEL(highlighted in pink);
- worksheets V1 to Vn perform all calculations for variables V1 to Vn.

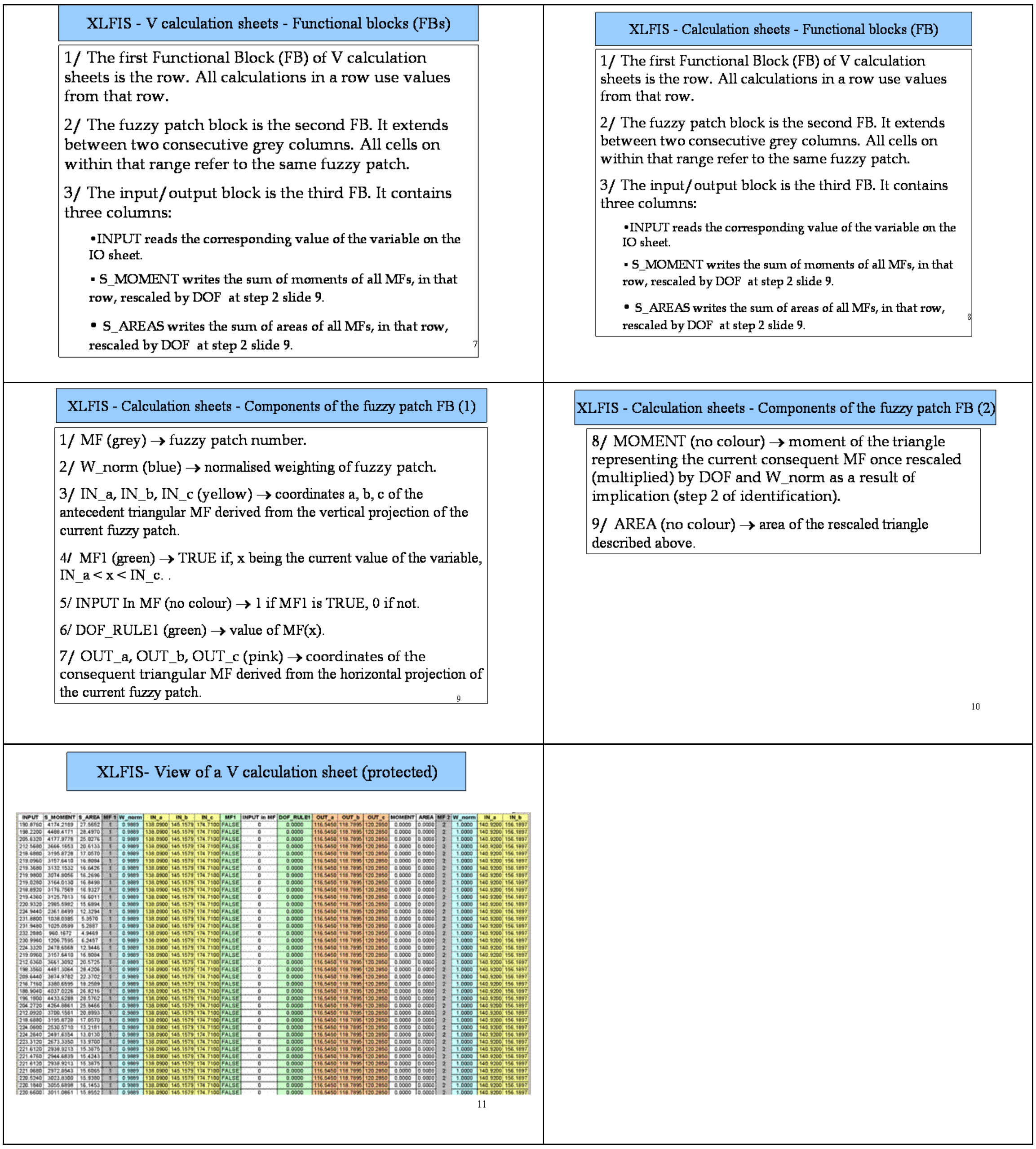


Figure A1.2: These slides introduce techniques used to build in Excel the functionality required in fuzzy rule-based modelling.

All V worksheets have the same structure. Each additional variable requires a new V worksheet. They are simply copied and pasted as the number of variables of the model increases.

Fuzzy inference system (FIS) and fuzzy rule-based modelling are equivalent expressions for all practical purposes. The acronym FIS common in the fuzzy modelling literature is not used in the body of this thesis to avoid confusions. This term, however, was used to name this Excel application of fuzzy rule-based modelling.

XLFIS (Excel Fuzzy Inference System) is a functional Excel implementation of fuzzy rule-based modelling. XLFIS, however, is cumbersome and can only accommodate, in its current version, a set number of membership functions: 9 per variable. In addition, only triangular membership functions are available.

XLFIS however provides an excellent opportunity to experiment with fuzzy rule-based modelling concepts. XLFIS, on the other hand has good weightings functionality.

XLFIS was rapidly replaced by Matlab first, and by Scilab later, for the development of fuzzy rule-based models described in this thesis.

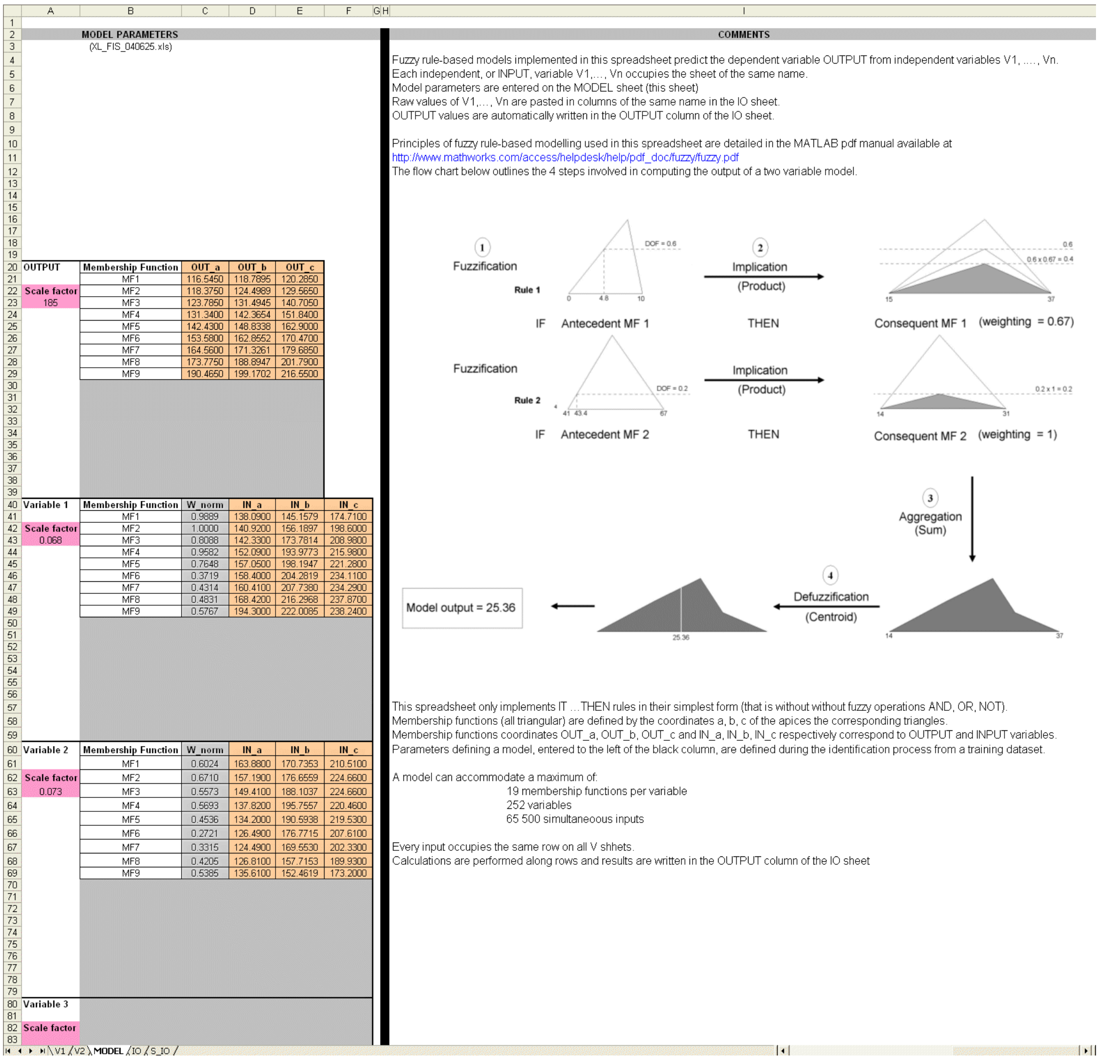
This modular structure, as it stands, accommodates reasonably large models comprising 9 membership functions per variable, tens of variables and up to 65,535 records. Practically model size is limited by the processing power of Excel.

XLFIS allows GIS users to implement single output FIS models that can be imported in a GIS software to generate a grid of maximum size 255 x 255.

The MODEL sheet in Figure A1.3 comprises two panels. To the left of the black column the user enters the parameters of the model. These parameters define the antecedent (yellow coordinate columns) and consequent membership functions (pink coordinate columns). Antecedents MFs are characterised by:

- their scale factor (pink), a factor calculated by the user to give all variables a common range. The purpose is to facilitate graphical operations performed during the identification process and enable COG defuzzification. All calculations are performed on scaled values as the model itself is defined, during the identification phase, from scaled values. All scaled data is available in the S_IO sheet;
- their normalised weightings in field W_norm (blue) rank all MFs. They combine correlation coefficient and density of information, generally as a product. They rank rules according to their ability to explain the dependent variable OUTPUT. The maximum value is 1 and corresponds to the most important/reliable rule;
- left corner of triangular membership function in field IN_a (yellow);
- apex of triangular membership function in field IN_b (yellow);
- right corner of triangular membership function in field IN_c (yellow).
- consequent membership functions are similarly defined in OUT_a, OUT_b and OUT_c (orange);

Values calculated by the model are written in the column OUTPUT of the IO worksheet as shown in Table A2.1.



MODEL PARAMETERS
(XL_FIS_040625.xls)

OUTPUT	Membership Function	OUT_a	OUT_b	OUT_c
	MF1	116.5450	118.7895	120.2850
Scale factor	MF2	118.3750	124.4989	129.5650
185	MF3	123.7850	131.4945	140.7050
	MF4	131.3400	142.3654	151.8400
	MF5	142.4300	148.8338	162.9000
	MF6	153.5800	162.8552	170.4700
	MF7	164.5600	171.3261	179.6850
	MF8	173.7750	188.8947	201.7900
	MF9	190.4650	199.1702	216.5500

Variable 1	Membership Function	W_norm	IN_a	IN_b	IN_c
	MF1	0.9889	138.0900	145.1579	174.7100
Scale factor	MF2	1.0000	140.9200	156.1897	198.6000
0.068	MF3	0.8088	142.3300	173.7814	208.9800
	MF4	0.9582	152.0900	193.9773	215.9800
	MF5	0.7648	157.0500	198.1947	221.2800
	MF6	0.3719	158.4000	204.2819	234.1100
	MF7	0.4314	160.4100	207.7380	234.2900
	MF8	0.4831	168.4200	216.2968	237.8700
	MF9	0.5767	194.3000	222.0085	238.2400

Variable 2	Membership Function	W_norm	IN_a	IN_b	IN_c
	MF1	0.6024	163.8800	170.7353	210.5100
Scale factor	MF2	0.6710	157.1900	176.6559	224.6600
0.073	MF3	0.5573	149.4100	188.1037	224.6600
	MF4	0.5693	137.8200	195.7557	220.4600
	MF5	0.4536	134.2000	190.5938	219.5300
	MF6	0.2721	126.4900	176.7715	207.6100
	MF7	0.3315	124.4900	169.5530	202.3300
	MF8	0.4205	126.8100	157.7153	189.9300
	MF9	0.5385	135.6100	152.4619	173.2000

Variable 3
Scale factor

COMMENTS

Fuzzy rule-based models implemented in this spreadsheet predict the dependent variable OUTPUT from independent variables V1, ..., Vn.
Each independent, or INPUT, variable V1,..., Vn occupies the sheet of the same name.
Model parameters are entered on the MODEL sheet (this sheet)
Raw values of V1,..., Vn are pasted in columns of the same name in the IO sheet.
OUTPUT values are automatically written in the OUTPUT column of the IO sheet.

Principles of fuzzy rule-based modelling used in this spreadsheet are detailed in the MATLAB pdf manual available at
http://www.mathworks.com/access/helpdesk/help/pdf_doc/fuzzy/fuzzy.pdf
The flow chart below outlines the 4 steps involved in computing the output of a two variable model.

This spreadsheet only implements IT ...THEN rules in their simplest form (that is without without fuzzy operations AND, OR, NOT).
Membership functions (all triangular) are defined by the coordinates a, b, c of the apices the corresponding triangles.
Membership functions coordinates OUT_a, OUT_b, OUT_c and IN_a, IN_b, IN_c respectively correspond to OUTPUT and INPUT variables.
Parameters defining a model, entered to the left of the black column, are defined during the identification process from a training dataset.

A model can accommodate a maximum of:
19 membership functions per variable
252 variables
65 500 simultaneoous inputs

Every input occupies the same row on all V shhets.
Calculations are performed along rows and results are written in the OUTPUT column of the IO sheet

V1 V2 MODEL IO S_IO

Figure A1.3: The MODEL sheet is one of two user interfaces of a XLFIS. On the left panel, 3 fundamental classes of parameters are summarised: input membership functions coordinates (highlighted yellow), output membership functions coordinates (highlighted orange), rule weightings (highlighted blue), scale factors (highlighted pink) used during defuzzification to make all membership functions commensurate.

The following sections define the functionality of the various components of XLFIS by reference to the first row.

All rows in IO, S_IO and V sheets perform the same calculations on successive values of the respective variables. Rows in the IO, S_IO and V sheets are consequently copied to match the size of the batch of data processed.

In all following sections, unless stated otherwise, formulas refer to the first calculating row in the corresponding worksheets.

A1.2 MODEL worksheet

This worksheet, displayed in Figure A1.3 comprises two panes:

- the WORK PARAMETERS pane left of the black column contains all the model parameters defined by the modeler;
- the COMMENTS pane, right of the black column, is the documentation section where the user can enter additional information.

All calculations are based on the content WORK PARAMETERS. Grey areas show where each section can be further extended by copying and pasting cells. Adding one row in a grey area corresponds to adding one membership function to the description of the corresponding variable. The number of fuzzy patch Functional Blocks (FB) in V sheets matches the number of records in the corresponding Variable area of the WORK PARAMETERS pane.

A 1.3 IO and S_IO worksheets

All formulas in this section refer to the first row of values in the corresponding worksheets.

Table A1.1: Example of an IO worksheet of XLFIS containing two input (V1 and V2) and one output (OUTPUT) variable.

OUTPUT	V1	V2
0.83	2807	1851
0.86	2915	1810
0.91	3024	1811
0.96	3126	1849
1.01	3216	1877
1.01	3222	1977
1.01	3226	2011
1.01	3235	2060
1.00	3221	2110

Table A1.2: Example of an S_IO sheet of XLFIS containing the scaled input and out variables.

OUTPUT	V1	V2
153.90	190.88	135.12
158.78	198.22	132.13
167.78	205.63	132.20
178.06	212.57	134.98
186.36	218.69	137.02
186.15	219.10	144.32
186.15	219.37	146.80
186.08	219.98	150.38
184.11	219.03	154.03

The S_IO sheet displays the content of the IO sheet multiplied by the corresponding scaling factors read from the pink areas of the MODEL sheet.
The formula in the OUTPUT column performs the defuzzification of the calculations carried out by the corresponding rows in all V sheets. In this example there are only two input variables and therefore only 2 V worksheets. These 2 worksheets named V1 and V2 are visible at the bottom of Figure A1.3.

A1.3.1 <u>OUTPUT in IO worksheet</u>

A2 = (V1!B2+V2!B2)/(V1!C2+V2!C2)/MODEL!$A$23
The scaled coordinate of the centroid, read from OUTPUT in S_IO, is divided by the scale factor of the consequent or dependent variable in pink on the MODEL sheet.
The result of this operation, that is the sum of moments divided by corresponding areas, is the x coordinate of the centroid of the aggregation of all rescaled MFs. These rescaled MFs are generated by inference rules according to the diagram pasted on the MODEL sheet.

A1.3.2 <u>Variable V1 and V2 in the IO worksheet</u>

Table A1.1 displays initial values of the 3 variables Output, Variable 1and Variable 2 entered in the IO sheet. In Table A1.2 the same values have been rescaled by multiplying them by the scaling factor of Variable1 and Variable 2 read from the corresponding bright cells of the MODEL sheet. All computations in V calculation sheets are performed on scaled values to enable the COG defuzzification visualised in the flowchart in the right panel of Figure A2.3.

A1.3.3 OUTPUT in S_IO worksheet

A2 =(V1!B2+V2!B2)/(V1!C2+V2!C2)

V1!B2 and V2!B2 are respectively the sum of moments of variables V1 and V2. They are calculated by sheets V1 and V2 from scaled values of Variable 1 and Variable 2 in S_IO.

V1!C2 and V2!C2 are summed areas of scaled membership functions of V1 and V2. This is the centroid calculated by the V worksheets. All calculations in V worksheets are performed on scaled values. These scaling factors are used to display in ArcView all variables with a constant range of 100.

A1.3.4 Variable 1 and Variable 2 in S_IO worksheet

B2 =IO!B2*MODEL!$A$43 and C2 =IO!C2*MODEL!$A$63

The above values are raw data read from the IO sheet and multiplied by the corresponding scaling factors in bright pink on the MODEL sheet. These are the initial values read by all V worksheets.

A1.4 V worksheets

There is one V worksheet per variable. Table A1.3 displays the top section of a V worksheet. V worksheets calculate the membership of each input value in each membership function of the corresponding variable.

All formulas in this section refer to the first row in the successive screenshots displayed.

V worksheets contain 3 Functional Blocks (FB):

- Row: all calculations within one row refer to the same row in the input column.
- Fuzzy patch FB: between two grey columns all information refers to the same fuzzy patch.
- Input/output FB: the first 3 columns of a V worksheet display in the INPUT column the rescaled data input in the model. S_MOMENT and S_AREA are the output of the V worksheet to S_IO sheet.

Only V1 is documented here. Corresponding formulas in V2 and in successive worksheets, when they exist, are similar.

Table A1.3: The row, the fuzzy patch and the input/output are three functional blocks (FB) of the V worksheets. A fuzzy patch FB extends from one grey column on the left to the next to the AREA column before the next grey column to the right. The corresponding membership function or fuzzy patch is displayed in the corresponding grey column. The input/output FB corresponds to the first 3 white columns.

INPUT	S_MOMENT	S_AREA	MF 1	W_norm	IN_a	IN_b	IN_c	MF1	INPUT in MF	DOF_RULE1	OUT_a	OUT_b	OUT_c	MOMENT	AREA	MF 2	W_norm	IN_a
190.8760	4174.2189	27.5652	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
198.2200	4488.4171	28.4970	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
205.6320	4177.9778	25.0276	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
212.5680	3666.1653	20.6133	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
218.6880	3195.8728	17.0570	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
219.0960	3157.6410	16.8084	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
219.3680	3132.1532	16.6426	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
219.9800	3074.8056	16.2696	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200
219.0280	3164.0130	16.8498	1	0.9889	138.0900	145.1579	174.7100	FALSE	0	0.0000	116.5450	118.7895	120.2850	0.0000	0.0000	2	1.0000	140.9200

A1.4.1 INPUT field

A2 = S_IO!B2

The mixed reference above reads input from the S_IO sheet.

A2.4.2 S_MOMENT field

B2 = O2+AB2+AO2+BB2+BO2+CB2+CO2+DB2+DO2

This is the sum of moments of all MFs the INPUT 190.8760 belongs to.

A1.4.3 S_AREA field

C2 = P2+AC2+AP2+BC2+BP2+CC2+CP2+DC2+DP2

This is sum of areas of all MFs the INPUT 190.8760 belongs to.

A1.4.4 MFx field

1=< x =< maximum number of memberships per variable

These information fields do not play any role in calculations. They are reminders of the membership function index the fields to the right of the grey column refer to.

A1.4.5 W_norm field

E2 = MODEL!$C$41

The absolute reference above reads the normalised weighting of the corresponding membership function, in a blue column of the MODEL sheet.

A1.4.6 IN_a, IN_b, IN_c

F2 = MODEL!$D$41 G2=MODEL!$E$41 H2=MODEL!$F$41

Absolute references above read membership function coordinates a, b, c in yellow columns on the MODEL sheet.

A1.4.7 MF1

I2 = AND($A2>F2,$A2<H2)

This formula returns TRUE if the input data belongs to the membership function defined by IN_a, IN_b, IN_c and FALSE if it does not.

A1.4.8 INPUT in MF

J2 = IF(I2,1,0)

This formula translates the previous text information into either 1 or 0. This value allows eliminating the contribution of this membership function to S_MOMENT and S_AREA if the input data does not belong to that membership function.

TRUE $\rightarrow$ 1

FALSE $\rightarrow$ 0

A2.4.9 DOF_RULE1

K2 = IF($A2<=G2,E2*J2*($A2-F2)/(G2-F2),E2*J2*($A2-H2)/(G2-H2))

This formula calculates the Degree Of Fulfillment (DOF) of the rule whose antecedent corresponds to the membership function referred to in 2.

If the value in the INPUT column ($A2) is less than the x coordinate (G2) of the apex of the corresponding triangular function, the equation to be used is

E2*J2*($A2-F2)/(G2-F2) corresponding to left side triangular membership function. If the condition $A2<=G2 is not met, the equation of the right side of the membership function, that is E2*J2*($A2-H2)/(G2-H2), must be used.
This number is always between 0 and 1.

A1.4.10 OUT_a, OUT_b, OUT_c

L2 = MODEL!$C$21 M2=MODEL!$D$21 N2=MODEL!$E$21
The above absolute references read from the MODEL sheet the coordinates of the corresponding consequent membership function on the MODEL sheet.

A1.4.11 MOMENT

O2 = (M2^3*K2/(M2-L2)/3)+(M2^2*K2*L2/(L2-M2)/2)-(L2^3*K2/(M2-L2)/3)-(L2^2*K2*L2/(L2-M2)/2)+(N2^3*K2/(M2-N2)/3)+(N2^2*K2*N2/(N2-M2)/2)-(M2^3*K2/(M2-N2)/3)-(M2^2*K2*N2/(N2-M2)/2)
This formula calculates the moment of the rescaled consequent membership function. The MF defined by coordinates L2, M2, N2 in 8 is multiplied by the DOF coefficient K2 calculated in 7.
Figure A1.4 helps understanding the defuzzification process. By definition, the X coordinate of the centroid is the moment divided by the area:

$$X = \frac{\int x.f(x)dx}{\int f(x)dx} \qquad \text{Equation A1.1}$$

The above formula is applied to the 2 right angle triangles that make up the MF in Figure A1.4:

$$X = \left(\int x.(a.x+b)dx + \int x.(c.x+d)dx\right) / \left(\int (a.x+b)dx + \int (c.x+d)dx\right) \qquad \text{Equation A1.2}$$

$$= A/B$$

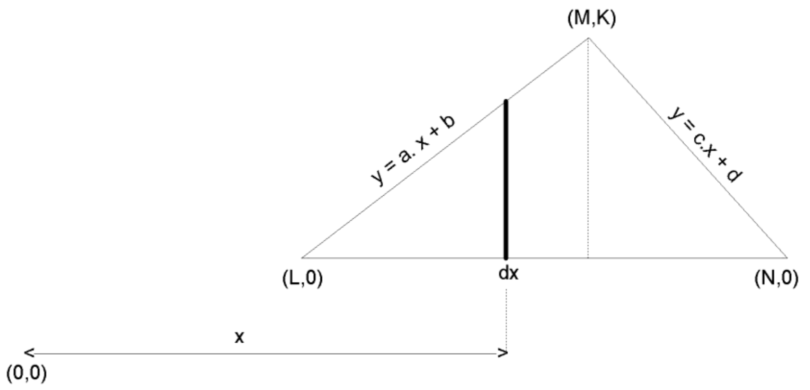


Figure A1.4: Triangular membership function defined by a piecewise linear function comprising 2 equations. Equation y = a.x+b describes the left hand side of this membership function between points (L,0) and points (M,K). Equation y=c.x+d describes the right hand side between points (M,K) and (N,0). These equations allow to readily calculate the membership of any x value in the fuzzy class represented by this membership function.

The triangular MF is described by two linear functions which lead to the calculation of two integrals.

$\int x.(a.x+b)dx$ = a.x^3/3 + b.x^2/2 Equation group A1.1

$\int x.(c.x+d)dx$ = c.x^3/3 + d.x^2/2

From Fig.A1.2 we express a, b, c and d in function of the coordinates L, K, M, N of the MF and the DOF:

a = K/(M-L) b = K.L/(L-M) c = K/(M-N) d = K.N/(N-M)

Replacing a, b, c and d and evaluating the first integral between L and M and the second between M and N we obtain:

A = (M^3*K/(M-L)/3)+(M^2*K*L/(L-M)/2)-(L^3*K/(M-L)/3)-(L^2*K*L/(L-M)/2)+(N^3*K/(M-N)/3)+(N^2*K*N/(N-M)/2)-(M^3*K/(M-N)/3)-(M^2*K*N/(N-M)/2)

The denominator B is the area of the triangle.

B = (N – L).K/2

A2.3.12 <u>AREA</u>

P2 = K2*(N2-L2)/2

Appendix 2 Anindilyakwa Aquaculture GIS

Sections A 2.1, A 2.2 and A 2.3 respectively cover the 3 following aspects of AAGIS: suitability criteria, fuzzy mapping strategies and data source. Further details can be obtained from the report (Puig, 2001; Puig, 2003) prepared for the NT Government.

A2.1 – Prawn farming suitability criteria

A2.1.1 Slope

This layer is derived from the 1:250,000 vector map of land systems of Arnhem Land. Suitability is:

High → slope<2%

Low → slope between 2% and 5%

Unsuitable → slope more than 5%

A2.1.2 Access by air and land

This layer is derived from IGDS data at 1:50,000. Suitability is:

Very Low → more than 5km from track

Low → between 500m and 5km from track

Medium → more than 500m from a track

Very High and High do not occur as they respectively correspond to proximity to airstrips and major road which only occur in unsuitable areas mainly because of the proximity of infrastructure and mining activity.

A2.1.3 Access by sea

This layer is derived from the IGDS coastline and anecdotal evidence. Suitability is from the lowest to the highest

Low → more than 2.5km from the coast

Medium to Low → no shelter

Medium → shelter of uncertain value

Medium to High → generally good shelter with some limitation

High → good shelter and well surveyed

This theme describes the suitability for aquaculture if transportation of material and equipment to establish a prawn farm relies on barges.

A2.1.4 Proximity of infrastructure

This layer is derived from IGDS data. Suitability is as follows:

High → locations 3 to 5km from infrastructure (community, mine site)

Low → more than 5km from infrastructure.

While proximity to infrastructure offers advantages, the risk of pollution and contamination results in all locations within a 3km radius of human settlements and activities being unsuitable for aquaculture.

A2.1.5 Risk of flooding

This layer is derived from the 1:250,000 vector map of land systems of Arnhem Land. Suitability is decoded as High, Medium or Low:

High → no flooding

Medium → flooding no more than 1 day a year

Low → flooding between 1 day and three weeks a year

Unsuitable → flooding events occur more than three weeks a year

A2.1.6 Proximity of creeks

This layer is derived from IGDS data. A source of surface water (even if it requires building a small dam) is advantageous to prawn farming. Suitability is:

High → between 10m and 2km from a creek

Low → more than 2km from a creek

Unsuitable → less than 10m from creek line

Creek beds however (10m on either side of creek lines) are unsuitable and interfering with natural drainage patterns is to be avoided as much as possible.

A2.1.7 Pond size/contiguity

This layer is derived from IGDS data. Contiguous suitable areas are favoured by developers who tend to focus on areas covering no less than 100 ha. A square block of 1 km by side is used as the minimum desirable for a prawn farm. This site is inscribed in a circle with diameter square root of 2 km. Any point further than ½ x √2 = 0.707 km from unsuitable locations is the centre of a suitable square block of no less than 100 ha. Finding such locations is therefore achieved by buffering all unsuitable locations by 707 m and retaining all lands beyond this buffer as land offering good contiguity of suitable land. The latter has the highest suitability, the rest (outside unsuitable land) the lowest.

A2.1.8 Distance to coast

This layer is derived from IGDS data. Suitability is:

High → distance from the coast no greater

Low → between 5km and 10km from the coast

Unsuitable → more than 10km from the coast

A2.1.9 Soil depth

This layer is derived from 1:250,000 vector map of land systems of Arnhem Land. Suitability is:

High → soil depth in excess of 1m

Medium → Soil depths between 30cm and 100cm

Low → Soils shallower than 30cm are unsuitable.

A2.1.10 Ground water availability

This layer is derived from the ArcView shapefile “Groundwater.shp”, part of the Water Resources of East Arnhem dataset, groundwater suitability is rated High (350 l/s), Medium (homeland supply), Low (small homeland supply).

A2.1.11 Unsuitable for aquaculture

Any of the land properties below, in isolation, is sufficient to make the corresponding location unsuitable for aquaculture:

- less than one km from the edge of a sacred site
- less than 1km from an outstation;
- less than 3km from community or mining infrastructure;
- presence of permanent surface water (lake, swamp);
- regular flooding (billabong);
- mangrove;
- slope > 5% ; and
- soil shallower than 30 cm
- unsuitability (prone to erosion … etc) for land development listing in the Report on Land Systems of Arnhem Land.

A2.2 – Some strategies to generate fuzzy maps

A2.2.1 Commensurate maps

Criteria, regardless of the units they are measured in, must be described using the same linguistic terms for identical portions of their range.

Example: If the slope varies between 0 and 15^o, a slope of 14^o has a normalised value of 14/15= 0.93 and is described as “Very high”. If an acceptable distance to the high water mark varies between 0 and 2km, a distance of 1.9km has a normalised value of 1.9/2=0.95 and is described as “Very high” too.

This is achieved by:

– normalising all criteria: for a given criterion all values are divided by the maximum value, and consequently all normalised values are between 0 and 1;

– by referring to an established scale of linguistic terms such as: Very Low, Low, Medium, High, Very High.

These linguistic terms are then translated, for the purpose of GIS calculations, into fuzzy numbers which reflect the absence of crisp boundaries associated with linguistic terms.

A2.2.2 Decision rules

The decision rule dictates how the commensurate criterion maps and their respective weightings are "fuzzily" aggregated. This process could be prohibitively time consuming. Fortunately ArcView with Spatial Analyst is a raster GIS processing environment well suited to this operation tackled as a succession of raster overlays. An example of this process is described below for criterion map C1:

- criterion map C1 is transformed into four maps (C1M1 to C1M4).
    - in the first map, C1M1, each cell is assigned the first of the four numbers making up the "trapezoidal fuzzy number" corresponding to the linguistic term this cell contains.
    - in the second map C1M2 each cell is assigned the second of the four numbers making up the "trapezoidal fuzzy number" corresponding to the linguistic term this cell contains.
    - the same process is repeated to create C1M3 and C1M4.
- weighting W1 corresponding to C1 is "fuzzified" using a suitable established scale (the scale corresponding to the same number of linguistic terms). W1 is now associated as well to a "trapezoidal fuzzy number".
    - the first of the four numbers of W1 "trapezoidal fuzzy number" is used to multiply all cell contents in C1M1 to produce C1M1*W1_1.
    - the second of the four numbers of W1 "trapezoidal fuzzy number" is used to multiply all cell contents in C1M2 to produce C1M2*W1_2.
    - the same process is repeated to create C1M3*W1_3 and C1M4*W1_4.
- all CnM1*Wn_1 are added using the raster overlay function of ArcView Spatial Analyst. The same process is repeated for all the CnM2*Wn_2, CnM3*Wn_3, CnM4*Wn_4.
- all maps can be added again. High cell values correspond to the more suitable sites.

A2.3 – AAGIS source data

A2.3.1 Unclassified IGDS data

Provided by the Defence Imagery and Geospatial Organisation in Bendigo this dataset comprises 4 sheets (6169, 6170, 6269, 6270). This 1:50,000 coverage of Groote Eylandt is the most detailed and reliable dataset used in this project. Digital information, in vector format, covers topographical (e.g. elevations) as well environmental features (e.g. type of vegetation). Under an existing agreement this data was made available to the Northern Territory Government.

This dataset is the reference for topographical and locational accuracy in this report.

A2.3.2 Land Systems of Arnhem Land

All information comes from Technical Report Number R97/1 (Lynch & Wilson, 2000).

This report and the digital map of land systems represent the most comprehensive dataset used in this project. Although at a scale of 1:250,000 (therefore a lot less detailed than the previous dataset) it encapsulates the field observations and expertise of two experienced scientists.

This dataset is the reference for most land properties in this project.

A2.3.3 Water Resources of East Arnhem Land

Report Number 02/1999D and digital maps (Zaar et al., 1999) are the source of all information on groundwater availability used in this project.

A2.3.4 Aboriginal Areas Protection Authority data

The information provided to the Channel Island Aquaculture Centre represents Authority records as at 11th June 2002, and should in no way be seen as a definitive statement about sacred sites in the area.

Digital maps included were used to exclude sites which, for cultural reasons, are unsuitable for land use including aquaculture. The status of some sites may change and the Anindilyakwa Council therefore remains the ultimate authority on this matter.

A2.3.5 AUSLIG Topo_250k Series 2 vector topographic data for GIS

This data was acquired before IGDS data became available. The latter was preferable in terms of resolution, therefore the former was not used in this project.

A2.3.6 SLAPS

These high resolution CAD drawings were used to extract the actual footprint of the communities.

A2.3.7 Personal notes of Captain J. Abbey of PERKINS SHIPPING Pty Ltd

Tom Pinder, PERKINS Operations Manager in Darwin, when approached to provide information on the bathymetry of Groote Eylandt waters, kindly offered to share with the Aquaculture Centre, the experience of one of their captains. Notes prepared by Captain John Abbey were invaluable in assessing year round access by sea to the coastline. This is the only reliable source of information on weather patterns and shelter around this coastline. Data from BOM is too coarse to be useful in this project.

A2.3.8 Obliques aerial photographs

A collection of 117 oblique aerial photographs spread around the coastline of Groote Eylandt and Bickerton Island were taken in late 1999 from a light plane flying at low altitude. Provided by the Natural Resources Division of the NT Government, these photos offer a valuable visual impression of the coastline (see Plates 1, 2, 3).

A2.3.9 Marine Chart

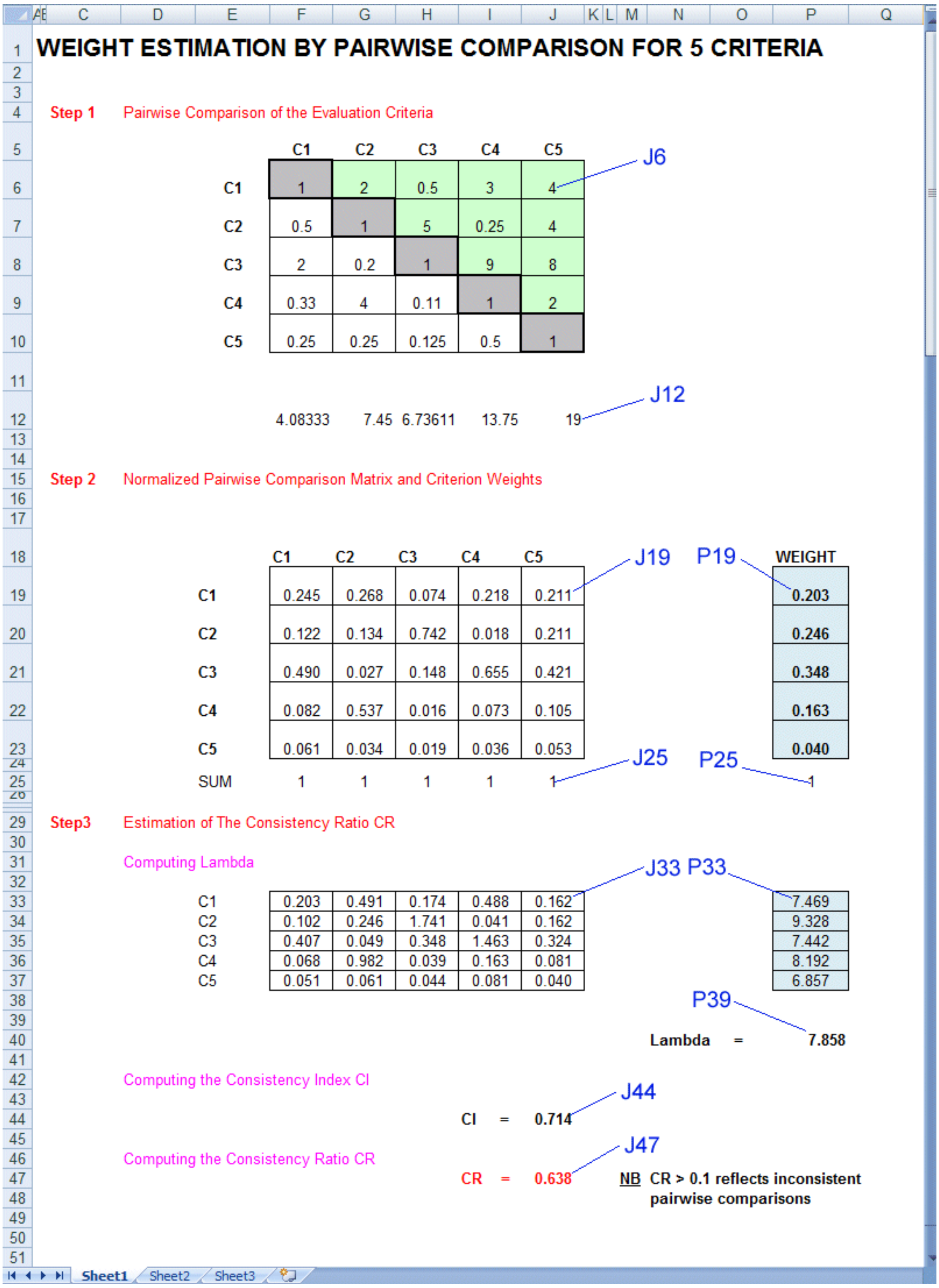
The Vanderlin 1:300,000 marine chart has the lowest scale of whole dataset. The bathymetric isolines of this map, however, were required to calibrate the sea reflectance in the satellite image classification. This map is the only consistent source of bathymetric data available at the time of this study for that area.

A2.4 – Calculation of AHP weightings

The fundamentals of the AHP method (Saaty, 2001) rely on mathematics which are beyond the scope of this thesis. Central to the AHP are the concepts of eigenvectors and eigenvalues "…regarded as the most difficult topic in matrix algebra" (Davis, 1986: p.126) particularly when it comes to understand the actual meaning of the results. What follows therefore provides only an account of the formulas used to implement the AHP and makes no attempt to justify them as the mathematical theory behind are clearly beyond the scope of this thesis.

Table A2.1: This table implements the AHP principles behind the calculation spreadsheet displayed Figure 2.1. Calculations performed by that spreadsheet, for all cells identified by blue labels, are displayed below. Calculations for nearby cells in the same block can easily be derived. Some results in the Value column slightly differ as displayed values are all rounded off to the 3rd decimal unlike actual values used in calculations.

Cell	Formula	Value
J6	C1 is of moderate to strong importance compared with C5	4
J12	= SUM(J6:J10) = 4 + 4 + 8 + 2 + 1	19
J19	= J6/J12 = 4/19	0.211
P19	= SUM(F19:J19)/5 = (0.245 + 0.268 + 0.074 + 0.218 + 0.211)/5	0.203
J25	= SUM(J19:J23) = 0.211 + 0.211 + 0.421 + 0.105 + 0.053	1
P25	= SUM(P19:P24) = 0.203 + 0.246 + 0.348 + 0.163 + 0.040	1
J33	= J6*P23 = 4 * 0.040	0.162
P33	= SUM(F33:J33)/P19 = (0.203 + 0.491 + 0.174 + 0.488 + 0.162)/0.203	7.469
P40	= SUM(P33:P37)/5 = (7.469 + 9.328 + 7.442 + 8.192 + 6.857)/ 5	7.858
J44	= (P40-5)/(5-1) = (7.858 -5)/4	0.714
J47	= J44/1.12 = 0.714/1.12	0.638



WEIGHT ESTIMATION BY PAIRWISE COMPARISON FOR 5 CRITERIA

Step 1 Pairwise Comparison of the Evaluation Criteria

	C1	C2	C3	C4	C5
C1	1	2	0.5	3	4
C2	0.5	1	5	0.25	4
C3	2	0.2	1	9	8
C4	0.33	4	0.11	1	2
C5	0.25	0.25	0.125	0.5	1
	4.08333	7.45	6.73611	13.75	19

J6 J12

Step 2 Normalized Pairwise Comparison Matrix and Criterion Weights

	C1	C2	C3	C4	C5	WEIGHT
C1	0.245	0.268	0.074	0.218	0.211	0.203
C2	0.122	0.134	0.742	0.018	0.211	0.246
C3	0.490	0.027	0.148	0.655	0.421	0.348
C4	0.082	0.537	0.016	0.073	0.105	0.163
C5	0.061	0.034	0.019	0.036	0.053	0.040
SUM	1	1	1	1	1	1

J19 P19 J25 P25

Step3 Estimation of The Consistency Ratio CR

Computing Lambda

C1	0.203	0.491	0.174	0.488	0.162	7.469
C2	0.102	0.246	1.741	0.041	0.162	9.328
C3	0.407	0.049	0.348	1.463	0.324	7.442
C4	0.068	0.982	0.039	0.163	0.081	8.192
C5	0.051	0.061	0.044	0.081	0.040	6.857

J33 P33 P39

Lambda = 7.858

Computing the Consistency Index CI

CI = 0.714 J44

Computing the Consistency Ratio CR

CR = 0.638 J47

NB CR > 0.1 reflects inconsistent pairwise comparisons

Sheet1 Sheet2 Sheet3

Figure A2.1: The spreadsheet above was used to perform the calculations described in section 3.2.3. The top table records the pairwise comparisons of evaluation criteria C1 to C5. The middle table automatically calculates, from the values calculated in the top table, the normalized criteria weightings displayed in the top blue column. The bottom table automatically calculates the values used to compute λ. Finally the consistency ratio CR is automatically calculated to reflect the consistency of the pairwise comparisons, which in this instance are clearly unsatisfactory.

Appendix 3 Data driven fuzzy-rule based modelling

Section A.3.1 provides the sample Fisher's iris dataset used in Chapter 4 in its original format. Section A.3.2 provides additional clustering results of Nakanishi *et al.*'s (1993) data by Fuzme (Minasny & McBratney, 2002). Section A 3.3 contains some additional information on Scilab. Section A 3.4 contains the original Elephant seals dataset provided by Bradshaw *et al.* (2004), not provided in Chapter 4 as they play a minor role in the discussion.

A3.1 Fisher's iris dataset

The version of the dataset used in this thesis was downloaded from the website below
(http://www.csse.monash.edu.au/~lloyd/tildeFP/‖/200312/20041124/)
This dataset can be obtained from many other websites. Fisher's dataset is often used to test the performance of classification algorithms developed for machine learning and artificial intelligence.
This dataset was used by Ronald Fisher (Upton & Cook, 2008) one of the most influential statisticians of the twentieth century to teach classification by discriminant analysis. The data, however, was originally collected by Edgar Anderson, a botanist who briefly worked in 1929 with Fisher who, besides statistics, had a keen interest in genetics.

Table A3.1: Fisher's iris dataset (1 of 3).

ID	Sepal_length	Sepal_width	Petal_length	Petal_width	Species_name	Species_code
1	5.1	3.5	1.4	0.2	Iris-setosa	1
2	4.9	3.0	1.4	0.2	Iris-setosa	1
3	4.7	3.2	1.3	0.2	Iris-setosa	1
4	4.6	3.1	1.5	0.2	Iris-setosa	1
5	5.0	3.6	1.4	0.2	Iris-setosa	1
6	5.4	3.9	1.7	0.4	Iris-setosa	1
7	4.6	3.4	1.4	0.3	Iris-setosa	1
8	5.0	3.4	1.5	0.2	Iris-setosa	1
9	4.4	2.9	1.4	0.2	Iris-setosa	1
10	4.9	3.1	1.5	0.1	Iris-setosa	1
11	5.4	3.7	1.5	0.2	Iris-setosa	1
12	4.8	3.4	1.6	0.2	Iris-setosa	1
13	4.8	3.0	1.4	0.1	Iris-setosa	1
14	4.3	3.0	1.1	0.1	Iris-setosa	1
15	5.8	4.0	1.2	0.2	Iris-setosa	1
16	5.7	4.4	1.5	0.4	Iris-setosa	1
17	5.4	3.9	1.3	0.4	Iris-setosa	1
18	5.1	3.5	1.4	0.3	Iris-setosa	1
19	5.7	3.8	1.7	0.3	Iris-setosa	1
20	5.1	3.8	1.5	0.3	Iris-setosa	1
21	5.4	3.4	1.7	0.2	Iris-setosa	1
22	5.1	3.7	1.5	0.4	Iris-setosa	1
23	4.6	3.6	1.0	0.2	Iris-setosa	1
24	5.1	3.3	1.7	0.5	Iris-setosa	1
25	4.8	3.4	1.9	0.2	Iris-setosa	1
26	5.0	3.0	1.6	0.2	Iris-setosa	1
27	5.0	3.4	1.6	0.4	Iris-setosa	1
28	5.2	3.5	1.5	0.2	Iris-setosa	1
29	5.2	3.4	1.4	0.2	Iris-setosa	1
30	4.7	3.2	1.6	0.2	Iris-setosa	1
31	4.8	3.1	1.6	0.2	Iris-setosa	1
32	5.4	3.4	1.5	0.4	Iris-setosa	1
33	5.2	4.1	1.5	0.1	Iris-setosa	1
34	5.5	4.2	1.4	0.2	Iris-setosa	1
35	4.9	3.1	1.5	0.1	Iris-setosa	1
36	5.0	3.2	1.2	0.2	Iris-setosa	1
37	5.5	3.5	1.3	0.2	Iris-setosa	1
38	4.9	3.1	1.5	0.1	Iris-setosa	1
39	4.4	3.0	1.3	0.2	Iris-setosa	1
40	5.1	3.4	1.5	0.2	Iris-setosa	1
41	5.0	3.5	1.3	0.3	Iris-setosa	1
42	4.5	2.3	1.3	0.3	Iris-setosa	1
43	4.4	3.2	1.3	0.2	Iris-setosa	1
44	5.0	3.5	1.6	0.6	Iris-setosa	1
45	5.1	3.8	1.9	0.4	Iris-setosa	1
46	4.8	3.0	1.4	0.3	Iris-setosa	1
47	5.1	3.8	1.6	0.2	Iris-setosa	1
48	4.6	3.2	1.4	0.2	Iris-setosa	1
49	5.3	3.7	1.5	0.2	Iris-setosa	1
50	5.0	3.3	1.4	0.2	Iris-setosa	1

Table A3.2: Fisher's iris dataset (2 of 3).

51	7.0	3.2	4.7	1.4	Iris-versicolor	2
52	6.4	3.2	4.5	1.5	Iris-versicolor	2
53	6.9	3.1	4.9	1.5	Iris-versicolor	2
54	5.5	2.3	4.0	1.3	Iris-versicolor	2
55	6.5	2.8	4.6	1.5	Iris-versicolor	2
56	5.7	2.8	4.5	1.3	Iris-versicolor	2
57	6.3	3.3	4.7	1.6	Iris-versicolor	2
58	4.9	2.4	3.3	1.0	Iris-versicolor	2
59	6.6	2.9	4.6	1.3	Iris-versicolor	2
60	5.2	2.7	3.9	1.4	Iris-versicolor	2
61	5.0	2.0	3.5	1.0	Iris-versicolor	2
62	5.9	3.0	4.2	1.5	Iris-versicolor	2
63	6.0	2.2	4.0	1.0	Iris-versicolor	2
64	6.1	2.9	4.7	1.4	Iris-versicolor	2
65	5.6	2.9	3.6	1.3	Iris-versicolor	2
66	6.7	3.1	4.4	1.4	Iris-versicolor	2
67	5.6	3.0	4.5	1.5	Iris-versicolor	2
68	5.8	2.7	4.1	1.0	Iris-versicolor	2
69	6.2	2.2	4.5	1.5	Iris-versicolor	2
70	5.6	2.5	3.9	1.1	Iris-versicolor	2
71	5.9	3.2	4.8	1.8	Iris-versicolor	2
72	6.1	2.8	4.0	1.3	Iris-versicolor	2
73	6.3	2.5	4.9	1.5	Iris-versicolor	2
74	6.1	2.8	4.7	1.2	Iris-versicolor	2
75	6.4	2.9	4.3	1.3	Iris-versicolor	2
76	6.6	3.0	4.4	1.4	Iris-versicolor	2
77	6.8	2.8	4.8	1.4	Iris-versicolor	2
78	6.7	3.0	5.0	1.7	Iris-versicolor	2
79	6.0	2.9	4.5	1.5	Iris-versicolor	2
80	5.7	2.6	3.5	1.0	Iris-versicolor	2
81	5.5	2.4	3.8	1.1	Iris-versicolor	2
82	5.5	2.4	3.7	1.0	Iris-versicolor	2
83	5.8	2.7	3.9	1.2	Iris-versicolor	2
84	6.0	2.7	5.1	1.6	Iris-versicolor	2
85	5.4	3.0	4.5	1.5	Iris-versicolor	2
86	6.0	3.4	4.5	1.6	Iris-versicolor	2
87	6.7	3.1	4.7	1.5	Iris-versicolor	2
88	6.3	2.3	4.4	1.3	Iris-versicolor	2
89	5.6	3.0	4.1	1.3	Iris-versicolor	2
90	5.5	2.5	4.0	1.3	Iris-versicolor	2
91	5.5	2.6	4.4	1.2	Iris-versicolor	2
92	6.1	3.0	4.6	1.4	Iris-versicolor	2
93	5.8	2.6	4.0	1.2	Iris-versicolor	2
94	5.0	2.3	3.3	1.0	Iris-versicolor	2
95	5.6	2.7	4.2	1.3	Iris-versicolor	2
96	5.7	3.0	4.2	1.2	Iris-versicolor	2
97	5.7	2.9	4.2	1.3	Iris-versicolor	2
98	6.2	2.9	4.3	1.3	Iris-versicolor	2
99	5.1	2.5	3.0	1.1	Iris-versicolor	2
100	5.7	2.8	4.1	1.3	Iris-versicolor	2

Table A3.3: Fisher's iris dataset (3 of 3).

101	6.3	3.3	6.0	2.5	Iris-virginica	3
102	5.8	2.7	5.1	1.9	Iris-virginica	3
103	7.1	3.0	5.9	2.1	Iris-virginica	3
104	6.3	2.9	5.6	1.8	Iris-virginica	3
105	6.5	3.0	5.8	2.2	Iris-virginica	3
106	7.6	3.0	6.6	2.1	Iris-virginica	3
107	4.9	2.5	4.5	1.7	Iris-virginica	3
108	7.3	2.9	6.3	1.8	Iris-virginica	3
109	6.7	2.5	5.8	1.8	Iris-virginica	3
110	7.2	3.6	6.1	2.5	Iris-virginica	3
111	6.5	3.2	5.1	2.0	Iris-virginica	3
112	6.4	2.7	5.3	1.9	Iris-virginica	3
113	6.8	3.0	5.5	2.1	Iris-virginica	3
114	5.7	2.5	5.0	2.0	Iris-virginica	3
115	5.8	2.8	5.1	2.4	Iris-virginica	3
116	6.4	3.2	5.3	2.3	Iris-virginica	3
117	6.5	3.0	5.5	1.8	Iris-virginica	3
118	7.7	3.8	6.7	2.2	Iris-virginica	3
119	7.7	2.6	6.9	2.3	Iris-virginica	3
120	6.0	2.2	5.0	1.5	Iris-virginica	3
121	6.9	3.2	5.7	2.3	Iris-virginica	3
122	5.6	2.8	4.9	2.0	Iris-virginica	3
123	7.7	2.8	6.7	2.0	Iris-virginica	3
124	6.3	2.7	4.9	1.8	Iris-virginica	3
125	6.7	3.3	5.7	2.1	Iris-virginica	3
126	7.2	3.2	6.0	1.8	Iris-virginica	3
127	6.2	2.8	4.8	1.8	Iris-virginica	3
128	6.1	3.0	4.9	1.8	Iris-virginica	3
129	6.4	2.8	5.6	2.1	Iris-virginica	3
130	7.2	3.0	5.8	1.6	Iris-virginica	3
131	7.4	2.8	6.1	1.9	Iris-virginica	3
132	7.9	3.8	6.4	2.0	Iris-virginica	3
133	6.4	2.8	5.6	2.2	Iris-virginica	3
134	6.3	2.8	5.1	1.5	Iris-virginica	3
135	6.1	2.6	5.6	1.4	Iris-virginica	3
136	7.7	3.0	6.1	2.3	Iris-virginica	3
137	6.3	3.4	5.6	2.4	Iris-virginica	3
138	6.4	3.1	5.5	1.8	Iris-virginica	3
139	6.0	3.0	4.8	1.8	Iris-virginica	3
140	6.9	3.1	5.4	2.1	Iris-virginica	3
141	6.7	3.1	5.6	2.4	Iris-virginica	3
142	6.9	3.1	5.1	2.3	Iris-virginica	3
143	5.8	2.7	5.1	1.9	Iris-virginica	3
144	6.8	3.2	5.9	2.3	Iris-virginica	3
145	6.7	3.3	5.7	2.5	Iris-virginica	3
146	6.7	3.0	5.2	2.3	Iris-virginica	3
147	6.3	2.5	5.0	1.9	Iris-virginica	3
148	6.5	3.0	5.2	2.0	Iris-virginica	3
149	6.2	3.4	5.4	2.3	Iris-virginica	3
150	5.9	3.0	5.1	1.8	Iris-virginica	3

A3.2 Output membership values calculated by Fuzme for 5 clusters

Fuzme (http://www.usyd.edu.au/su/agric/acpa/fkme/program.html), a freeware created at Sydney University (Minasny & McBratney, 2002), is used to cluster the whole output Y from the Nakanishi dataset investigated in section 4.2 of Chapter 4. Class numbers between 2 and 9 are considered. For reasons detailed in section 4.2.1.3 and displayed in Figure 4.7, the optimal number of classes appears to be 5.

The dataset made up of the 6 variables X1, X2, X3, X4, X5, Y displayed in Table 4.6 is segmented by Fuzme into 5 clusters. The text file automatically generated for Y is reproduced below. Fuzme produces a similar text file for the 5 input variables X1 to X5. These text files list the membership of each value of the corresponding variable in each of the 5 classes 5a to 5c imposed by Fuzme. The class each element is most representative of is where the element considered has the highest membership. This class is written in column MaxCls. Below is a typical Fuzme output for variable Y.

***** Clusters centre *****

class	Y
5a	5075.87
5b	1058.49
5c	6899.31
5d	3674.39
5e	6351.41

***** Membership *****

Y	MaxCls	CI	5a	5b	5c	5d	5e
700.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
900.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
1900.00	5b	0.01390	0.00014	0.99297	0.00001	0.00687	0.00001
3700.00	5d	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000
3900.00	5d	0.00003	0.00002	0.00000	0.00000	0.99998	0.00000
3900.00	5d	0.00003	0.00002	0.00000	0.00000	0.99998	0.00000
4900.00	5a	0.00001	1.00000	0.00000	0.00000	0.00000	0.00000
6000.00	5e	0.00538	0.00158	0.00000	0.00190	0.00000	0.99652
6400.00	5e	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000
6400.00	5e	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000
6600.00	5e	0.44961	0.00000	0.00000	0.22480	0.00000	0.77519
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
6900.00	5c	0.00000	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000

7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
700.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
800.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
1400.00	5b	0.00001	0.00000	1.00000	0.00000	0.00000	0.00000
2500.00	5d	0.40920	0.00422	0.20229	0.00012	0.79308	0.00029
3800.00	5d	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000
3900.00	5d	0.00003	0.00002	0.00000	0.00000	0.99998	0.00000
4400.00	5a	0.76781	0.61577	0.00001	0.00010	0.38359	0.00052
5400.00	5a	0.00158	0.99919	0.00000	0.00004	0.00001	0.00076
6100.00	5e	0.00098	0.00009	0.00000	0.00045	0.00000	0.99947
6400.00	5e	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000
6600.00	5e	0.44961	0.00000	0.00000	0.22480	0.00000	0.77519
6700.00	5c	0.04700	0.00000	0.00000	0.97650	0.00000	0.02350
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
500.00	5b	0.00002	0.00000	0.99999	0.00000	0.00001	0.00000
700.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
800.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
800.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
1000.00	5b	0.00000	0.00000	1.00000	0.00000	0.00000	0.00000
1600.00	5b	0.00026	0.00000	0.99987	0.00000	0.00013	0.00000
2300.00	5b	0.67458	0.00309	0.66099	0.00011	0.33556	0.00025
2800.00	5d	0.02180	0.00168	0.01000	0.00003	0.98820	0.00009
3800.00	5d	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000
3800.00	5d	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000
3900.00	5d	0.00003	0.00002	0.00000	0.00000	0.99998	0.00000
3900.00	5d	0.00003	0.00002	0.00000	0.00000	0.99998	0.00000
4000.00	5d	0.00070	0.00035	0.00000	0.00000	0.99965	0.00000
4700.00	5a	0.00254	0.99870	0.00000	0.00001	0.00124	0.00005
5200.00	5a	0.00000	1.00000	0.00000	0.00000	0.00000	0.00000
5600.00	5a	0.16804	0.91483	0.00000	0.00215	0.00016	0.08286
6000.00	5e	0.00538	0.00158	0.00000	0.00190	0.00000	0.99652
6400.00	5e	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000
6400.00	5e	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000
6400.00	5e	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000
6500.00	5e	0.00274	0.00000	0.00000	0.00137	0.00000	0.99863
6600.00	5e	0.44961	0.00000	0.00000	0.22480	0.00000	0.77519
6700.00	5c	0.04700	0.00000	0.00000	0.97650	0.00000	0.02350
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004

6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
6800.00	5c	0.00009	0.00000	0.00000	0.99996	0.00000	0.00004
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000
7000.00	5c	0.00001	0.00000	0.00000	1.00000	0.00000	0.00000

Class	Mean	Min	Max
5a	0.0792	0.0000	1.0000
5b	0.1838	0.0000	1.0000
5c	0.3805	0.0000	1.0000
5d	0.1787	0.0000	1.0000
5e	0.1778	0.0000	1.0000

Membership values for each record of Y, X1, X3 are plotted for each of the 5 classes 5a to 5e as shown in Figure A3.1 and A3.2 for X1 and X3.

Y is the output variable. The whole dataset is therefore sorted by Y which imposes the pattern of its variations on the explanatory variables X1 to X5. Variables associated with the output Y therefore increase or decrease progressively with Y depending on whether they are positively or negatively correlated with Y. Variables which are not correlated vary independently from Y in a random manner.

When input and output are strongly correlated the membership functions have a smooth envelope following that of the output: X3 displayed in Figure A3.2. When input and output are weakly correlated, no matter how smooth the envelope of the output function, input values are erratic and result in a very noisy envelope: see X1 in Figure A3.1. In extreme cases when input and output are not correlated drawing the envelope of the input membership function is impossible.

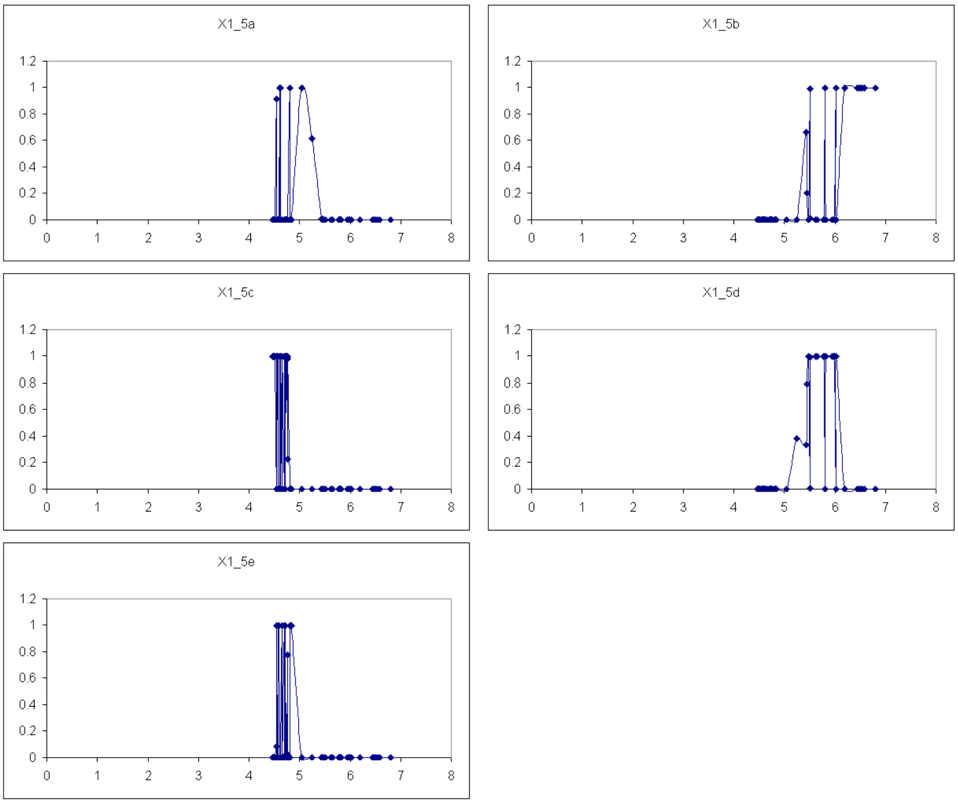


Figure A3.1: Trapezoidal membership functions derived from projecting Y class memberships on independent variable X1.

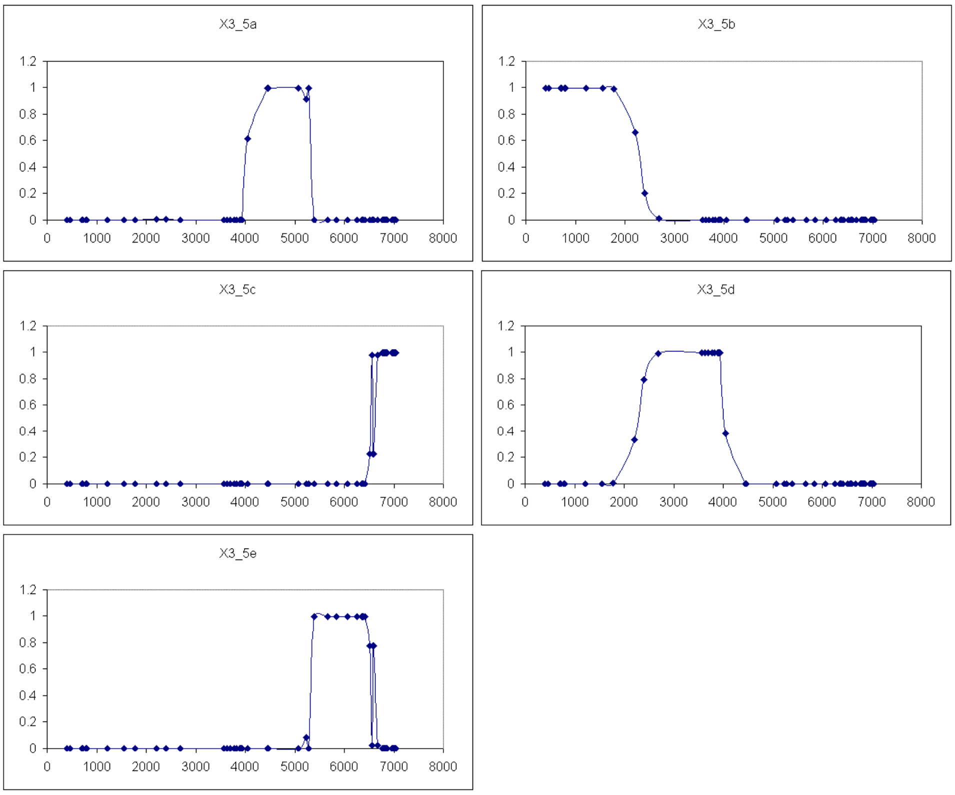


Figure A3.2: Trapezoidal membership functions derived from projecting Y class memberships on independent variable X3.

A3.3 Fuzzy rule-based modelling with Scilab

The fuzzy rule-based model in this article is designed in Scilab (http://www.scilab.org/), a free open source clone of MATLAB rapidly gaining in popularity worldwide. MATLAB is the standard for scientific and engineering applications. Scilab is a MATLAB clone excellent alternative, supported by a large community of students, researchers and developers. The Fuzzy Logic Toolbox (FLT), one of many Scilab extensions, provides all the necessary functionality to create Mamdani and Takagi Sugeno types fuzzy rule-based systems.

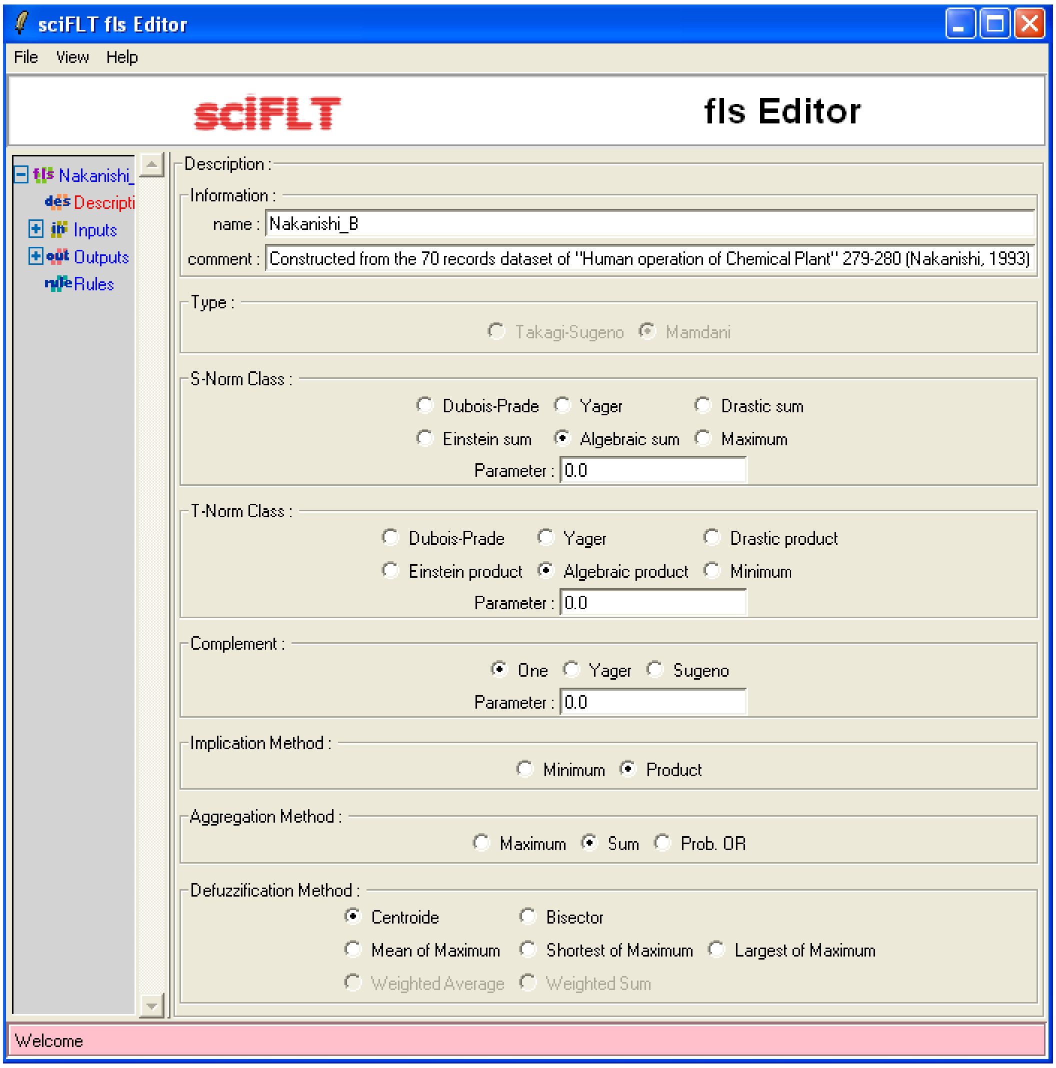


Figure A3.3: Screenshot of the fls Editor of Scilab's fuzzy logic toolbox sciFLT showing the description pane.

Once fuzzy logic parameters and membership functions coordinates are entered in the fls Editor above, rules can be created.

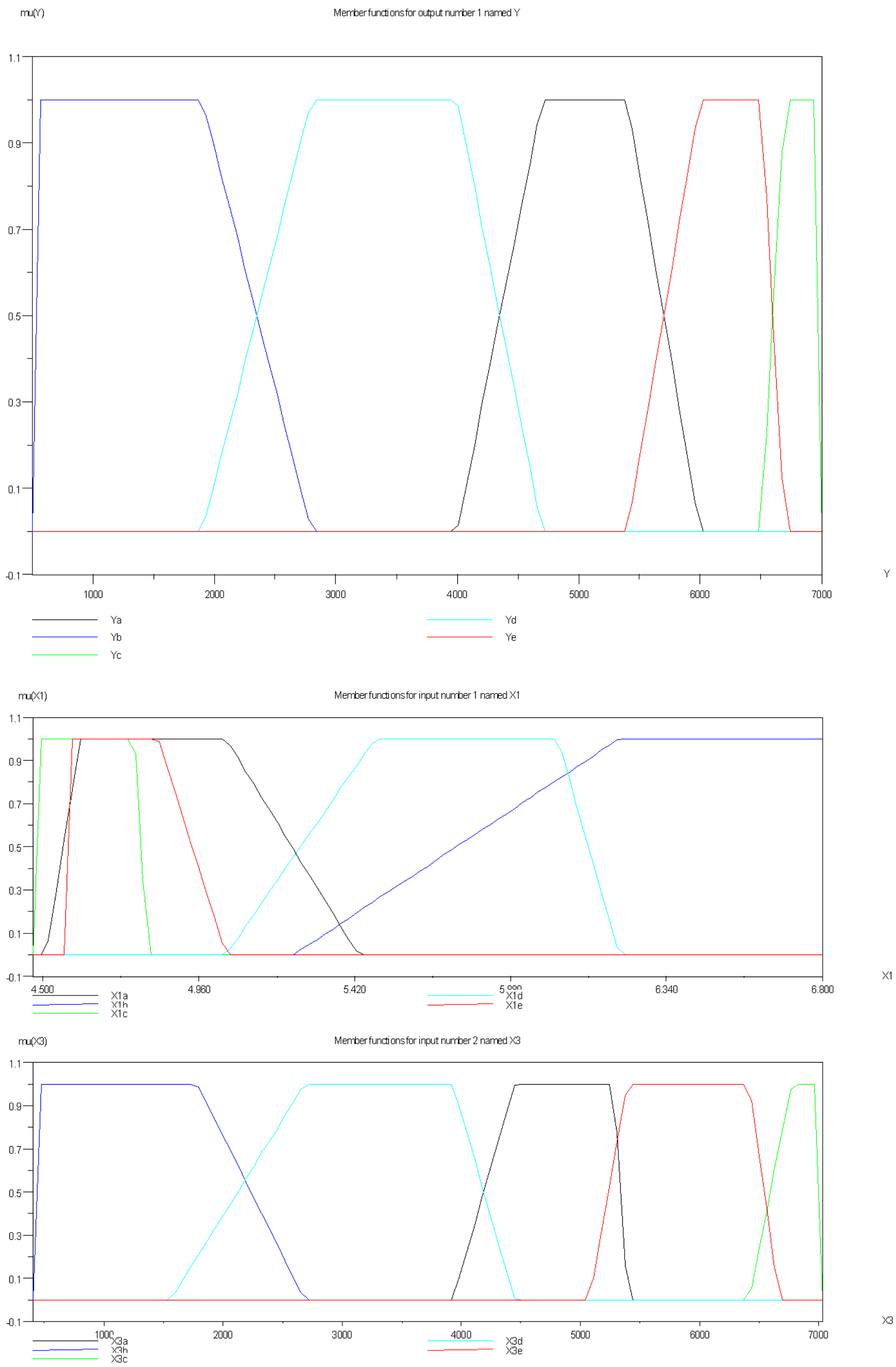


Figure A3.4: Membership functions of Y, X1 and X3 generated by Scilab FLT from membership coordinates derived from Figures A4.1 and A4.2.

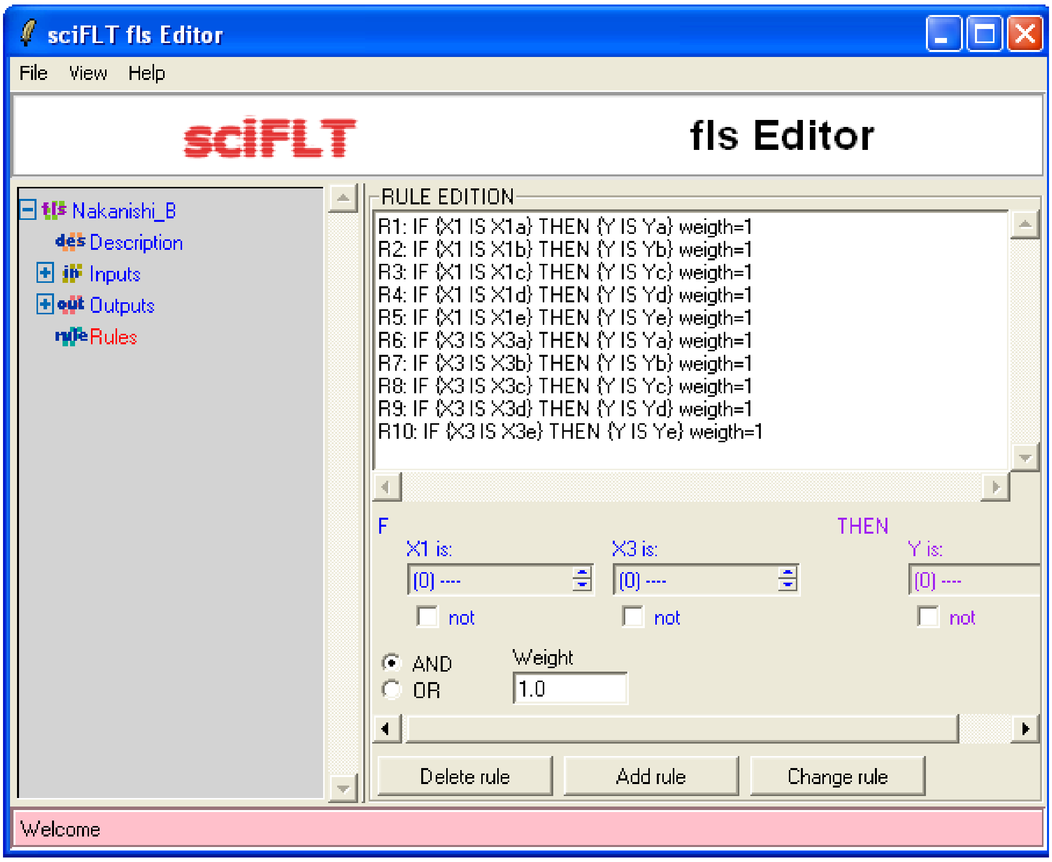


Figure A3.5: Screenshot of the fls Editor of Scilab's fuzzy logic toolbox sciFLT showing the Rules pane.

Regardless of rule weightings displayed in the Weight editor in Figure A3.5, all rules of fuzzy rule-based models written in sciFLT have the same weighting of 1. This function has not yet been implemented.

The fuzzy rule-based model is then ready to calculate predictions from arrays of input values easily imported as Excel text files.

A3.4 Elephant seals dataset

Below is a reformatted version of the Elephant seals dataset kindly provided by Dr Corey Bradshaw, Charles Darwin University.

Table A3.4: First seven of the 15 variables (printed in black) of the dataset provided by Bradshaw (2004). These variables include the time spent by fifty foraging Elephant seals as well as environmental variables describing the locations where they foraged.

ID	MNTH	YEAR	THIS_ID	LON	LAT	TIME	PCTIME	DIST	COLMEAN	COLGRAD
882	8	2001	1	199.421	-39.147	0.04	0.00	3395.99	0.168	0.018
137	8	2001	2	209.269	-49.946	3.45	0.06	3326.89	0.157	0.025
787	8	2000	3	204.345	-58.045	6.40	0.10	2716.06	0.183	0.054
500	8	2001	4	179.725	-55.346	16.18	0.28	1263.02	0.163	0.020
414	8	2001	5	174.801	-49.946	16.91	0.29	1133.53	0.152	0.033
461	8	2001	6	194.497	-55.346	17.29	0.30	2186.31	0.171	0.033
559	8	2000	7	135.409	-63.445	21.57	0.34	1697.33	0.193	0.010
574	8	2001	8	214.193	-49.946	20.76	0.36	3635.68	0.160	0.025
522	8	2001	9	204.345	-60.745	23.43	0.41	2673.14	0.211	0.030
656	6	2001	10	140.333	-49.946	23.69	0.43	1423.16	0.187	0.023
102	7	2001	11	194.497	-55.346	24.67	0.44	2186.31	0.117	0.008
111	8	2001	12	189.573	-58.045	28.13	0.49	1853.04	0.173	0.028
297	8	2001	13	204.345	-39.147	28.46	0.49	3706.97	0.149	0.016
759	8	2000	14	209.269	-58.045	33.39	0.52	2998.73	0.205	0.128
477	8	2001	15	174.801	-52.646	51.62	0.89	1003.11	0.160	0.030
664	8	2001	16	204.345	-41.847	54.52	0.94	3510.65	0.172	0.017
733	8	2000	17	174.801	-60.745	68.31	1.07	1115.18	0.180	0.277
390	8	2001	18	194.497	-41.847	64.13	1.11	2886.23	0.224	0.034
475	8	2001	19	209.269	-44.546	71.25	1.23	3645.35	0.166	0.012
471	7	2001	20	169.877	-52.646	82.17	1.46	690.71	0.128	0.025
208	7	2001	21	214.193	-49.946	89.69	1.59	3635.68	0.148	0.031
613	8	2000	22	164.953	-60.745	103.05	1.61	747.29	0.246	0.093
504	8	2001	23	169.877	-55.346	104.62	1.81	640.88	0.170	0.025
854	8	2001	24	164.953	-55.346	114.48	1.98	332.40	0.147	0.024
159	8	2001	25	209.269	-47.246	135.35	2.34	3477.76	0.165	0.019
232	8	2000	26	174.801	-63.445	157.66	2.46	1296.36	0.319	0.187
54	8	2001	27	204.345	-44.546	147.10	2.54	3328.17	0.177	0.015
402	8	2001	28	194.497	-58.045	159.53	2.76	2142.44	0.171	0.021
857	8	2000	29	164.953	-58.045	177.25	2.77	494.39	0.191	0.040
447	7	2001	30	145.257	-49.946	159.03	2.82	1120.03	0.168	0.026
532	7	2001	31	189.573	-58.045	165.79	2.94	1853.04	0.121	0.028
88	7	2001	32	209.269	-49.946	166.95	2.96	3326.89	0.148	0.028
1027	8	2001	33	199.421	-41.847	185.64	3.21	3196.09	0.179	0.013
605	7	2001	34	209.269	-52.646	183.50	3.26	3195.13	0.156	0.051
42	8	2001	35	194.497	-60.745	206.09	3.56	2138.58	0.169	0.019
333	8	2000	36	179.725	-63.445	234.82	3.66	1491.18	0.256	0.131
418	8	2001	37	145.257	-47.246	218.39	3.77	1307.78	0.195	0.053
187	8	2001	38	164.953	-58.045	219.78	3.80	494.39	0.156	0.022
238	8	2000	39	204.345	-60.745	247.21	3.86	2673.14	0.183	0.022
943	8	2001	40	145.257	-49.946	234.43	4.05	1120.03	0.154	0.023
250	8	2001	41	169.877	-58.045	271.79	4.70	723.89	0.169	0.020
331	7	2001	42	145.257	-47.246	281.95	5.00	1307.78	0.170	0.031
893	8	2000	43	164.953	-55.346	321.02	5.01	332.40	0.157	0.039
71	8	2001	44	189.573	-60.745	295.10	5.10	1872.37	0.177	0.020
811	8	2000	45	209.269	-60.745	330.94	5.16	2938.61	0.176	0.015
101	8	2001	46	199.421	-60.745	331.03	5.72	2406.06	0.206	0.023
347	8	2001	47	204.345	-63.445	374.30	6.47	2661.56	0.161	0.091
315	8	2001	48	179.725	-52.646	385.96	6.67	1319.66	0.163	0.034
521	6	2001	49	140.333	-52.646	416.81	7.58	1305.20	0.156	0.054
883	7	2000	50	164.953	-55.346	558.91	8.69	332.40	0.181	0.040

Table A3.5: Below are the eight environmental variables that complete Bradshaw's dataset. Together with COLMEAN and COLGRAD in Table3.4, these were derived from remotely sensed data to account for the time spent by Elephant seals at sea while feeding in specific locations.

THIS_ID	PFMEAN	PFGRAD	SLAMEAN	SLAGRAD	ICEMEAN	ICEGRAD	BATMEAN	BATGRAD
1	12.092	1.361	29.284	95.995	0.000	0.000	-5323.128	152.625
2	7.639	0.583	2.305	186.161	0.000	0.000	-5197.504	96.317
3	-0.452	1.369	-36.646	150.946	2.841	15.572	-4816.746	224.580
4	5.152	1.393	-74.923	303.977	0.000	0.000	-2475.067	1258.586
5	7.146	0.599	56.139	84.084	0.000	0.000	-1049.183	1458.880
6	3.626	1.685	-6.464	198.617	0.000	0.000	-5083.932	124.678
7	-1.843	0.506	55.540	63.264	84.583	32.431	-3979.049	273.226
8	7.441	0.481	-46.607	145.808	0.000	0.000	-5454.676	60.933
9	-1.476	0.705	-58.532	132.710	32.398	55.487	-4574.967	381.584
10	7.504	2.166	113.140	564.458	0.000	0.000	-4920.027	443.286
11	4.047	1.873	4.605	194.181	0.000	0.000	-5083.932	124.678
12	1.934	1.043	0.339	166.937	0.000	0.000	-5155.171	91.561
13	12.045	1.102	32.069	81.090	0.000	0.000	-5304.712	65.729
14	-1.225	1.058	13.080	119.261	35.367	63.167	-4556.885	266.902
15	6.315	0.973	29.845	141.978	0.000	0.000	-756.893	674.900
16	10.384	1.163	2.933	65.582	0.000	0.000	-5404.524	116.880
17	0.695	1.653	-32.999	206.366	18.159	54.794	-2866.432	1193.498
18	10.927	1.070	40.250	111.254	0.000	0.000	-5420.170	171.669
19	8.646	0.781	-13.327	125.166	0.000	0.000	-5442.796	107.577
20	7.514	0.529	89.901	53.667	0.000	0.000	-829.799	1390.306
21	7.685	0.597	-34.978	170.250	0.000	0.000	-5454.676	60.933
22	-0.153	2.040	53.322	159.149	51.920	64.623	-2753.790	1078.044
23	6.428	1.280	18.167	330.881	0.000	0.000	-740.060	462.701
24	5.920	2.643	50.155	404.807	0.000	0.000	-3085.169	1517.395
25	7.922	0.403	-42.500	127.938	0.000	0.000	-5309.952	143.607
26	-1.019	2.021	-19.719	99.761	90.810	21.868	-5049.835	402.427
27	8.721	0.718	-1.732	92.056	0.000	0.000	-5490.647	70.938
28	1.416	0.980	-49.384	132.849	0.000	0.000	-5024.941	46.707
29	2.593	2.014	6.061	465.968	0.000	1.210	-2389.557	1931.310
30	7.830	2.165	95.957	439.849	0.000	0.000	-1471.987	1493.027
31	2.378	1.497	9.090	187.899	0.000	0.000	-5155.171	91.561
32	8.176	0.637	9.489	163.364	0.000	0.000	-5197.504	96.317
33	10.308	0.938	14.018	55.257	0.000	0.000	-5390.555	107.724
34	6.438	1.840	-94.927	401.025	0.000	0.000	-5168.969	98.577
35	0.000	1.299	-15.578	116.808	7.220	26.613	-4969.776	84.401
36	-1.189	1.331	-42.694	130.739	82.402	36.785	-5152.706	58.298
37	9.769	2.325	59.447	332.387	0.000	0.000	-69.708	200.891
38	2.635	2.722	-28.275	424.942	0.000	0.131	-2389.557	1931.310
39	-1.408	0.883	-8.534	92.711	49.867	58.461	-4574.967	381.584
40	7.640	1.912	100.541	567.819	0.000	0.000	-1471.987	1493.027
41	5.159	3.121	-4.658	494.827	0.000	0.000	-578.486	258.359
42	10.289	2.289	61.813	349.125	0.000	0.000	-69.708	200.891
43	5.838	2.877	-56.894	363.336	0.000	0.000	-3085.169	1517.395
44	0.196	1.404	-41.903	107.938	1.000	12.360	-5181.308	137.997
45	-1.322	0.693	-1.924	57.108	81.879	20.951	-4416.385	176.424
46	-0.783	1.154	-67.018	145.673	18.250	39.728	-4717.137	165.965
47	-1.636	0.495	-38.818	101.560	91.985	21.541	-3919.279	236.775
48	5.794	0.574	0.573	205.345	0.000	0.000	-1220.576	897.299
49	4.427	2.335	62.769	210.726	0.000	0.000	-4682.882	253.410
50	5.106	2.603	9.620	290.421	0.000	0.000	-3085.169	1517.395

Appendix 4 Knowledge driven modelling

Section A 4.1 describes an Excel worksheet set up to speed up the processing of questionnaire results for the purpose of producing membership functions for fuzzy rule-based expert systems. Section A 4.2 is a set of notes prepared for an introduction to fuzzy logic and rule based-modelling given at Charles Darwin University in 2007. Section A 4.3 is a transcript of emails exchanged with Cheung in regards to the calculation of the vulnerability of the main target species of the Timor Reef Fishery to fishing pressure.

A4.1 Deriving membership functions from questionnaires

When the number of informants is large it may not be possible to process informants questionnaires in the very detailed manner described in Chapter 5. Informants who score high are likely to balance those who score low. In that context it becomes useful to rapidly assess group membership functions after simply checking, on the basis of the means, that all views are compatible. If they are not, the cause should investigated while informants are still available. A spreadsheet was set up for that purpose but was not used as only two questionnaires were collected.

Here we assume that 9 informants participated in the survey and we use therefore an array of 9 rows (one per informant) and 10 columns (for scares 1 t o 10). The spreadsheet allows to rapidly generate a membership function from informant knowledge recorded in a questionnaire. Below are the 4 computation tables exactly as they appear in the Excel spreadsheet. Steps leading to the calculation of all 3 triangular membership function coordinates are as follows.

Table A4.1: A scratchpad allows to rapidly record informant's views. All boxes selected by informants are assigned a value of 1.

0	0	0	0	1	1	1	1	0	0
0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	1	1	1	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	1	1	1	1	0	0
0	0	0	0	1	1	1	0	0	0
0	0	0	0	1	1	1	1	1	0
0	0	0	0	1	1	1	0	0	0
Scratch pad									

Values in the scratchpad (Table A4.1) are automatically copied in calculation cells of the array below in Table A4.2 where pre recorded formulas perform two tasks;

– it converts each 0/1 answer into the corresponding rank (1 to 10) in the questionnaire;
– it assigns 1000 to columns to be ignored in further calculations and 1 to those retained.

Table A4.2: A calculation table reads values from the scratchpad in A4.1 and translates them into scores selected by informants. Scores are tallied for further computations.

Calculation of a & c	1	2	3	4	5	6	7	8	9	10
	0	0	0	0	5	6	7	8	0	0
	0	0	0	0	0	0	7	8	0	0
	0	0	0	0	0	0	7	8	9	0
	0	0	0	0	0	0	7	0	0	0
	0	0	0	0	0	0	7	0	0	0
	0	0	0	0	5	6	7	8	0	0
	0	0	0	0	5	6	7	0	0	0
	0	0	0	0	5	6	7	8	9	0
	0	0	0	0	5	6	7	0	0	0
Tally	**0**	**0**	**0**	**0**	**5**	**5**	**9**	**5**	**2**	**0**

Table A4.3: All information in Table A4.1 and A4.2 is summarised to define parameters a, b and c of the triangular membership function that reflects all informants' views. Parameter b, the x coordinate of the apex of the membership function is the average of all selections. Individual averages in the rightmost column reflect the consistency of all informants' views.

Summary Sheet	Rank	1	2	3	4	5	6	7	8	9	10	Calculation of b
												Average
Informant 1	→	0	0	0	0	1	1	1	1	0	0	6.5
Informant 2	→	0	0	0	0	0	0	1	1	0	0	7.5
Informant 3	→	0	0	0	0	0	0	1	1	1	0	8
Informant 4	→	0	0	0	0	0	0	1	0	0	0	7
Informant 5	→	0	0	0	0	0	0	1	0	0	0	7
Informant 6	→	0	0	0	0	1	1	1	1	0	0	6.5
Informant 7	→	0	0	0	0	1	1	1	0	0	0	6
Informant 8	→	0	0	0	0	1	1	1	1	1	0	7
Informant 9	→	0	0	0	0	1	1	1	0	0	0	6
	Tally	0	0	0	0	5	5	9	5	2	0	

Triangular Membership Function coordinates			
	a	=	5.00
	b	=	6.83
	c	=	9.00

Roles of the Summary Sheet above are to:

- reproduce all 0/1 answers recorded by informants;
- calculate Average for each informant to rescale answers if necessary;
- write minimum and maximum ranks recorded respectively as a and c;
- calculate the average of all ranks selected.

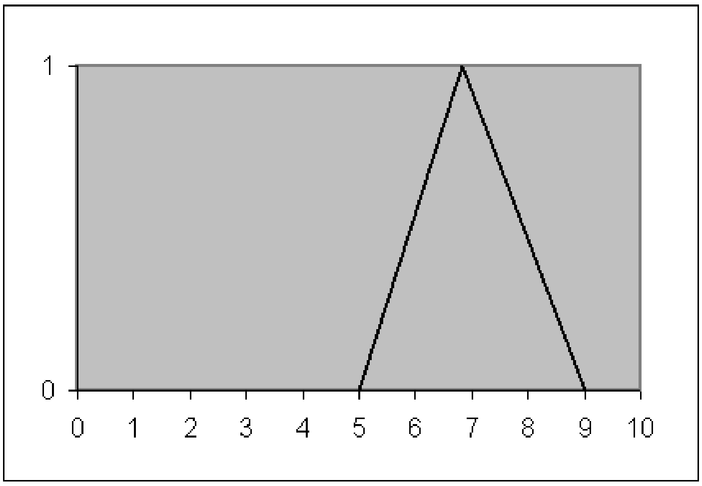


Figure A4.1: Triangular membership function automatically derived from informants' responses tabulated in Table A4.3.

Figure A4.1 shows the triangular membership function automatically generated by the points derived from the questionnaire completed by the informants. It summarises the views of all informants.

A4.2 Introduction to sciFLT, a fuzzy logic toolbox for Scilab

Below is an extract of the material which was presented at a 2 day workshop funded by the FRDC as part of the project on the development of improved management strategy for the TRF. The workshop was run at Charles Darwin University on 28 and 29 February 2007 for members of the Darwin marine NRM community. The attached documents and a CD were given to all attendants. The purpose was to introduce them to some of the techniques and software used in 2008 to complete FRDC 2005/047 research project funded by the Commonwealth Government.

SciFLT is clearly inspired from FLT, the Fuzzy Logic Toolbox for Matlab. They are both equally user friendly and can be accessed through commands or through a GUI. The latter, being more user friendly, is the focus of these notes.

SciFLT allows to build and run two types of fuzzy inference systems:

- Mamdani;
- Takagi-Sugeno (T-S).

Only the former type is considered here as it is better suited to the creation of both knowledge and data driven models while T-S systems are more suited to data driven models. Mamdani type models tend to be more transparent as well but are not as well suited to optimization as T-S models.

SciFLT offers many choices of operators and defuzzification techniques:

- the defuzzification technique preferred here is the “centre of gravity”, called “centroid” in sciFLT and generally considered as the most reliable;
- operators OR and AND can have a number of different mathematical expressions under the generic names of S-norm and T-norm. Those we choose here are the default options: algebraic sum and algebraic product.
- the default option complement to one is selected as well;
- the aggregation method however is sum instead of maximum.

Once these options are selected the remaining tasks consists in;

1/ defining/drawing the membership functions of all input and output variables;

2/ writing the rules that make up the fuzzy model;

3/ running the fuzzy model on a set of input values to calculate the output;

4/ visualising the transfer surface which is the 3D surface obtained when all but two input variables have a set value. This 3D surface allows to observe how the output, plotted vertically (Z) changes with the two “free” variables plotted along the X and Y axes.

Owing to time constraints and the lack of prior knowledge of most of the audience we will go against the chronologic order. Tasks 2 and 1 particularly are more time consuming and somewhat easier to complete when one has an overview of all steps involved.

We will use Cheung’s expert system already coded in Scilab to:

- learn how to access the scFLT GUI,
- explore its transfer surface;
- calculate the intrinsic extinction vulnerability of a commercial species given some its biological characteristics;
- discover the rule editor;
- modify some membership functions.

Although a very capable and useful tool, sciFLT 0.2, the latest version available, completed by Jaime Urzua Grez in 2004 suffers from some limitations. Two were identified through the implementation of Cheung's expert system described in Chapter 6:

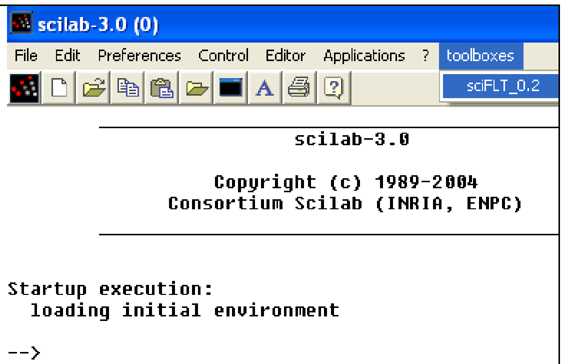
- the first one relates to flaws in graphic functions resulting in artificially truncated tips of triangular membership functions clearly noticeable in Figure 6.1 in membership functions M and H of Age_first_mat and Lw and Lw and M of VBGF_param_K;
- the second one less obvious but more troublesome is the inability of sciFLT to assign weightings to rules. The software allows weightings to be entered and recorded as displayed in Figure 6.4. Weightings used in all calculations, however, remain equal to 1.

When Jaime Urzua (jaime_urzua@yahoo.com) was contacted after noticing that changing weightings had no effect on the output of Cheung's model. He confirmed that weighting functionality was planned (the shell had been created) but not implemented in sciFLT 0.2, the latest version of the software he released in 2004.

1/ <u>Loading the sciFLT functions:</u>

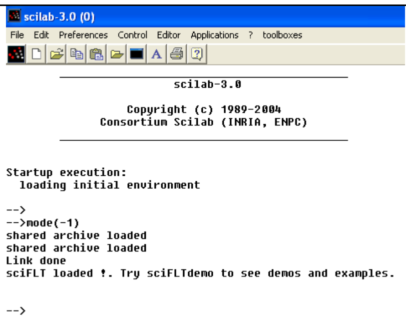
- open the toolboxes pull down menu,
- double click on sciFLT_0.2,
- press ENTER.

21



The sciFLT tool box is now loaded.

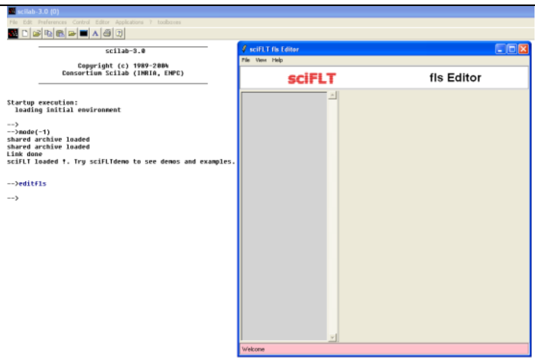
22



2/ <u>Open the sciFLT GUI called "sciFLT fls Editor"</u>

- at the command line type **editfls**;
- type ENTER;
- the Graphic User Interface (GUI) is now loaded.

23

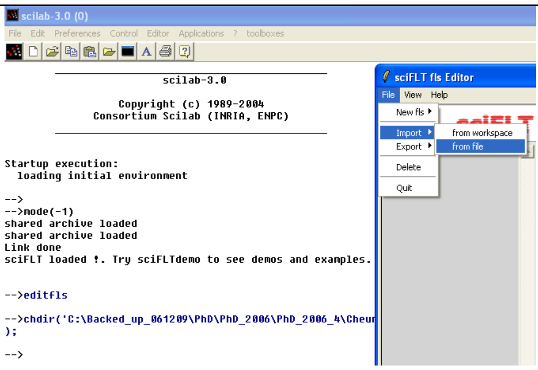
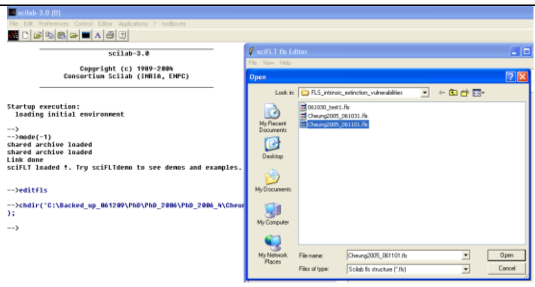
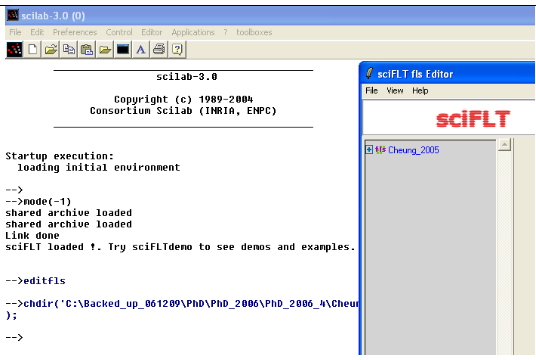
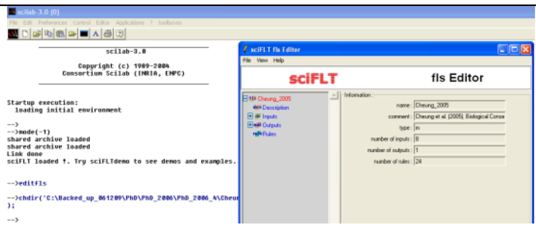


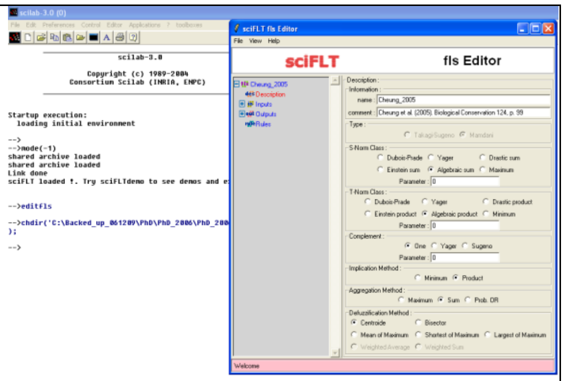
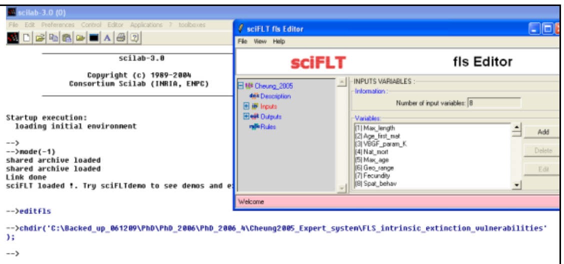
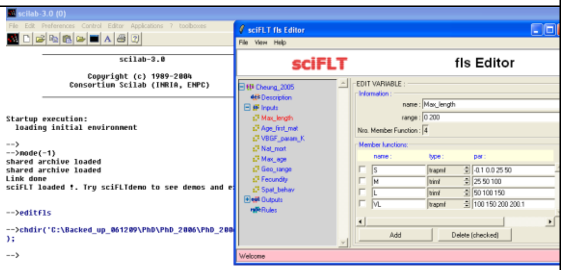
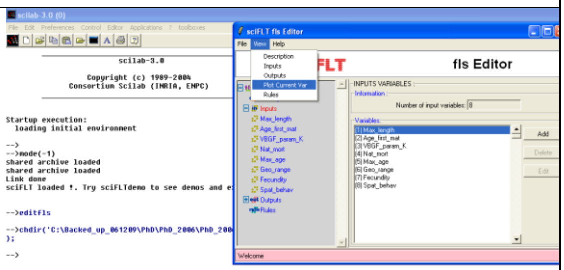
3/ <u>Change to the directory where Cheung's expert system is saved</u>

C:\TEMP\FRDC_WORKSHOP\SCILAB\DATASET\Fls_intrinsic_extinction_vulnerability

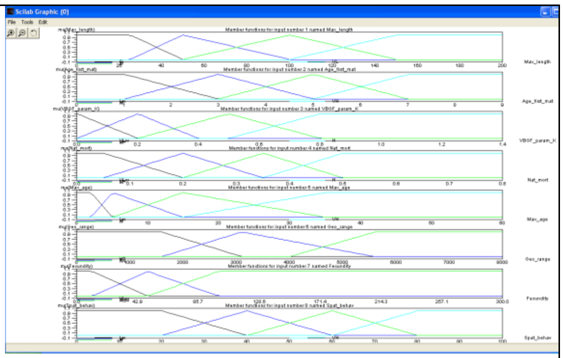
use the technique shown in **13**

24

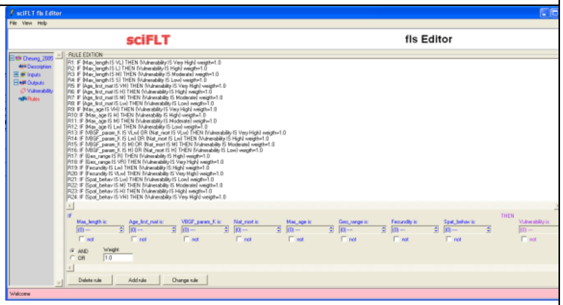
4/ <u>Open the expert system</u> - in the sciFLT fls Editor, in the File pull down menu click Import from file **25**	
5/ <u>Select “Cheung2005_61101.fls”</u> **26**	
- press Open; - the truncated name “Cheung_2005” of the expert system now appears in the sciFLT fls Editor; - Cheung’s expert system is now loaded in Scilab. **27**	
- press on the blue + in the square immediarely to the left of the expert system name; - details of the expert sys tem appear type: m number of inputs: 8 number of outputs: 1 number of rules: 24 **28**	

6/ Click on Description to view a detailed description of the choices made to build this expert system **29**	
7/ Click on Inputs to see the list of Input (independent) variables **30**	
8/ To view the coordinates membership functions and their type - click on the blue + immediately to the left of inputs; - click on the name of the membership function you want to check, Max_length for instance. **31**	
9/ To view the plots of all membership functions - click on the View pull down menu; - click on Plot Current Var. **32**	

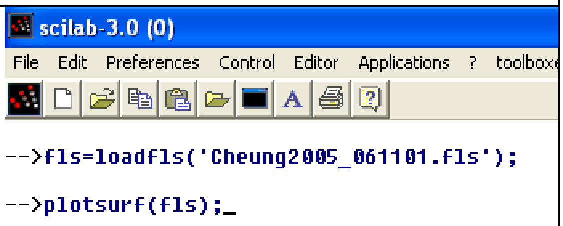
<table>
<tr><td>Membership of all variables are displayed

33</td><td></td></tr>
<tr><td>10/ <u>To display all rules that make up the expert system</u>

click on Rules

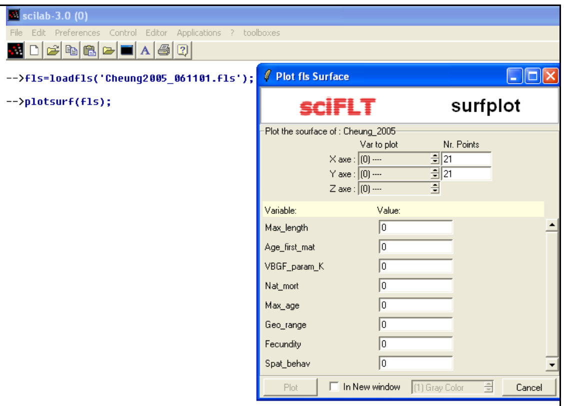
34</td><td></td></tr>
<tr><td>11/ <u>To plot the output surface of the fuzzy logic system</u>

- at the command line type **clc** to clear the screen;
- load Cheung expert system and name it fls;
- call **plotsurf** to view the output surface of this fls.

35</td><td></td></tr>
</table>

- press ENTER to access to access the output surface GUI;
- click the bottom border of the surfplot window to resize it until you can see all variables.

36

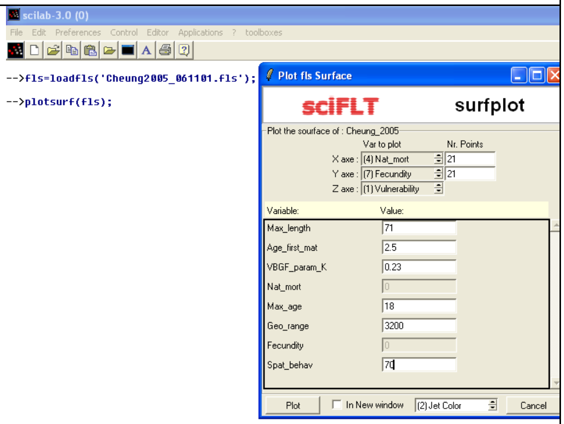


12/ <u>Enter all following parameters</u>

X axe	Nat_mort
Y axe	Fecundity
Z axe	Vulnerability

Max- Length	71
Age_first_mat	2.5
VBGF_param_K	0.23
Max_age	18
Geo_range	3200
Spat_behav	70

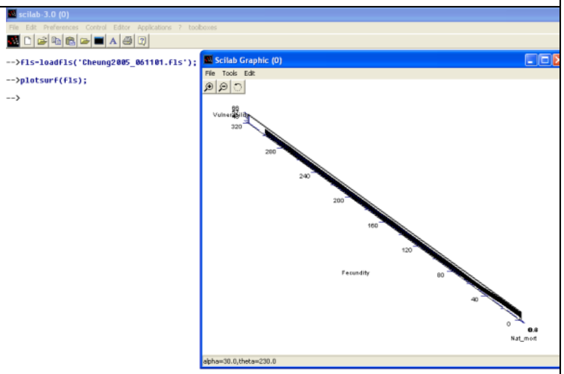
37

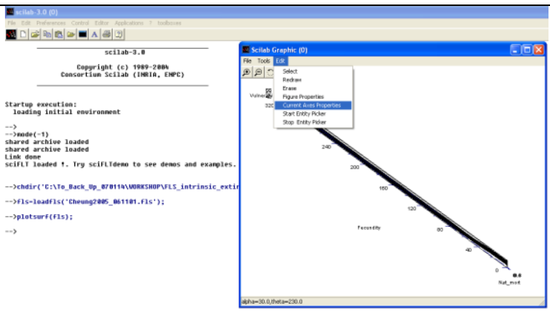
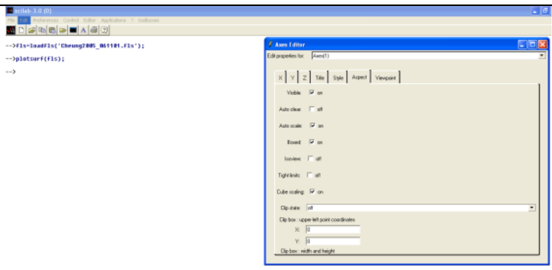
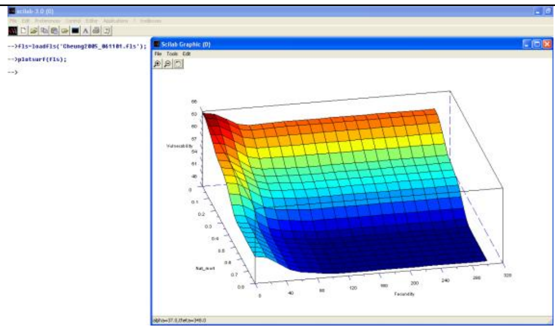
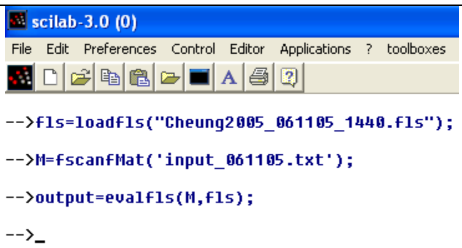


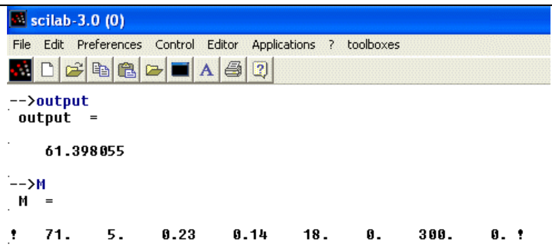
13/ <u>Default settings need to be changed</u>

- the default setting of Axes properties causes the 3D surface to be compressed;
- this setting needs to be changed.

38



14/ <u>Edit graphic box properties</u> in the Scilab Graphic editor where the compressed 3D surface is displayed, click on Current Access Properties in the Edit pull down menu' **39**	
15/ <u>Edit Axes Properties</u> check the Cube scaling box **40**	
The coloured 3D surface provides an easy way of exploring the effects of fluctuations in Fecundity and Natural Mortality on the Vulnerability of the species characterized by: Max- Length 71 Age_first_mat 2.5 VBGF_param_K 0.23 Max_age 18 Geo_range 3200 Spat_behav 70 **41**	
16/ <u>Find information on sciLab commands</u> - the sciFLT Help files are **<u>not</u>** available on line under Windows (they are under Linux); - check the syntax of the evalfls and fscanfMat command respectively from the pdf sciFLT Help Files and the compiled HTML Help files (these documents are saved in the work directory); - type these commands. **42**	

- loadfls loads the required fuzzy logic system from the workspace; - fscanfMat translates rows of input parameters (initially entered in Excel and saved as .txt tab delimited text file) into a matrix of 1 row and 8 columns; - evalfls saves the value of fls in output. - read output and M. **43**	

Although a very capable and useful tool, sciFLT 0.2, the latest version available, completed by Jaime Urzua Grez in 2004 suffers from some limitations. Two were identified through the implementation of Cheung's expert system described in Chapter 6:

– the first one relates to flaws in graphic functions resulting in artificially truncated tips of triangular membership functions clearly noticeable in Figure 6.1 in membership functions M and H of Age_first_mat and Lw and Lw and M of VBGF_param_K;

– the second one less obvious but more troublesome is the inability of sciFLT to assign weightings to rules. The software allows weightings to be entered and recorded as displayed in Figure 6.4. Weightings used in all calculations, however, remain equal to 1.

A4.3 William Cheung's comments

Below is an exchange of emails with William Cheung referring to calculations of the vulnerability of the Gold band snapper (*Pristipomoides multidens*) to fishing pressure.

Dear Philippe,

I estimated the intrinsic vulnerability index for Pristipomoides multidens based on the parameters that you provided. My estimate is very close to yours, although slightly lower 60.2. I wonder whether the difference is because of some differences in the implementation of the fuzzification/defuzzification process somewhere between the two. But it is good that we have consistent estimates.

Based on the information from fishbase, P. multidens is described as a schooling fish. Based on the calculation noted in the Cheung et al 2005 paper, a schooling fish will get a score of spatial behaviour strength (measure of the tendency/frequency) to form aggregations) of 80. When I included this in the calculation, the predicted intrinsic vulnerability increased to 66.9. The rationale behind this rule is that it is generally agree that species that from aggregations, particularly those that are predictable (e.g. schooling, spawning aggregation) will be more vulnerable to exploitation because 1. it can be easily targeted, 2. catch-per-unit-effort would like to remain stable under stock decline because dense schools may continue to form by range contraction or situation of actual fishing time from targeting different aggregation (similar to a type II predator-prey functional response) leading to hyper depletion, i.e. catch-per-unit-effort remains high even stock abundance level is low, marking the stock/species prompt to serious depletion, 3. disruption of this aggregation may like have an impact on the population (e.g. depletion of spawning aggregation may considerably affects recruitment). Therefore, this attribute is included in the calculation and in fact, from our analysis, it seems to be an important factor in ranking the relative intrinsic vulnerability in some cases (e.g. reef fishes).

The geographic range is too wide for this species to trigger any rule to be fired so it doesn't matter if this is not included. Also, our analysis and other empirical studies suggest that this is not an important factor affecting the intrinsic vulnerability of

MARINE fishes, unless the geographic range is very small (e.g. endemic only to a small patch of reefs or around a small island).

I hope the above is useful for your analysis. Again, I am very happy that if this study can be taken to practical uses. I should be greatly appreciated if you would let me know how your works go later. Please feel free to let me know if you need further information from me.

By the way, for your interest, a paper is published applying this method to evaluate seamount fishes (see attached) and there will be a couple more that hopefully will come out soon. Also, we have a paper in view using the average intrinsic vulnerability weighted by the annual catches of assemblages and we show that it can be a useful indicator to evaluate changes in species composition resulted from fishing.

Best regards,

William

Member, IUCN Specialist Group of Groupers and Wrasses

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From: *Puig, Philippe (EWLS) [mailto:Philippe.Puig@ewlsciences.com.au]*
Sent: *Monday, November 06, 2006 2:33 PM*
To: *William Cheung*
Cc: *Julie.Lloyd@nt.gov.au*
Subject: *Expert system*

<<Scilab_screencapture_061105.doc>>

Dear William

I found your 2005 paper "A fuzzy logic expert system to estimate the intrinsic extinction vulnerabilities of marine fishes to fishing" particularly interesting.

I built your expert system in sciFLT, the fuzzy logic toolbox for Scilab, an open source freeware clone of MATLAB. Screenshots are attached.

Julie Lloyd, senior fishery research scientist from Northern Territory Fisheries and I are co-investigator in a Commonwealth funded research project. Our aim is to develop of ecologically based management strategies for the Timor Reef Fishery, about 200km north of Darwin in Australia.

We believe that your extinction vulnerability ranking of commercial fishes should be part of a long term management of the Timor Reef Fishery. I tested your model with the life history parameters for P. multidens, the main target species in that fishery.

Maximum length =71.1 cm
Age at first maturity=5 years
VBGF parameter k=0.23
Natural Mortality rate=0.14
Maximum age= 18 years
Geographic range?
Fecundity=$1.65x10^5$ *eggs/individual/year*
Spatial behaviour?

As I was missing two parameters, I eliminated all corresponding rules from the expert system. This, according to your tests, should only have a minor impact on the output of the model.

I found a vulnerability index of 61.4. This puts P. multidens in the same vulnerability category as the Atlantic cod.

This leads me to two questions:

1/ would you mind checking that you find the same vulnerability index for P. multidens with your model;

2/ I did not include in my model rules 24 and 25 corresponding to attribute 8 on page 101 of your article. I assume that they play the role of edges. Could you please elaborate on these last two rules.

Thank you very much for a very good article which will hopefully contribute to giving to fuzzy logic the importance it should have in fishery science.

Regards

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