Interdisciplinary Multivariate Analysis for Adaptive Co-Management

Project R7834

Final Technical Report

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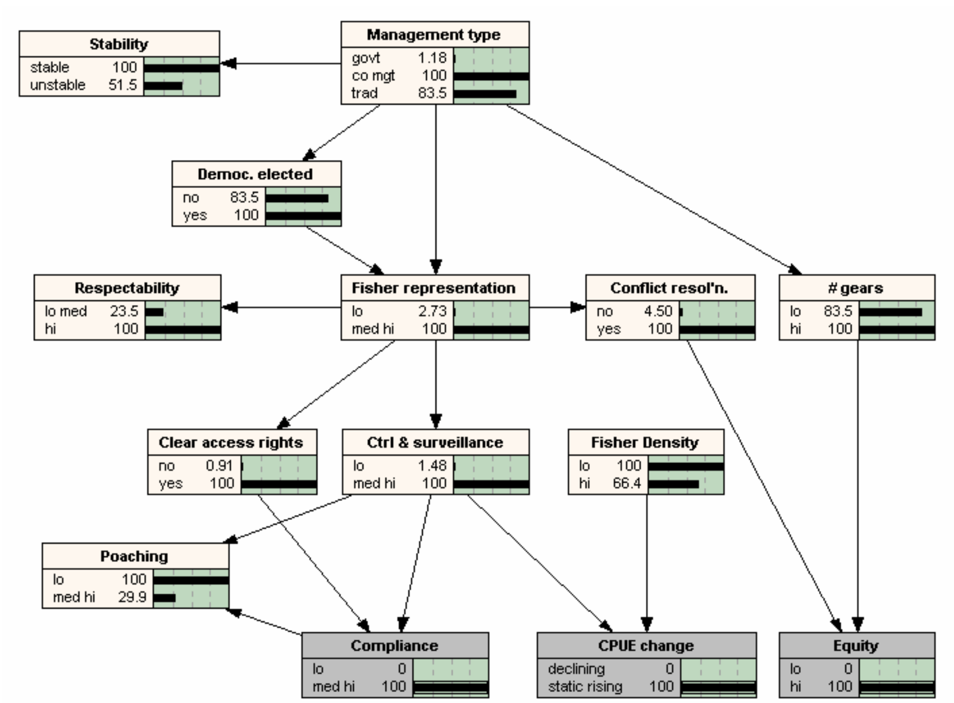

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FINAL TECHNICAL REPORT

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1. DFID Summary

1.1 Executive Summary

The co-management of fisheries, particularly when undertaken in an *adaptive* manner, is increasingly promoted as an effective strategy to redress the commonly cited failures associated with “top-down”, resource-orientated approaches to management. In spite of this re-orientation, analytical methods to help support adaptive management decision-making by local management bodies are poorly developed.

Using the Institutional Analysis and Design (IAD) framework as a theoretical basis, 258 variables describing the interdisciplinary (resource, technical, socio-economic and political) attributes and performance of (co-)managed artisanal fisheries were defined on the basis literature reviews, previous studies, field manuals and after considerable discussion and debate with project collaborators and invited co-management experts during overseas workshops. Data for these 258 variables were then assembled for 119 observations of artisanal (co-)managed fisheries from 13 different countries across Africa, Asia and Melanesia.

On the basis of (i) this dataset, (ii) a review of previous approaches, and (iii) hypotheses concerning co-management performance, two improved complementary techniques for modeling management performance are proposed here which can be used to feedback knowledge and advice to local managers to help them achieve their management objectives:

- GLM regression modelling for identifying and assessing the effects of key attributes on outcomes – a tool for statistical inference; and
- Bayesian network modelling (supported by logistic and log-linear methods) serving as a management tool, or expert system, for diagnosing strengths and weaknesses among co-management units and for exploring ‘what if’ scenarios.

The GLM is a very well developed technique and provides a powerful means of describing the more quantitative (“hard data”) response elements of management systems to a good degree of approximation. A particularly attractive feature of BNs is their ability to model, in a very visual and interactive manner, the more complex and intermediate pathways of causality which appear so very intrinsic to the IAD and Sustainable Livelihoods frameworks where the roles of “soft” response and explanatory variables become “blurred” by complex human behaviour. Their ability to learn, as more cases (evidence) become available, is also a particularly relevant feature for adaptive management applications. Managers can be readily trained in the skills needed for constructing network models, and the Netica software used for this project is very user-friendly and inexpensive.

Whilst the emphasis of the project was on exploring and comparing different methodological approaches, the two methods were applied to the “trial” dataset in an attempt to identify globally important (co-)management attributes affecting six (co-)management outcomes, and to help identify important variables for inclusion in future monitoring programmes (see Sections 1.5, and Chapter 6 for details). Considerable scope exists for similar applications of BNs in other sectors such as agriculture or forestry, particularly when the mode of analysis is pursued from an IAD for SL framework perspective.

Guidelines for field applications of the two modeling approaches are provided including practical advice on identifying sampling units, important variables, data levels and cleaning, exploratory analysis including dimension reduction, minimum sample sizes, sensitivity analysis…etc.

Phase I of this process project has successfully delivered all planned outputs. Opportunities for rigorous validation of the proposed models and approaches were, however, severely limited by the problem of missing data. We therefore recommend that field applications be undertaken under Phase II as described in the project memorandum alongside the previous approaches (excluding RAPFISH) to further assess their relative validity, utility and performance.

1.2 Background

Artisanal fisheries are fundamentally important in the developing world. At the same time they are inherently complex from resource, technical, operational, institutional and social perspectives making them notoriously difficult to manage. Traditional 'top-down' approaches to managing these fisheries have, in the past, failed to coordinate and restrain resource users, leading to depleted resources, inequity and conflict. This paradigm failure is prevalent in the developing world; commonly exacerbated by a single disciplinary perspective, a paucity of resources to sustain adequate monitoring, control and surveillance programmes and inadequate management decision-aiding models (Section 2.1).

The sharing of management roles and responsibilities between governments and fishing communities is increasingly promoted as an effective strategy to redress these paradigm failures and thereby facilitate improved sustainable livelihoods, particularly when undertaken in an *adaptive* manner (Hoggarth et al 1999). Numerous advantages of this type of 'co-management' have been cited. In spite of these apparently intrinsic benefits, designing and refining strategies and arrangements to improve performance or to achieve specific management objectives remain fundamental (co-)management activities. The holistic perspective from which co-management theory evolved encourages decision-making that not only takes account of the resource and the technology or capital used to exploit it, but also the institutional arrangements and other external factors that affect fisher behaviour – a key factor affecting many management outcomes or objectives. Co-management decision-making is therefore inherently complex. Consideration must be given to numerous important outcomes, and interdisciplinary variables (or attributes) and their interactions.

Whilst informal and *passive* approaches to adaptive management are likely to be adopted by local communities as a means of monitoring and evaluating their management performance, support from higher-level managers or research institutions can help accelerate this process making it less wasteful and potentially more effective. This can be achieved by constructing models of (co-) management performance on the basis of comparisons of the attributes and performance of a contrasting array of different co- or community managed fisheries. These models can then be used to help guide local decision-making. These models should also provide insights into *key conditions* for successful co-management as well as key attributes for inclusion in future monitoring programmes (Section 2.1).

In spite of widespread promotion and adoption of co-management few attempts have been made to develop an effective interdisciplinary statistical methodology to construct these types of models. Those documented in the literature have been generally been over-simplistic, running the risk of not identifying the correct set of attributes determining management success, and at worse, fundamentally flawed.

1.3 Project Purpose

The purpose of the project was to develop and promote a robust statistical methodology employing simple multidisciplinary measures and indicators of co-management strategies and arrangements (attributes) and outcomes to build empirical models of co-management performance and thereby to support adaptive co-management in capture fisheries important to poor people. By developing the methodology using data generated from case studies, it was also anticipated that key conditions for successful co-management, as well as key attributes for inclusion in future monitoring programmes, could be also be identified. Given the wide geographical range and different ecosystem focus of the case studies, the models presented in this report are anticipated to be quite general in nature. However, the guidelines for model development can be employed to construct other performance models specific to countries, regions or fisheries where variation will be restricted to a fewer number of attributes allowing specific recommendations to be made and tested. The outputs were sought through a number of planned activities (Figure 1.1).

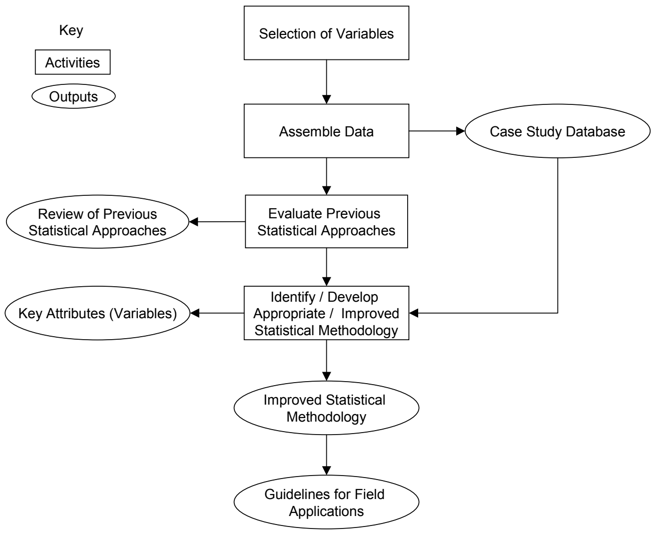

Figure 1.1 Project Activities and Outputs

1.4 Research Activities

The project activities focused upon (i) generating a trial dataset to develop the statistical methods by first identifying appropriate model variables (Chapters 3) and then assigning values to them on the basis of case studies (Chapter 4), (ii) reviewing previous approaches (Chapter 5), and finally (iii) developing improved methods (Chapter 6) and guidelines for their field applications (Chapter 7) using (i) and the findings from (ii).

1.4.1 Selection of Model Variables

Using the Institutional Analysis and Design (IAD) framework as a theoretical basis, 258 variables describing the interdisciplinary (resource, technical, socio-economic and political) attributes and performance of (co-)managed artisanal fisheries were defined on the basis literature reviews, previous studies, field manuals and after considerable discussion and debate with project collaborators and invited co-management experts during overseas workshops (Chapter 3). The variables were described with multiple measurement scales (continuous, ordinal and nominal) reflecting their multi-disciplinary nature. The large number of variables reflected the need to provide alternative indicators to describe a range of different fishery types, ecosystems, management institutions and interventions, and economic and political environments. The number of relevant variables is likely to decline as the focus of analysis moves from an international to a national or local scale (specific fisheries). Hypotheses concerning co-management performance generated at the same workshops were used to identify subsets of explanatory and response variables with which to construct the models.

1.4.2 Generation of Example Data Set

Data for these 258 variables were assembled from the various sources, including DFID-funded projects, for 119 management units (observations of artisanal (co-)managed fisheries) from 13 different countries across Africa, Asia and Melanesia. A fully documented Access 97 relational database was developed to store, process and retrieve these data for model development purposes (Chapter 4).

1.4.3 Evaluation of Previous Statistical Approaches

Quantitative multivariate approaches to evaluate the sustainability of fisheries in an interdisciplinary manner or to identify factors contributing to successful co-management were reviewed in preparation for the development of the alternative and arguably more appropriate methodological approaches described below (Chapter 5).

The review found that previous approaches have generally been over-simplistic, running the risk of not identifying the correct set of attributes determining management success. A lack of awareness of the capabilities of more appropriate statistical methods ie general linear models, was also apparent. The ‘Rapfish’ approach described by Pitcher (1999) and others including Preikshot & Pauly (1998) and Pitcher et al (1998) suffers the most from a series of serious shortcomings from a statistical point of view to the extent of raising doubt over the value or meaning of any of the results generated by the approach. These shortcomings are particularly alarming given the degree funding, promotion and exposure this technique has continued to receive since 1998 in the form of numerous publications, United Nations funding for its development, and the creation of a ‘Rapfish Research Group’ at the UBC which hosts a dedicated website and offers training courses in the methodology.

1.4.4 Development of Improved Statistical Analysis

Drawing on the findings of the review described above, the merits of alternative potentially appropriate methodological approaches were appraised including *proportional odds* and *multi-level* models. It was concluded that *General Linear Models* (GLM) and *Bayesian Network* (BN) models (supported by logistic regression and log-linear modelling techniques) offer the most scope for constructing models of co-management performance given the objectives of the study, the data structure and the types of outcome variable being modeled. Cluster analysis and PCA with biplots were identified as being particularly useful dimension-reduction methods during the initial stages of analysis, prior to the application of these two methods (Chapter 6).

1.4.5 Identification of Important (Key) Attributes

Both methods were applied to the trial dataset described above to: (i) demonstrate the application, and examine the utility, of the two methodologies, (ii) identify key attributes affecting management performance, and (iii) identify important attributes for inclusion in future monitoring programmes.

1.4.6 Guidelines for Field Applications

Whilst not a planned activity, general guidelines for field applications of these two methods were also developed providing practical advice on identifying sampling units, data collection, levels, and cleaning, exploratory analysis, data analysis and missing data (Chapter 7).

1.5 Outputs

1.5.1 Development of Improved Statistical Analysis

The project succeeded in delivering its main output. Having considered a number of possible modelling strategies, two improved and complementary approaches for the analysis of data in support of adaptive co-management have been identified and developed. These are:

- GLM regression modelling for identifying and assessing the effects of key attributes on outcomes – a tool for statistical inference;
- Bayesian network modelling for describing complex patterns of causality between several variables thereby serving as a management (rather than a statistical inference) tool, or expert system, for diagnosing strengths and weaknesses among co-management units and for exploring ‘what if’ scenarios.

The choice of these two methods reflects the (i) structure in the data, (ii) manner in which the data were obtained, (iii) nature of the variables, continuous, categorical, ordinal, etc., and (iv) distinction between what are sometimes called “hard” (eg counts of observable phenomena) and “soft” (eg indicators of perception or opinion) data.

To a large extent GLM models accommodate mixed data types, at least in the set of explanatory variables. “Soft” data in the form of categorised attitudes or perceptions may be easily incorporated as *explanatory* variables in GLMs provided that the ordinal nature of the categories is ignored. It would, however, be easier if these variables took the form of scores, preferably derived from a composite-scoring scheme as described in Section 7.5.2. However, the appropriate regression method for modelling categorical *response* variables is log-linear models or logistic regression. These methods have been proposed for helping construct BN models that are particularly well suited to dealing with these types of variables typical of “soft” data.

Although GLM provides a powerful statistical procedure for testing and measuring the main effects and *interaction* of explanatory variables in the way they affect the response, the joint effect of the explanatory variables is modelled *directly* on the response. That is, they offer no scope for modeling more complex, intermediate pathways of causality.

Perhaps the most important feature of BN's, and hence their particular suitability and complementarity for this application, is their ability to model, in a very visual and interactive manner, these more complex and intermediate pathways of causality which appear so very intrinsic to the IAD and Sustainable Livelihoods frameworks where the roles of response and explanatory become "blurred" by complex human behaviour. Their ability to "learn" also makes BN's particularly appealing for adaptive management applications.

1.5.2 Important Co-Management Attributes

Although the emphasis in this project has been on exploring and comparing different methodological approaches, it was hoped that the application of the methods described above to the "trial" dataset would reveal important factors determining (co-)management success, and help identify important variables for inclusion in future monitoring programmes.

1.5.2.1 Management Success Factors

The project had planned to identify key attributes for management success associated with all management outcome variables contained in the dataset. However, for the reasons described, identification of these factors was restricted to those associated with the six important management outcomes selected. For the GLM modelling these were important 'hard' response variables: Production measured in terms of catch per unit area (CPUA), sustainability measured in terms of catch per unit effort (CPUE), and community well-being measured in terms of average annual household income per year. For the BN modeling these were important 'soft' response variables: equity, compliance with rules and regulations, and perceived changes in CPUE (Section 6.4).

For CPUA, ten attributes were found to have an important influence on CPUA. Ecosystem and fishing intensity (fisher density) were unsurprisingly important in 5 out of the 7 models fitted. Other key factors included primary production, the types of gears employed, the use of destructive fishing practices, bans on fish drives, landing size restrictions, numbers of reserves, the type of management, and the presence of access restrictions. For example, a fishery with a high level of primary production is likely to have a CPUA that is 20 t km^{-2} yr^{-1} higher than a fishery with low primary production. The use of liftnets, bagnets, castnets, or seines can give 16 t km^{-2} yr^{-1} higher CPUA compared to using gillnets. Banning destructive fishing practices or banning fish drives can increase CPUA by about 20 t km^{-2} yr^{-1}. Landing size restrictions, co-management (as opposed to government management) or a local management decision-making body can improve CPUA by 15 t km^{-2} yr^{-1}. CPUA is generally also higher in restricted compared to open access fisheries. Too many reserves are predicted to depress CPUA (Section 6.4).

For CPUE, ecosystem, gear and management type, gear and access restrictions, and fisher density were also found to be important in addition to: fishing purpose, existence of management plans, effective control and surveillance measures and conflict resolution mechanisms, and incidence of poaching. Fisher density was by far the most important explanatory variable explaining 88% of the variation in CPUE with ecosystem type.

No reliable models of household income could be constructed, possibly reflecting low precision and accuracy in the estimates of household income. Because of their sensitivity to data from a few observations, several potentially good models had to be discarded. It is therefore likely that with more information, many other attributes may emerge as being important, while some of the attributes identified in our analysis as important, may well become redundant.

Further examination of the relationship between CPUA and fisher density using an expanded dataset provided estimates of optimal fisher density and maximum sustainable yield by major ecosystem type (Section 6.5). Estimates of fisher density coinciding with maximum sustainable yields are as follows:

Floodplain River Fisheries:	12 fishers km^{-2} (95% CI [9, 17])
African Lakes:	11 fishers km^{-2} (95% CI [8, 16])
Asian Lakes:	78 fishers km^{-2} (95% CI [40, 223])

These estimates provide a useful starting point for iteratively refining adaptive management strategies aimed at maximising yield through effort restrictions.

The results from the Bayesian network model suggest that the main factors affecting equity were (in order of the strength of their effects) effective conflict resolution mechanisms, numbers of gears employed in the fishery, fisher representation in rule making, management type and democratically elected decision-making body (Section 6.6). The attributes influencing CPUE change were found to be effective control and surveillance, fisher representation, fisher density, management type and democratically elected decision-making body. Those affecting compliance were found to be effective control and surveillance, fisher representation, clear access rights, management type and democratically elected decision-making body. This last result should be regarded as tentative pending further investigation of attributes affecting compliance by means of another BN model focusing on this outcome. These results should be seen as indicative of the kind of finding that is possible with this approach rather than definitive results that are generally valid.

Further development and application of the proposed methods will be more fruitful in a more limited domain, fisheries of a particular management type in a particular region, for instance. This is not the only scenario for application of these methods, however. With sufficient data, and proper sampling procedures, it would be possible to use the GLM approach to make comparisons between different domains (regions or ecosystems for example). On the other hand, the BN approach appears to be best suited to developing models on the basis of comparisons within such domains.

1.5.2.2 *Variables for Inclusion in Future Monitoring Programmes*

Because of the tentative and 'global' nature of these analyses it is difficult to prescribe a definitive list of attributes for inclusion in future monitoring programmes to support more local scale (practical) field applications. However, we recommend that the attributes identified above be included. Consideration should also be given to excluding those variables found to be redundant or unhelpful for a variety of reasons (Annex VI of the report). Selecting additional variables from those remaining in Annex II should be undertaken judiciously taking into consideration available resources and local conditions. Other, alternative variables should also be considered (See Section 7.5).

1.5.3 Data Collection and Analysis Guidelines

Whilst not a planned output, guidelines for field applications of the two modeling approaches have been included in Chapter 7. Sections provide practical advice on identifying sampling units, variables to include in future monitoring and evaluation programmes, levels of data, cleaning data, exploratory analysis including dimension reduction, data analysis including guidance notes on minimum sample sizes for both methods, missing data, sensitivity analysis and updating models as new data become available.

1.5.4 Other Project Outputs

The list of variables in Annex II represents an attempt to develop a standardised and internationally agreed set of variables for describing interdisciplinary attributes and performance of (co-)managed artisanal fisheries. This list is regarded an important resource for designing future fisheries (co-)management performance monitoring and evaluation programmes.

The database contains almost 20,000 items of data relating to these variables and, whilst "patchy" in places, is a significant project output that will be made freely available at the FMSP website: http://www.fmsp.org.uk where it may be periodically updated as further data becomes available.

Whilst not originally defined as a planned output at the PM stage, the review of previous statistical approaches (Chapter 5) is also regarded as an important output given the significance of its findings, particularly with respect to the *Rapfish* technique. A draft paper has been prepared on the basis of this review that will be submitted for publication shortly.

1.6 Contribution of Outputs

1.6.1 Contribution of Outputs Towards DFID Development Goals

This project has developed improved statistical approaches for modeling the (co)-management performance of artisanal fisheries accompanied by practical guidelines for field applications. Models of (co-)management performance developed with these approaches can be used to elicit important factors contributing to management success, make predictions, and in the case of BNs also explore 'what if' scenarios. This knowledge can be fed back to local communities or management decision-making bodies to help accelerate the achievement of goals and objectives in an adaptive manner. The development of these approaches and guidelines therefore provide a direct means of developing "….improved strategies and plans for the management of capture fisheries important to poor people" (RNRKS FMSP Purpose 1).

The GLM is a very well developed technique and provides a powerful means of describing the more quantitative ("hard data") response elements of these management systems to a good degree of approximation. The application of the BN approach is, however, a particularly significant contribution to this goal given its ability to model, in a very visual and interactive manner, complex and intermediate pathways of causality between explanatory and "soft" response variables which appear so very intrinsic and relevant to the IAD and SL frameworks. Their ability to learn, as more cases (evidence) become available, is also a particularly relevant feature for adaptive management applications. Managers can be readily trained in the skills needed for constructing network models, and the Netica software used for this project is very user-friendly. It is also inexpensive and a free version can be downloaded from the world-wide web and so is suitable for use in low-budget situations.

Example Application

The following example illustrates how the proposed statistical approaches might typically be employed:

A DFID-funded project lead by a research institution or fisheries department (an advisory body), is seeking to provide technical support for the co-management of 30 local, small-scale fisheries, each comprising a well-defined community exploiting a discrete resource such as a small lake or section of a river channel. Each co-management community currently employs a number of different interventions eg reserves, gear bans, landing size restrictions, closed areas / seasons…etc, often in combination, to manage their resources which are exploited at different intensities. Management decision-making arrangements and measures to monitor, control and enforce rules also vary among the communities, as do the outcomes (performance) of their management efforts. In response to consultation with the fishing communities, the advisory body has been asked to provide advice on what measures could be taken to improve yields and the equitable distribution of related benefits.

Using the 'Recommendations for Field Applications' described in Section 7.5, and in consultation with the communities, the advisory body selects and scores a sub-set of relevant variables through observations and interview based-methods for each of the 30 co-managed fisheries.

Using these data, models of yield (eg catch per unit area) are developed by the advisory body using the GLM approach described in Chapter 6. Alternative yield models may be fitted depending on the range of different interventions employed by the communities and other factors affecting production eg levels of fishing intensity and primary production.

Using these models, the effects of new, or changes to existing, interventions on yield are explored with each community interactively, taking account of uncontrollable factors such as primary production or fishing effort, but also beliefs, preferences and capacity, to help the community decide upon the best course of action.

Using the guidelines presented in Sections 6.6 and 7.5, the advisory body also constructs a BN to examine how important management decision-making factors, measures and community attributes (and their interaction), affect relative equity among the communities. Through interactive visual demonstrations using the Netica software, advice, *tailored* according to their *existing* management arrangements, is offered to each community to improve equity. For example, depending upon the existing numbers of gears employed, and the extent of conflict resolution capacity, it may be demonstrated that equity within particular co-management community could be increased if fisher representation in rule making was improved.

These models may be updated annually or until changes in performance following the adoption of management advice become marginal or no longer cost-effective. The same process may be applied to provide advice to improve other management outcomes such as biodiversity, compliance or conflict.

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No doubt there is considerable scope for applying BN approaches to management performance evaluation in other sectors such as agriculture or forestry, particularly when the mode of analysis is pursued from a sustainable livelihoods framework perspective.

The case study database and hypothesis matrix is an important reference resource for developing further knowledge and understanding about co-managed fisheries. In addition, the results from the analyses of subsets of these data have identified a number of attributes globally important in determining productivity, sustainability, equity and compliance, and provided some useful guidance for identifying potentially (non-) relevant variables for future monitoring programmes.

1.6.2 Promotion of Outputs

Distribution of FTR and Database

In addition to those required to satisfy DFID's contractual reporting requirements, it is intended, at least in the first instance, to also send copies of the FTR and Database to the following (other copies will be made available on request):

RRAG, Imperial College
CEMARE, University of Plymouth
ICLARM, Malaysia and Bangladesh
IFM, Denmark
FAO, Rome
DoF, Bangladesh
Fourth Fisheries Project, Bangladesh
Lake Uganda Project, DFID
SADC FIMS Project
Project collaborators and workshop participants, and other workers acknowledged in the FTR.

Publications

No Papers have yet been accepted for publication from this report. The following papers are, at this time, in preparation:

Abeyasekera, S., Burn, R.W., & Halls, A.S. Factors contributing to sustainable fisheries and their successful co-management – a review of multivariate statistical applications. To be submitted to *Canadian Journal of Fisheries and Aquatic Sciences*.

Abeyasekera, S., Halls, A.S., & Burn, R.W. Factors contributing to yield and sustainability in artisanal fisheries – a comparative analysis. To be submitted to *Fisheries Research.*

Burn, R.W., Halls, A.S. & Abeyasekera, S. Factors contributing to successful management of artisanal fisheries – a comparative approach using Bayesian network models. To be submitted to *Canadian Journal of Fisheries and Aquatic Sciences*.

Burn, R.W., Halls, A.S. & Abeyasekera, S. The utility of Bayesian network models for aiding fisheries management decision-making. To be submitted to *The Statistician.*

Dissemination Seminars

A seminar describing the application of Bayesian network models in support fisheries management decision-making was presented at the Statistical Services Center, Reading University on 17th January 2002. A very positive response was received. Further seminar presentations at RRAG and other research groups/institutions are planned.

Websites
Both the FTR and the case study database will be made available on the FMSP and ICLARM Co-Management Website.

1.6.3 Recommended Follow-Up Research

Phase I of this process project has successfully delivered all planned outputs. Opportunities for rigorous validation of the proposed models and approaches were, however, severely limited by the problem of missing data. We therefore recommend that field applications be undertaken under Phase II as described in the project memorandum alongside the previous approaches (excluding RAPFISH) to further assess their relative validity, utility and performance.

Participating projects (and sources of funding) have yet to be identified but potentially include the initiatives running under the ongoing ICLARM/IFM 'Fisheries Co-Management Research Project' in Asia and Africa or the FAO/DFID 'Sustainable Fisheries Livelihoods (SFL) Programme in West Africa. In Bangladesh, they might include the fish sanctuary (harvest reserve) component of the DFID-funded Fourth Fisheries Project involving up to 50 local fishing communities, and Phase III of the CBFM project.

It is recommended that data collection protocols be developed with collaborating project partners and incorporated into monitoring and evaluations programmes to ensure data homogeneity among the units of observation. Collaboration at an early stage of these projects would therefore be required.

The realisation of improved outcomes following the adoption of management recommendations generated from the application of the methodology will depend upon the response time of the institutions involved and resources exploited. It is therefore recommended that Phase II be undertaken with stakeholders and institutions who (i) are willing to adopt an adaptive approach to management, (ii) are able to respond to feedback generated from analyses, and (iii) are exploiting short-lived, fast growing resources where the evidence of improved outcomes may be detectable within one or two years, thereby providing the opportunity to demonstrate the utility of the proposed methods during the typical duration of most donor-funded pilot studies.

2. Background

2.1 Introduction

Artisanal fisheries are fundamentally important in the developing world. It is estimated that between 14-20 million people depend upon these fisheries for their livelihoods, and about 1 billion rely on them for their main source of animal protein (Pomeroy & Williams 1994). At the same time, they are also very complex from resource, technical and institutional perspectives. They are typically characterised by multispecies assemblages exploited with numerous different gear types from diverse habitats under a variety of different institutional and decision-making arrangements by heterogenous users pursuing multiple livelihoods. Livelihood outcomes based around these fisheries are often further complicated by dynamic spatial and temporal variations in these characteristics under the wider political and natural environments.

Until recently, artisanal fisheries management has tended to focus mainly upon resource orientated objectives pursued using a suite of technical *operational rules* or regulations set and enforced by a centralised (government) administrative authority. By largely ignoring important (dynamic) elements of *livelihood assets, strategies, transforming structures, processes,* the *external environment*, and other factors that affect fisher behaviour and livelihood outcomes, this paradigm has often failed to coordinate and restrain resource users, leading to depleted resources, inequity and conflict (Mahon 1997; Pomeroy & Williams 1994). This paradigm failure is prevalent in the developing world; commonly exacerbated by the state's paucity of resources and institutional capacity to conduct (and interpret) formal assessments, and monitor and enforce rules and regulations among the widely dispersed resource users. Moreover, the technical management models employed to guide decision-making processes are often inadequate to capture the dynamic complexity of the fisheries.

Co-management, where an idealised balance of management roles and responsibilities are shared between the government and user groups, is increasingly regarded as an effective strategy to redress these paradigm failures and thereby facilitate improved sustainable livelihoods (Pomeroy & Berkes, 1997), particularly when undertaken in an adaptive manner (Hoggarth *et al* 1999). A huge literature has evolved reviewing past experiences and the benefits and prospects for co-management in agriculture, fisheries and forestry. Frequently cited advantages of co-management include:

- Increased sense of ownership encouraging more responsible exploitation.
- Policy and practice are sensitive to local socio-economic and ecological constraints;
- Appropriate and relevant policy is honed by local knowledge and expertise;
- Participation in decision making engenders a collective ownership ethic;
- Increased compliance through perceived legitimacy and local peer pressure; and
- Greater incentives for reliable monitoring via the user.

Halls *et al* (2000) describe the economic rationale for co-management and Sen & Nielson (1996) provide a useful typology of co-management based on the level and mode of communication between government and the resource user.

2.1.1 Designing and Refining Co-Management Strategies and Arrangements

Designing and refining strategies and arrangements to improve performance or to achieve specific management objectives are fundamental co-management activities. The holistic perspective from which co-management theory evolved naturally demands that decision-making with respect to these activities takes account of not only the resource and the technology or capital used to exploit it, but also the institutional arrangements and other external factors that affect fisher behaviour – a key factor affecting many management outcomes or objectives. Therefore, decision-making with respect to ‘intermediate’ outcomes such as compliance or social cohesion also becomes important to examine given their influence over more ‘terminal’ outcomes such as production or conflicts. Co-management decision-making is therefore inherently complex. Consideration must be given to numerous important outcomes, and interdisciplinary variables (or attributes) and their interactions.

2.1.2 Decision-Making Approaches

Three main categories of approaches to guide management decision-making may be identified:

- Customs, traditions or beliefs, taboos…etc (typical of traditional management).
- Adaptive management.
- Formal mechanistic (deterministic or stochastic) or empirical models with their associated reference points (see Caddy & Mahon 1997).

The approach employed will be largely influenced by the institutional capacity, resources, preferences and traditions of the decision-making body (Halls *et al* 2000).

Co-management arrangements often develop or exist between government decision-making bodies (eg Department of Fisheries) and Local Decision-Making Bodies (LDMBs) or (institutions) comprising single or groups of villages – Village Management Unit (VMU) and Intermediate Management Unit (IMU), respectively. Local decision-making bodies typically do not employ formal modelling approaches to support their management decision-making because the associated institutional capacity and resources demands are significant. Local decision-making bodies are more likely to employ informal monitoring programmes and an adaptive or traditional approach to management. Self-monitoring and evaluation programmes of this type are encouraged at the local level (Hoggarth *et al* 1999). Participation allows users to see for themselves the impact of their management strategy and will be more likely to believe the results if they are involved in the collection of (informal) data or observations.

2.1.3 Adaptive Management

An adaptive or iterative approach to developing and refining management strategies and arrangements is often employed where resources and institutional capacity are scare, or where mechanistic models are likely to fail because of inherent complexities and uncertainties. Adaptive management is therefore well suited to co-managed artisanal fisheries.

The *passive* approach to this style of management (i) monitors and evaluates the outcome of management interventions and arrangements (ii) compares the outcomes with those made in previous times; and thus (iii) refines the strategy and arrangements to improve outcomes (Figure 2.1). However, when conducted at the individual VMU or IMU level, this passive approach may "…cause the system to be locked in a narrow range of behaviour without any data ever being gathered to help decide whether the optimum is in fact within this range" (Hilborn & Walters 1992, p489).

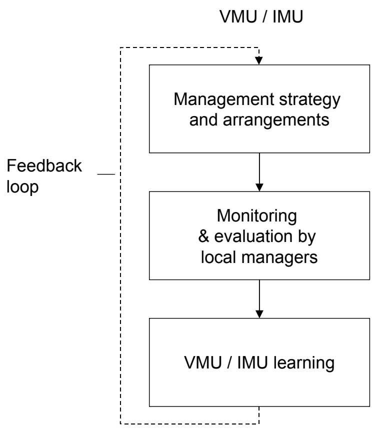

Figure 2.1 Passive adaptive management at VMU or IMU level.

Evolutionary adaptive management attempts to overcome this problem by trying a variety of strategies and arrangements, often at random, in order to accumulate experience about which ones might be best. However, whilst this approach is more likely to identify the best strategy and arrangements compared to the passive approach, it tends to be wasteful and can take many years when undertaken in isolation at the VMU or IMU level.

2.1.4 Help from Higher Level Decision-Makers and Research Institutions

By comparing and analysing the outcomes of a contrasting array of different management strategies and institutional arrangements adopted by individual VMUs or IMUs, formal models of co-management performance can be rapidly developed by institutions such as fisheries departments or research institutes and organisations with the necessary resources and institutional capacity. These models can then be used to *accelerate* the evolutionary adaptive management approach employed at the local VMU or IMU level thereby supporting a more *active* and less wasteful adaptive management approach (Figure 2.2). On the basis of these models, it should also be possible to identify *key conditions* for successful co-management as well as key attributes for inclusion in future monitoring programmes.

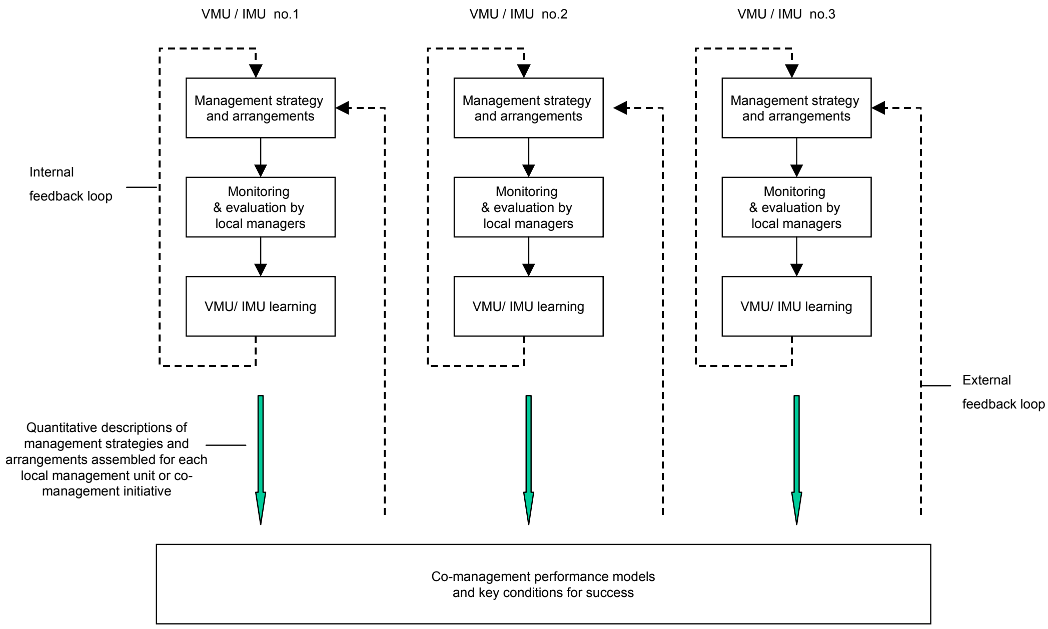

Figure 2.2 Schematic diagram illustrating how formal performance models and the identification of key conditions and attributes can be used to accelerate *passive* or *evolutionary* adaptive management.

Despite the increasingly widespread adoption of adaptive co-management practices by many countries throughout both the developing and developed worlds, few attempts have been made to develop an effective interdisciplinary statistical methodology or formal models to support this strategy. All these attempts either perform poorly, are statistically inadequate, or, in the worst cases, invalid (see Chapter 5).

Much of the co-management research has focussed upon a qualitative case study approach to learning. Pollnac (1994; 1998) however, has long recognised the limitations of management learning based upon qualitative case studies alone: “Numerous attempts have been made to summarise case studies, fitting them to general theoretical frameworks from the social sciences; nevertheless, decision makers are still faced with a bewildering array of allegedly crucial factors, with no way of evaluating their relative importance or interrelationships. It is clear that systematic, quantitative research is needed to provide a solution to this problem” (Pollnac 1998 pages 5-6).

2.2 Project Purpose and Demand

The purpose of the project is to develop and promote a robust statistical methodology employing simple multidisciplinary measures and indicators of co-management strategies and arrangements (attributes) and outcomes to build empirical models of co-management performance and thereby to support adaptive co-management in capture fisheries important to poor people. By developing the methodology using data generated from case studies, also identify generic *key conditions* for successful co-management as well as key attributes for inclusion in future monitoring programmes, and disseminate the new knowledge to national and international organisations. Given the wide geographical range of the case studies from which data were assembled to develop the methodology and models, the co-management performance models presented in this report are anticipated to be quite general in nature. However, the guidelines for model development can be employed to construct other performance models specific to countries, regions or fisheries where variation will be restricted to a fewer number of attributes allowing specific recommendations to be made and tested. The project is expected to achieve step D on DFID's A-H scale of project impact assessment.

A planned second Phase II (if funded) will field-test the utility, validity and performance of the methodology and model outputs with on-going co-management projects. The on-going projects have yet to be identified but could potentially include the initiatives running under the ongoing ICLARM/IFM 'Fisheries Co-Management Research Project' in Asia and Africa or the FAO/DFID 'Sustainable Fisheries Livelihoods (SFL) Programme in West Africa. In Bangladesh, they might include the fish sanctuary (harvest reserve) component of the DFID-funded Fourth Fisheries Project involving up to 50 local fishing communities; and Phase III of the CBFM project.

ICLARM and IFM have indicated considerable interest in such a methodology to support their research in Asia and Africa. Staff at research groups, including (i) the Renewable Resources Assessment Group (RRAG), University of London; (ii) Centre for Development Studies, University of East Anglia; and (iii) the Centre for the Economics and Management of Aquatic Resources (CEMARE) have also indicated an interest in the methodology.

2.3 Research Approach and Activities

The project purpose and outputs were pursued on the basis of a combination of literature reviews, advice from experts, participatory workshops in South Africa and Malaysia and statistical analysis and modelling techniques in support of six main research activities:

(i) Participatory workshops in Asia and Africa involving project collaborators, research partners and invited experts to identify and agree upon a comprehensive range of multidisciplinary measures and indicators to quantitatively describe (co-)management performance (outcomes) and factors that have the potential to affect these outcomes. During the same participatory workshops, formulate hypotheses concerning which subsets of these factors are most likely to affect management performance.

(ii) 'Profile' case studies of (co-)management using the measures and indicators developed during the participatory workshops.

(iii) Review previous statistical approaches employed for interdisciplinary performance evaluations and models of co-managed fisheries and initiatives. Identify an appropriate approach and methodology.

(iv) Develop performance models of co-management using the methodology identified from (iii) and the dataset generated from (ii).

(v) Based on the results of (iv), identify key conditions for successful co-management and key attributes for inclusion in future monitoring programmes.

(vi) Disseminate and promote the results of the project.

2.4 Institutional Collaborations

With a central project base at the Marine Resources Assessment Group, London, UK, formal collaborations were established with the International Centre for Aquatic Living Resources Management (ICLARM), Malaysia; The Institute for Fisheries Management (IFM), Denmark; and The Statistical Services Centre (SSC), Reading University, UK. Informal collaboration was also established with the research partners of the ICLARM/IFM 'Fisheries Co-management Research Project' (FCMRP). Experts from other institutions, including Ian Baird from the Laos 'Community-Based Fisheries Co-Management and Protected Areas Management Project' also attended the participatory workshop held in South Africa.

2.5 Report Structure

This final technical report comprises seven chapters, seven annexes and an electronic database. Chapter 1 of the report provides a brief summary of the work, in the format required by DFID for Final Technical Reports. This Chapter 2 provides the background and rationale for the study and an overview of the research approach and activities, including details of institutional collaborations, personnel and authorship of this report. Chapter 3 then introduces the research frameworks that provided the theoretical basis for identifying important groups of variables (*attributes*), and their interactions, that are likely to affect management performance or outcomes. This chapter also describes the approaches used to identify and select appropriate indicators and measures to quantitatively describe these attributes and outcomes, and to formulate hypotheses concerning (co-)management performance. Chapter 4 provides details of the case studies used to generate data to develop the statistical methodology and performance models, including the electronic database used for storing and processing these data. Chapter 5 reviews, compares and evaluates previous statistical approaches employed for interdisciplinary performance evaluations of (co-)managed fisheries and initiatives, and related model development. Proposals for improved approaches and methods are made. Using the assembled case study data described in Chapter 5, these proposals are adopted in Chapter 6 to develop performance models of co-management, and to identify key: (i) conditions for successful management, and (ii) attributes for inclusion in monitoring programmes. Two complementary approaches are recommended: (i) General Linear Models (GLM) and (ii) Bayesian network models fitted using logistic and log-linear modeling techniques. The final Chapter 7 draws conclusions about the two methods, provides guidelines for field applications and makes recommendations for further research.

2.6 Personnel, Authorship and Acknowledgements

2.6.1 Personnel

This research was undertaken by the following personnel:

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Dr Kuperan Viswanathan (Project Leader, FCMRP)

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Mr Robert Burn (Principal Statistician)
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Institute for Fisheries Management (IFM), Hirtshals, Denmark
Dr Jesper Raakjaer Nielsen (Fisheries Economist)
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Ms Alexandretta Philomena, CASS, University of Zimbabwe, Zimbabwe
Mr Godfrey Milindi, Fisheries Research Division, Zambia
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2.6.2 Acknowledgements

MRAG would like to thank ICLARM, IFM and their national research partners for their collaboration. Thanks to Jim Anderson for his help and advice during the planning stages of this project including the provision and preparation of data for Melanesia, and to Ian Baird for his invaluable insights and contributions at the Cape Town workshops. The project team is grateful to Kuperan Viswanathan and Mafaniso Hara for hosting and organising the workshops and Penang and Cape Town, respectively. We would also like to thank the following for contributing data, insights and advice:

Dr Paul Thompson and colleagues from ICLARM
Dr Upali Amarasinghe, Department of Zoology, University of Kelaniya, Sri Lanka
Dr Robin Welcomme, RRAG, Imperial College, University of London
Dr Paul Dalzell, NOAA

We are also very grateful to David Preikshot for supplying a set of data used in his PhD thesis that assisted our evaluation of previous methodologies described in Chapter 5.

2.6.3 Authorship

This Final Technical Report was written by Dr Ashley Halls, Mr Robert Burn and Dr Savitri Abeyasekera. The last two authors were principally responsible for Chapters 5, 6 (except 6.5) and 7. The content of this FTR does, however, reflect the work of all the personnel listed in Section 2.6.1.

3. Selection of Variables and Hypothesis formulation

3.1 Introduction

The construction of useful and meaningful models of management performance requires a sound theoretical basis or analytical framework from which to begin. Employing such frameworks ensures that full account is taken of all the relevant explanatory variables, factors and their interactions that have the potential to affect (co-)management performance.

This chapter describes the theoretical framework employed to identify these variables and factors, and formulate hypotheses to construct the models of (co-)management performance described in Chapter 6. It also gives details of the measures and indicators selected to describe the variables.

3.1.1 Research Frameworks

A particularly useful and well established framework for studying common pool resource (e.g. fisheries) systems and their management is the Institutional Analysis and Design (IAD) framework (Figure 3.1) developed by the Workshop in Political Theory and Policy Analysis at Indian University, USA.

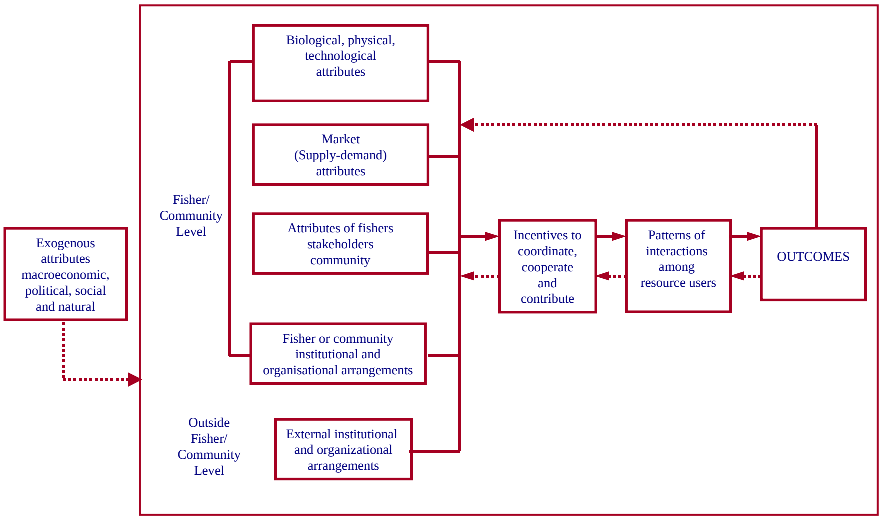


Figure 3.1 The ICLARM/IFM 'Institutional Analysis and Design Research Framework' (source: ICLARM 1998; adapted from Oakerson, 1992)

This framework has theoretical foundations on game theory, neoclassical microeconomics, institutional and transaction cost economics, political economy and public choice. The framework has been widely employed in the fisheries sector as a generic tool for documenting, evaluating and comparing artisanal fisheries management arrangements and co-management performance. It can also be used to design modified or new co-management institutions (Berkes 1992; Nielsen *et al.* 1995); Pido *et al*. 1996). The IAD framework lies at the heart of ICLARM's 'Handbook for Rapid Appraisal of Fisheries Management Systems' (Pido et al 1996) and its ongoing ten year 'Fisheries Co-management Research Project'.

The framework emphasises the relationship between the contextual variables (eg physical, biological and technical attributes) of the resource system and the institutional setting (decision-making arrangements), how these affect patterns of interaction and incentives to cooperate and coordinate, and in turn, how this determines outcomes or management performance (Oakerson 1992; Nielsen *et al*. 1995). It therefore provides a sound basis for identifying relevant variables and outcomes, and formulating hypotheses concerning the relationships between them to construct models of (co-)management performance. Drawing heavily from ICLARM (1998) and Pido et al (1996), the framework identifies six main groups of contextual variables or attributes with the potential to affect management performance (outcomes). The biophysical attributes (Group I) relate to important determinants of the biological productivity and sustainability of fisheries. These include the status of habitats and exploited resources, and the exploitation methods and intensity. Market attributes (Group II) focus on factors affecting supply and demand, and those related to market operations and functions. Group III (Stakeholder) attributes include social, cultural and economic conditions and characteristics that affect stakeholders' (fishers, fish traders, processors…etc) incentives to cooperate and contribute to management. Fisher/community decision-making arrangements are described in Group IV. They define the institutional arrangements specifying who decides what in relation to whom and the rights of fishers in relation to the resource. This group also contains details of the operational rules or interventions employed to manage the resource including monitoring, control and evaluation systems. Group V is composed of the attributes of the institutional and organisational arrangements external to the community at the national, regional or district levels relating to policy, legislation and institutional support. Finally, the Group VI covers external factors beyond the control of decision-making bodies including shocks and trends that can increase vulnerability or threaten sustainability. The institutional arrangements structured by the contextual variables determine the incentives of users to cooperate, coordinate and contribute to resource management and use. The incentives shape the patterns of interaction that results when resource users select and implement management strategies. These interactions give rise to outcomes, which in turn, can affect other outcomes. For a more detailed treatment of the IAD framework theory see Ostrom (1990), Oakerson (1992) and Pido *et al* (1996).

3.1.2 Relationship to DFID's Sustainable Livelihoods (SL) Framework

The Institutional Analysis Research Framework described above shares similar theoretical foundations with DFID's Sustainable Livelihoods (SL) framework designed to improve understanding of livelihoods and poverty (Scoones, 1998; DFID 1999). Both frameworks emphasise the need for a holistic and interdisciplinary approach to analysis but their foci differ. The SL framework is primarily concerned with household decision-making and therefore deals poorly with the issue of resource substractability. The IAD framework with its institutional focus, is on the other hand, more capable of dealing with the collective impact of the actions of individual household on the resource (Aeron-Thomas pers. comms.). However, the SL framework does help to improve our understanding of individual household behaviour as well as emphasising other important management performance criteria and dimensions of poverty such as empowerment, well-being, food security…etc.

3.2 Variables and their Indicators

3.2.1 Identification

An extensive range of different explanatory variables belonging to the six main categories of variables (attributes) described above has been employed in previous studies of fisheries co-management and common pool resource management. The most commonly employed and apparently widely applicable variables were selected as a basis for discussion, augmentation and refinement with the research collaborators (see below). Many of these variables, including their assigned indicators and units of measurement, were compiled from those employed by ICLARM's FCMRP (Pomeroy et al 1997; 1998; ICLARM 1998; Katon et al 1997; 1999), the RAFMS Manual (Pido et al 1996), and ReefBase (Pollnac, 1998). Other sources included: Hill (1995); Nielsen et al (1995); Garaway (1998); MRAG (1998); Preikshot et al (1998); Preikshot & Pauly (1998); Sverdrup-Jensen & Nielsen (1999); Thompson et al (1999); World Bank (1999; 2000); Bunce et al (2000); Baird (1999; 2000). Several were selected to represent the key conditions (variables) or established criteria for developing and sustaining successful co-management or institutional arrangements identified or hypothesised from research conducted during the last two decades (Pomeroy & Williams 1994; Ostrom 1990) including:

- Clearly defined boundaries
- Membership is clearly defined
- Group Cohesion
- Benefits of participation must exceed costs

- Individuals affected by management arrangements are included in decision-making
- Management rules are enforceable by resource users
- Legal frameworks exist that give users ownership over resources and management authority
- Cooperation and leadership at the community level exist
- Decentralisation and delegation of authority
- Graduated Sanctions for non-compliance.
- Performance monitoring by local community.

Inclusion of these provided an opportunity to test the relative importance or rank of these key conditions. Outcome (performance) variables were also identified on the basis of commonly sought management objectives and desirable outcomes identified from DFID's Sustainable Livelihoods Approach (SLA).

3.2.2 Screening, Augmentation and Refinement of Variables and Indicators

A five-day workshop involving the project collaborators and their research partners from Mozambique, Zambia, Malawi, South Africa and Laos (see Section 2.6.1) was held at the University of Western Cape, Cape Town, South Africa, between 2nd and 8th March 2001. The principle objective was to bring together the project collaborators and other workers with considerable co-management experience to discuss and scrutinise the validity, applicability and utility of the assembled list of variables and their indicators (and measurement units), and to formulate and agree upon a final set for the model development. The eighteen participants represented a range of disciplines including sociology, anthropology, economics, statistics, criminology, and fisheries biology and management and were able to draw upon their co-management research experience gained in numerous locations including Africa, Malaysia, Vietnam, Laos, Thailand, Indonesia, Philippines, and Bangladesh. Unfortunately, due to budget constraints, representatives from DFID's Integrated Lake Management Project in Uganda could not attend. Through considerable discussion and debate, the participants agreed upon a comprehensive list that was subject to only minor revisions following the workshop. The revised list employed for the model development is presented in Annex II. Full details of all the variables including their measurement units are also included in the project database (Section 4.4).

3.2.3 The Variables and their Units of Measurement

The list contains a total of 258 dependent and explanatory variables and factors loosely assigned along the basis of the ICLARM's IAD framework approach described above (Annex II). This large number of variables reflects the need to provide alternative indicators to describe a range of different fishery types, ecosystems, management institutions and interventions, and economic and political environments. It also reflects the fact that many outcome variables can be measured using either *static* or *trend* measures. For example, catch per unit area (CPUA) can be measured either in terms of tonnes/km2 for any given year, or by the trend in CPUA measured on a three-point ordinal scale (0-2): declining (0); Static (1); or rising (3). Therefore the number of variables that are likely to be relevant declines as the focus of analysis moves from an international to a national or local scale (specific fisheries) and when outcomes are considered either on a static or trend basis. Many of the variables are likely to be superfluous, of little practical use or simply analogues of one another. Whilst Chapter 6 identifies some analogue and redundant variables, superfluous and impractical variables are likely to be study-dependent.

Table 3.1 Numbers of variables belonging to each attribute and outcome group.

	IAD Group	Name	Number of variables
Explanatory Variables	-	Key Identifiers	21
	Group I	Resource	27
		Environment	28
		Technology	22
	Group II	Market Attributes	9
	Group III	Fisher/Stakeholder/Community Characteristics	20
	Group IV	Decision-Making Arrangements	55
	Group V	External Decision-Making Arrangements	5
	Group VI	Exogenous Factors	7
Dependent Variables	Outcomes	Production / Yield	3
		Sustainability/ Biodiversity	12
		Well Being	20
		Institutional Performance	26
		Institutional Stability	3
	Total		258

3.2.4 Units of measurement

The variables are described with multiple measurement scales reflecting their multi-disciplinary nature. Wherever possible, continuous measurement scales (eg ratios) are used to describe variables. Often, however, this is not possible, particularly with respect to variables that require subjective assessment. In this case, ordinal scales are employed – typically on a three point, but sometimes on a ten point, scale. For example, the explanatory variable *representation in rule making* (Group IV) is measured as: Low (0); medium (1); high (2). Three point ordinal scales were preferred to five or ten point because it was not possible to score the attributes any more precisely from secondary data sources. Factors (for example gear type) are measured using nominal scales (eg bottom-set (0); pelagic (1); and surface-set (2)). Nominal (binary) scales are also common. All outcome variable *trends* are measured on the three point ordinal scale described in Section 3.2.3.

Many variables are currently ‘scored’ in a subjective manner with ordinal scales. Explicit guidance notes for scoring these variables need to be developed to make these subjective assessments more objective! Guidelines for this are given in Section 7.5.2. Because all the case-study variables employed in this project were either scored or checked by the Principle Investigator, the lack of such guidance notes should not have significant implications for the results presented here.

This list of variables and their measurement units is not definitive but can effectively illustrate the model development process. Changes can be made or subsets of variables selected according to local conditions, preferences, available resources or as new knowledge is gathered. It should also be borne in mind that the division of explanatory and dependent variables is not rigid or always obvious. For example, social cohesion can be regarded as both an important explanatory variable for say conflict, but might well also be regarded as an important outcome.

The list could be regarded as a first attempt to develop a standardised and internationally agreed *profiling template* for collecting information on artisanal fisheries and their (co-)management systems for performance analysis purposes. Interest in this template has already been expressed by ICLARM for monitoring and evaluating the success of their Community-Based Fisheries Management (CBFM) project in Bangladesh.

3.3 Identification of Model Variables - Formulation of Hypothesis Matrix

Whilst the IAD framework described in Section 3.1 provides a useful checklist of important sets of variables in relation to outcomes, it does not explicate cause-and-effect relationships between them nor interactions among variables. Models of co-management performance were instead hypothecated on the basis of the framework. This hypothesis formulation process involved identifying which sub-sets of variables are most likely to effect management outcomes. This process, undertaken by the Cape Town workshop delegates (see above), generated a hypothesis matrix (Table 3.2 below) as the main theoretical basis for the model development described in the Chapter 6. For each main outcome (performance criteria), the matrix indicates (with a ‘Y’) potentially important explanatory variables and factors. These may be regarded as the main effects in the models.

The codes (1-19), described at the bottom of the table, indicate indirect effects or interactions among the variables. For example, the outcome ‘Annual Production per unit area’ may be indirectly affected by the variable ‘Area under co-management’ through the variable ‘Compliance’ (Code 1) because effective control and surveillance will be more difficult to achieve over large areas.

Similar to the list of variables, whilst these hypotheses were formulated through discussion and negotiation, they are not regarded as definitive or exclusive, but rather a guide for model development. Workshops delegates found the process of hypothesis formulation both enlightening and thought provoking, and helped strengthen institutional capacity, particularly of the African Research Partners. Participants were encouraged to think very carefully about exactly what factors could affect management performance and therefore how existing monitoring and management strategies may need to be appropriately revised. This process also emphasised the importance of good data collection, management and analysis practices. Further details of the workshop are described in the Project’s Annual Report.

Table 3.2 Hypotheses Matrix

		OUTCOMES																					
Main Attributes	**Sub Attributes**	**Annual production per unit area**	**Number of species whose abundance is increasing**	**Sustainability (Resource)**	**Biodiversity**	**Habitat condition**	**Annual fishing revenue per unit area**	**Annual fishing (& marketing) costs per unit area**	**Annual fishing profit (income) per unit area**	**Average household income**	**Assets**	**Savings and investments**	**Well-being of households**	**Food security**	**Perceived benefits**	**Empowerment**	**Equity**	**Compliance with rules and regulations**	**Efficiency**	**Conflicts**	**Conflict resolution capacity**	**Social cohesion**	**Sustainability (Institutions)**
Key Identifiers	Co-management unit type	1	1	1	Y	Y								1			Y	Y	Y	Y			Y
	Area under co-management	1	1	1	Y	Y								1			Y	Y	Y	Y			Y
	Numbers of villages	Y	Y	Y	14	Y								1		Y	Y	Y	Y	Y		Y	Y
	Numbers of households	Y	Y	Y	14	Y								1		Y	Y	Y	Y	Y		Y	Y
	Numbers of fishers	Y	Y	Y	14	Y								1		Y	Y	Y	Y	Y		Y	Y
	Date established	Y	Y	Y	Y	Y								4		Y	4	Y	Y	Y			
	Geographic position	Y	Y	Y	Y	Y								5									
	District																						
	Seasonality of water body (Permenance)	Y	Y	Y	Y			Y	Y	Y	Y	Y	Y	Y			15	Y	Y	Y			
	Ecosystem type	Y	Y	Y	Y			Y	Y	Y	Y	Y	Y	Y			15	Y	Y	Y			Y
	Position of water body in catchment	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	5			15	Y	Y	Y			
	Remoteness of co-management unit	1	1	1	1	1		Y	Y	Y	Y	Y	Y	1			15	Y	Y				Y
Resource (Group I)	Production potential	Y	Y	Y										Y				2					
	Abundance/Biomass	Y	Y	Y				Y	Y	Y	Y	Y	Y	Y			16	Y	1	Y			
	Resiliance of resource	Y	Y	Y	Y									Y						2			
	Rule enforcement potential	1	1	1	1	1								1			Y	Y	Y	Y			Y
	Divisibility of resource	1	1	1	1			Y	Y	Y	Y	Y	Y	1			Y	Y	Y	Y			Y
	Target species	Y	Y	Y	Y			Y	Y	Y	Y	Y	Y	6			2	17		17			17
	Discarded by catch	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	7				2		Y			16
	Multi- or single species fishery	Y	Y	Y	Y			Y	Y	Y	Y	Y	Y	Y				Y	Y	Y			16
	Connectivity of management area	Y	Y	Y	Y			2	2	2	2	2	2	5			15	2		2			
	Non-use value of resource (eg existence, bequest..etc)	14	14	14	14	Y								7				Y	1				Y
Environment (Group I)	Environmental health of habitat	Y	Y	Y	Y	99		3	3	3	3	3	3	5				2		2			
	Nutrient recycling	Y	Y	Y	Y			3	3	3	3	3	3	5				2					
	Habitat descriptors / factors	Y	Y	Y	Y	Y		3	3	3	3	3	3	5				2		2			
Technological (Group I)	Exploitation intensity	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	5				2	Y	Y			
	Exploitation methods	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	5			Y	2	Y	Y			16
	Preservation facilities	14	14	14	14			Y	Y	Y	Y	Y	Y	5									
	Stocking density	Y	Y	Y				Y	Y	Y	Y	Y	Y	5				2	Y				
	Mean stocking size	Y	Y	Y				Y	Y	Y	Y	Y	Y	5				2	Y				
	Habitat alteration activities	Y	Y	Y	Y	Y		3	3	3	3	3	3	5			Y	2	Y	Y			16
	Fishery type	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y			Y	Y	Y	Y			16
Market Attributes (Group II)	Economic value of resource	14	14	14	14	14	Y		Y	Y	Y	Y	Y	Y				Y	1	14			Y
	Market facilities/infrastructure	14	14	14	14	14	Y	Y	Y	Y	Y	Y	Y	Y				17					17
	Cost of marketing (market fees)	14	14	14	14	14	Y	Y	Y	Y	Y	Y	Y	6				17		Y			17
	Are there restrictions or rules in fish trading	14	14	14	14	14	Y	Y	Y	Y	Y	Y	Y	Y				17		Y			
	Market type	14	14	14	14	14	Y	Y	Y	Y	Y	Y	Y	Y				17		Y			Y
	Market (demand) stability	14	14	14	14	14	Y		Y	Y	Y	Y	Y	Y				17		Y			Y
	Price control mechanism	14	14	14	14	14	Y	Y	Y	Y	Y	Y	Y	Y				Y		Y			17
	Market orientation	14	14	14	14	14	Y	Y	Y	Y	Y	Y	Y	Y				17		17			Y
Fisher/Stakeholder/ Community Characteristics (Group III)	Homogeneity of users	1	1	1	1	1								1			Y	Y	1	Y	Y	Y	16
	Social cohesion	1	1	1	1	1								1			Y	Y	1	Y	Y	99	Y
	Years resident in village/community	1	1	1	1	1								1			Y	Y	1	Y	Y	Y	
	Dependence on fishery for livelihood	Y	Y	Y	Y	Y								Y			Y	Y	1	Y	Y		Y
	Level of local (ecological) knowledge	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	5				Y	1	Y			Y
	Level of education			Y	Y	Y								1				Y	1		Y		Y
Decision-making Arrangements (Group IV)	Type of management	1	1	1	1	1								1		Y	Y	Y	Y	Y	Y	Y	Y
	Local decision-making body	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Origin of co-management initiative	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Legitimacy / widely accepted	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Respectability	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Traditional decision-making body?	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Stability of decision-making body	1	1	1	1	1								8		8	Y	Y	1	Y	Y	Y	Y
	Membership to decision-making body	1	1	1	1	1								9		Y	Y	Y	1	Y		Y	Y
	Clear access (property) rights	1	1	1	1	1								1			Y	Y	1	Y		Y	Y
	Access (open/restricted)	14	14	14	14	14								Y			Y	18	1	Y		Y	Y
	Access control mechanism	1	1	1	1	1		Y	Y	Y	Y	Y	Y	5			Y	Y	1	Y		Y	
	Resources available to body	Y	Y	8	Y	Y								10			Y	Y	Y	Y	Y		Y
	Self financing mechanism	8	8	8	8	8								10		8		Y	Y	8	8		Y
	Management plan	Y	Y	Y	Y	Y								5				Y	Y	Y	Y		Y
	Management objectives	Y	Y	Y	Y	Y								Y			Y	Y	Y	Y			Y
	Management measures (operational rules)	Y	Y	Y	Y	Y								5			Y	Y	Y	Y			
	Reserve area as a % of total management area	Y	Y	Y	Y	Y								5				Y	1	Y			
	Reserve type	Y	Y	Y	Y	Y								5				5	Y	Y			
	Reserve depth	Y	Y	Y	Y	Y								5				2	2	Y			
	Reserve location	Y	Y	Y	Y	Y								5				Y	1	Y			
	Numbers of reserves	Y	Y	Y	Y	Y								5				Y	1	Y			
	Period of existence of operational rules	Y	Y	Y	Y	Y								5					Y	Y	Y		
	Mechanisms for enforcement	1	1	1	1	1								1			Y	Y	1	Y			1
	Overall support for rules	1	1	1	1	1								1			Y	Y	1	Y	Y	Y	Y
	Representation in rule making	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Level of transparency in rule making (general)	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Formal performance monitoring by community?	1	1	1	1	1									Y	Y		Y	Y	Y	Y	Y	Y
	Fora for discussion and dialogue (communication)	1	1	1	1	1								1		Y	Y	Y	1	Y	Y	Y	Y
	Relevance of rules to local conditions	1	1	1	1	1								1			Y	Y	1	Y	Y	Y	Y
	Available scientific research information on fishery	Y	Y	Y	Y	Y								1				Y	Y	Y	Y		Y
	Sanctions for non compliance	1	1	1	1	1								1			Y	Y	1	Y	Y		Y
	Graduated sanctions for non-compliance	1	1	1	1	1								1			Y	Y	1	Y	Y		Y
	Effective conflict resolution mechanisms	1	1	1	1	1								1			Y	Y	Y	Y	Y		Y
	Period of existence of institutional arrangements	1	1	1	1	1								1		8	Y	Y	Y	Y	Y	Y	Y
	Effectiveness of enforcement measures	1	1	1	1	1								1			Y	Y	Y	Y			Y
	Cost of enforcement	1	1	1	1	1								1			1	Y	Y	1			Y

Table 3.2 Hypotheses Matrix (continued)

Main Attributes	Sub Attributes	OUTCOMES: Annual production per unit area	Number of species whose abundance is increasing	Sustainability (Resource)	Biodiversity	Habitat condition	Annual fishing revenue per unit area	Annual fishing (& marketing) costs per unit area	Annual fishing profit (income) per unit area	Average household income	Assets	Savings and investments	Well-being of households	Food security	Perceived benefits	Empowerment	Equity	Compliance with rules and regulations	Efficiency	Conflicts	Conflict resolution capacity	Social cohesion	Sustainability (Institutions)
External Decision-Making	Enabling legislation for co-management	1	1	1	1	1								1		Y	Y	19	1	Y	Y		Y
Arrangements	Local political support for co-management	1	1	1	1	1								10		Y		19		Y	Y		Y
(Group V)	Effective coordinating body	1	1	1	1	1								10		Y		Y	Y	Y	Y		Y
	Institutional capacity of Fisheries Department	1	1	1	1	1								10				Y	Y	Y	Y		Y
	Changes in DoF to support co-management	1	1	1	1	1								10				Y	Y	Y	Y		Y
Exogenous Factors	Natural disasters (eg cyclones, extreme floods)	Y	Y	Y	Y	Y								Y				Y	Y	Y	Y		Y
(Group VI)	Macroeconomic/political/sociocultural changes	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y				Y	Y	Y	Y	Y	Y
	External financial assistance	Y	Y	Y	Y	Y								10				Y	Y	Y	Y		Y
	Capacity builiding support from NGO's	Y	Y	Y	Y	Y								10		Y	Y	Y	Y	Y	Y		Y
	Population growth	14	14	14	Y	Y								Y			Y	Y	1	14	Y		Y
	Economic growth	14	14	14	Y	Y								Y				Y	1	14			Y
	Ongoing war or armed conflict	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y		8		Y	Y	Y	Y		Y
Outcomes																							
Production/Yield	Annual production per unit area	99	99	14	14	14	Y		Y	Y	Y	Y	Y	Y	Y			Y		15			
	Number of species whose abundance is increasing	99	99	14	99		Y		Y	Y	Y	Y	Y	Y	Y			Y		15			
Sustainability/Biodiversity	Sustainability (Resource)	Y	Y	99	14		Y	Y	Y	Y	Y	Y	Y	Y	Y			Y		Y			Y
	Biodiversity	Y	Y	Y	99		5		5	5	5	5	5	7	Y					Y			Y
	Habitat condition	Y	Y	Y	Y	99	2	2	2	2	Y	Y	Y	Y	Y			Y		Y			Y
Wellbeing	Annual fishing revenue per unit area	14	14	14	14	14	99		Y	Y	Y	Y	Y	Y	Y			Y	1	6			
(Fishers/Households)	Annual fishing costs per unit area	14	14	14	14	14		99	Y	Y	Y	Y	Y	Y	Y			Y	1	6			
	Annual fishing profit (income) per unit area	14	14	14	14	14			99	99	Y	Y	Y	Y	Y			Y	1	Y			Y
	Household income from fishing	14	14	14	14	14	99		99	99	Y	Y	Y	Y	Y			Y	1				Y
	Assets										99	Y	Y	Y	Y			Y	1				
	Savings and investments										Y	99	Y	Y	Y			Y	1				
	Well-being of households												99	Y	Y			Y	1	Y			Y
	Food security										Y	Y	Y	99	Y			Y	1	Y			Y
	Perceived benefits										Y	Y	Y	8	99			Y	1	Y			Y
Institutional Performance	Empowerment										Y	Y	Y	1	Y	99		Y	1	Y	Y	Y	Y
	Equity	1	1	1	1	1					Y	Y	Y	11	Y		99	Y	1	Y	Y	Y	Y
	Compliance with rules and regulations	Y	Y	Y	Y	Y	2	2	2	2	Y	Y	Y	5	Y		Y	99	Y	Y			Y
	Efficiency										6	6	6	12	Y	8			99	Y	Y		Y
	Conflicts										Y	Y	Y	Y	Y		Y	Y	Y	99			Y
	Conflict resolution capacity																				99		Y
	Social Cohesion	1	1	1	1	1					Y	Y	Y	13	Y		Y	Y	Y	Y	Y	99	Y
Insititutional Sustainability	Sustainability (institutional)	1	1	1	1	1					Y	Y	Y	1	Y	Y	Y	Y	Y	Y	Y		99
		46	46	45	42	37	11	26	32	32	44	44	45	34	21	20	46	83	45	85	42	26	72

99 - direct relationship
1 - Indirectly through compliance
2- Indirectly through abundance/biomass
3- Indirectly through proudction potential and abundance/biomass
4 - Indirectly through cumulative effects of management
5 - Indirectly through CPUA
6- Indirectly through income
7 - Indirectly through resource sustainability
8 - Indirectly through institutional sustainability
9 - Indirectly through empowerment
10 - Indirectly through improved management
11 - Indirectly through improved cohesion
12 - Indirectly through costs
13 - Indirectly through reduced conflict
14 - Indirectly through exploitation intensity
15 - Indirectly through Access
16 - Indirectly through conflict
17 - Indirectly through economic value
18 - Indirectly through relevance of rules
19 - Indirectly through legitamacy

4. Case Study Data and Database

4.1 Introduction

This chapter describes the assembly of the dataset employed to develop the statistical methodology and models described in Chapter 6. The chapter also describes the database used to store, process and retrieve the data.

4.2 Case Studies

Data assembled for the six groups of explanatory variables (attributes) and management performance (outcomes) described in the previous chapter were used to develop the methodology and models of (co-)management performance described in Chapter 6. The data were assembled from case studies of co- or community-managed fisheries or management initiatives undertaken during the last two decades. Many of the case studies, particularly those undertaken under ICLARM's FCMRP, had been structured around the IAD research framework approach (Section 3.1). Others represented research funded by DFID's Fisheries Management Science Programme and the World Bank without reference to the IAD or SL frameworks. Together, these studies documented a total of 119 discrete local management units (VMUs and IMUs – see Section 2.1) or areas under national (government) control among 13 different countries in Africa, Asia and Melanesia (Figure 4.1). The units represented a range of different ecosystems and management arrangements. (Table 4.1). Each management unit was treated as a separate observation for the model development. Further details of each management unit including references are given in Annex III.

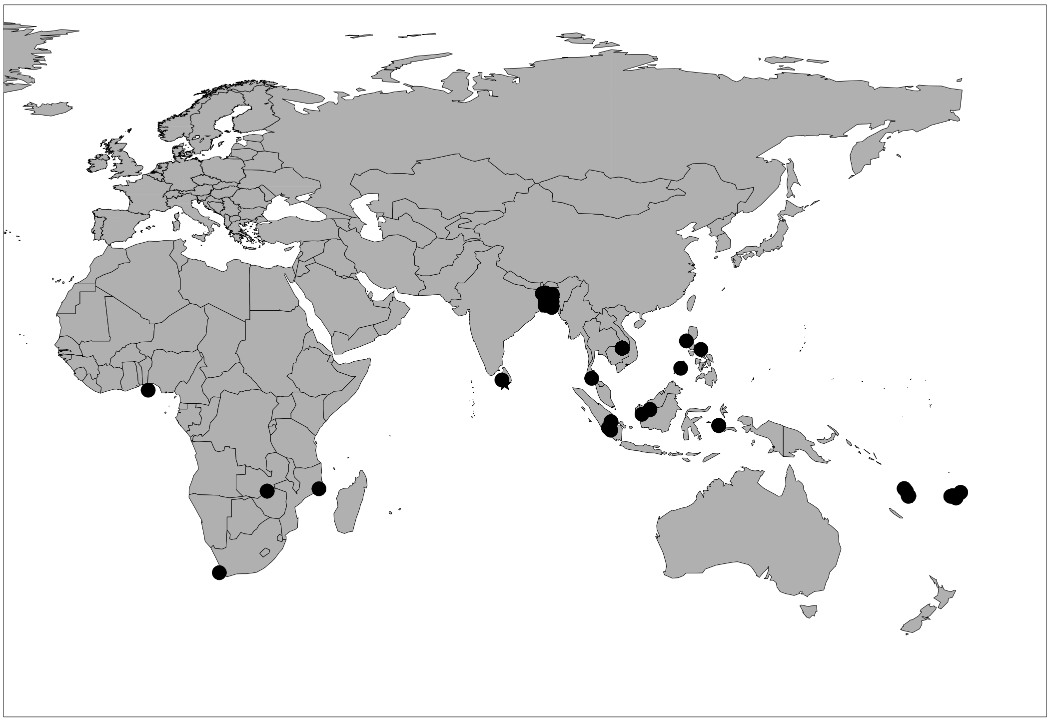


Figure 4.1 Location of management units used for model development

Table 4.1 Summary of the 119 management units (observations) used for model development.

Continent/Region	Country	Ecosystem	Management type	Number of units (observations)
Africa	Cote d'Ivoire	Coastal lagoon	Co-management	1
	Mozambique	Coastal (inshore)	Co-management	1
	South Africa	Estuary	Co-management	1
	Zimbabwe	Lake	Government	1
	Zambia	Lake	Government	1
Asia	Bangladesh	Floodplain-river	Co-management	10
		Beel	Co-management	7
		Lake	Co-management	2
	Indonesia	Fringing reef	Government	2
		Fringing reef	Traditional	4
		Floodplain-river	Government	3
		Floodplain-river	Traditional	4
		Floodplain-river	Co-management	1
	Laos PDR	Floodplain-river	Co-management	64
	Philippines	Coastal (inshore)	Government	1
		Estuary	Government	1
		Fringing reef	Co-management	1
	Sri Lanka	Estuary	Traditional	1
	Thailand	Coastal (inshore)	Co-management	1
Melanesia	Fiji	Fringing reef	Traditional	6
	Vanuatu	Patch reef	Traditional	1
		Fringing reef	Traditional	5

4.3 Case Study Profiling

For each management unit, data corresponding to relevant variables were entered into a database (see below). Often data could be simply extracted or calculated from information contained within the text or tables of the source material. Other more qualitative variables had to be 'scored' with ordinal scale measures in a more judicious and subjective manner. Trend variables describing management performance (outcomes) were, in the majority of cases, scored on the basis of the results of interview-based assessments reported in the source material. Where necessary additional sources were used to supplement the study documentation and published material. Data to help estimate indicators of resource resilience (for example, the *weighted mean age of maturity of target species*) were obtained from FishBase. Primary production was estimated from maps produced by the IMCS Ocean Primary Productivity Database (Behrenfeld & Falkowski 1997) on http://marine.rutgers.edu/opp/Database/DB.html (Annex IV) and mean annual water temperature from http://ocg.ori.u-tokyo.ac.jp:81/ocean/atlas/Levitus (Annex V). The global position of each site was taken from the 'j-sistem' latitude and longitude database available on http://www.j-sistem.hr/online/srchlalo.htm.

This variable *profiling* exercise was completed for all 119 discrete management units identified. All sites except those in Cote d'Ivoire and Indonesia were profiled with the help of the researchers responsible for the source material (Table 4.2). Profiling began at the Cape Town workshop and was completed at MRAG, UK and at second informal workshop held at ICLARM headquarters, Penang, Malaysia between 23rd March and 5th April 2001 involving MRAG, Reading University and ICLARM staff. Wherever possible, completed profiles were returned to the researchers responsible for the source material for checking, validation and comment. All profiles were then finally checked and where necessary, amended by the principle investigator before being entered into the database.

Because of the large numbers of context- and ecosystem-specific variables and limited scope of some studies, not all variables could be assigned values for every management unit identified. The dataset is therefore 'patchy' in many places. The implications of this for the model development are discussed in Chapters 6 and 7. Despite this, almost 20,000 items of data were assembled from the case studies.

4.3.1 *Problems Encountered During Profiling*

The variables and their indicators used for the analysis were selected to capture, as far as possible, the fundamental elements of complex management systems. Providing this is done effectively, any superfluous information forfeited during this data reduction process should not impact on the predictive capacity of models. However, obstacles were encountered during the case study profiling exercise arising from the rigid bounds imposed by some the variable indicators.

Table 4.2 Summary of case study profiling activities.

Continent/Region	Country	Profilers	Location
Africa	Cote d'Ivoire	Ashley Halls, MRAG	London, UK
	Mozambique	Simeão Lopes, IDPPE	Mozambique
		Horacio Gervasio, IDPPE	Cape Town, SA
		Ernesto Poiosse, IDPPE	London, UK
		Ashley Halls, MRAG	
	South Africa	Merle Sowman, UCT	Cape Town, SA
		Richard Martin, UCT	London, UK
		Ashley Halls, MRAG	
	Zimbabwe	Isaac Malasha, CASS	CASS, Zimbabwe
		Alexandretta Philomena, CASS	Cape Town, SA
		Ashley Halls, MRAG	London, UK
	Zambia	Ben Chanda, FRD	FRD, Zambia
		Cyprian Kapasa, FRD	London, UK
		Godfrey Milindi, FRD	
		Ashley Halls, MRAG	
Asia	Bangladesh	Paul Thompson, ICLARM;	Bangladesh;
		Ashley Halls, MRAG	London, UK
	Indonesia	Ashley Halls, MRAG	London, UK
	Laos PDR	Ian Baird	Laos PDR,
		Ashley Halls, MRAG	Cape Town, SA
		Savitri Abeyasekera	Penang, Malaysia
			London, UK
	Philippines	Kuperan Viswanathan	Penang, Malaysia
		Ashley Halls, MRAG	UK
	Sri Lanka	Upali Amarasinghe	Kelaniya, Sri Lanka
		Savitri Abeyasekera	Penang, Malaysia
		Ashley Halls, MRAG	London, UK
	Thailand	A, Masae	Songkla, Thailand
		Ashley Halls, MRAG	London, UK
Melanesia	Fiji	Jim Anderson	London, UK
		Ashley Halls, MRAG	
	Vanuatu	Jim Anderson	London, UK
		Ashley Halls, MRAG	

One of the most common problems was the need to assign a single value to inherently multivariate or multi-dimensional variables. For example, the variable *Gear Type* (Group I) allows only one gear to be recorded whilst several gears may be used in the fishery. In this case, the most important gear in terms of catch weight was recorded. This problem could be overcome by adding additional variables to record other important gears in order of importance (eg *Gear Type 1*, *Gear Type 2*, *Gear Type 3*…etc). However, it should be borne in mind that this project was primarily concerned with methodological development rather than developing definitive models of co-management performance and that fitting models with more variables invariably demands larger numbers of observations. Models with a more local focus could be developed to include more context-specific and fewer generally applicable variables.

A similar obstacle was encountered when attempting to score some of the more indiscriminant or general outcome variables. For example, the variable *Compliance with rules and regulations* does not distinguish compliance among specific rules, for example *mesh size regulations* and *gear bans*. In these cases, a judicious approach was adopted taking into consideration the relative importance of each rule or regulation. The same caveats and alternative model solutions to those given above apply.

Most of the explanatory variables describe the current state of the fishery resource and it's associated management institutions and interventions. This time-static focus assumes that the effects of the explanatory variables are manifest in the outcomes almost instantaneously or at least within the period between successive performance evaluations (typically one year). This is likely to be more valid for fisheries resources with high rates of intrinsic growth (turnover) exploited and managed by responsive stakeholders, than for less responsive resources and stakeholders. The variables: *Period of existence of current operational rules* and *Period of existence of current institutional arrangements* (Group IV) attempt to take account of the effects of historical change.

Even though data reported here were obtained from secondary sources, assigning values to so many variables was very time consuming. Resource demands would be considerable if field-based monitoring and evaluation programmes were employed to generate the data. However, the inclusion of a large number of variables was deemed necessary for the reasons described in Section 3.2.3, and because important variables could not be identified prior to the model development. All *potentially* important variables were therefore included. No information could be obtained for several variables including some of those used to describe the production potential of the resource eg *water transparency (secchi depth)* and *total phosphate concentration*. Other redundant variables are detailed in Annex VI. Variables for which data were readily available and which were found to be statistically significant for determining management performance based upon the models are detailed in Section 6.4.

4.4 The Case Study Database

A relational database 'IMA DATABASE' was built upon a Microsoft Access 97 software platform to store, process and retrieve the data assembled for the 119 management units and 258 variables described above.

The IMA DATABASE comprises 19,750 entries in the following 10 tables:

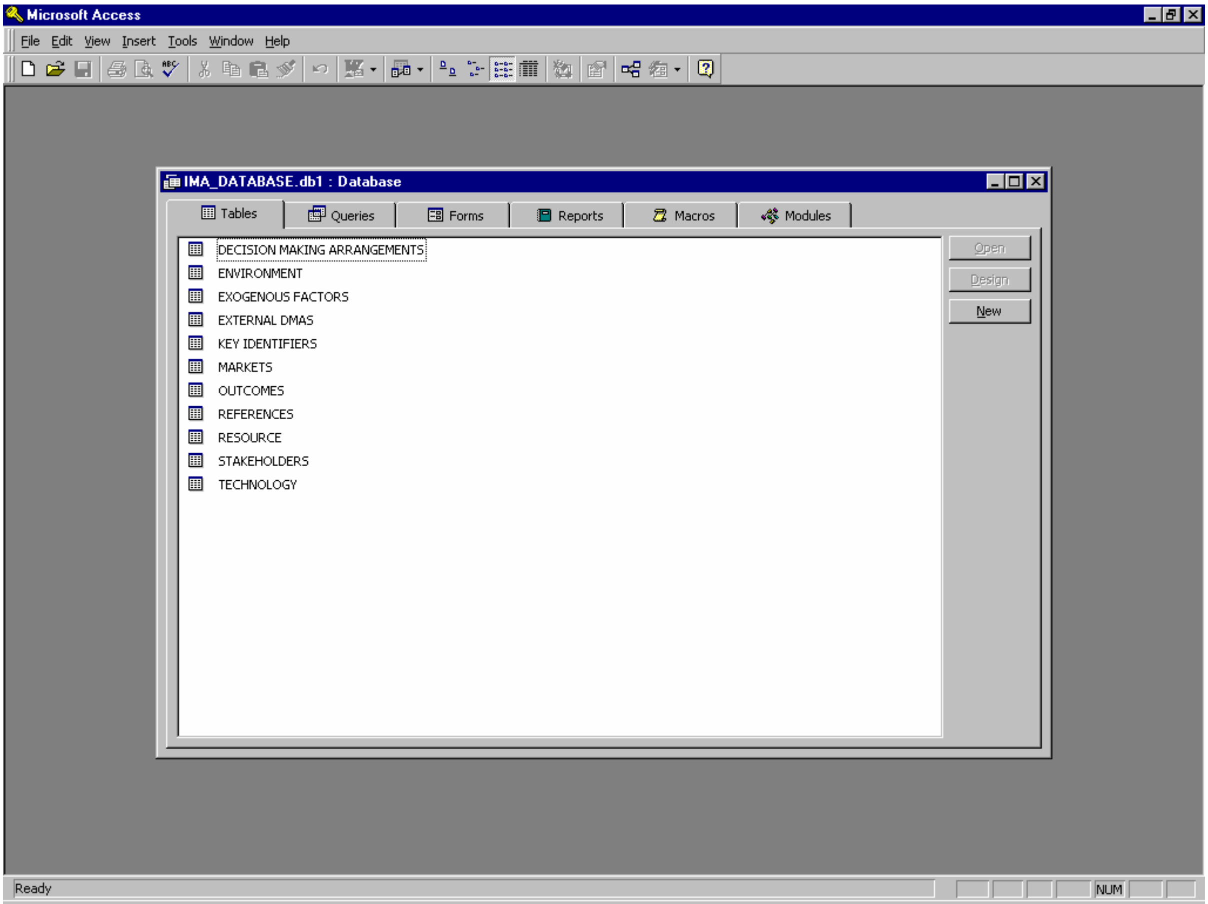
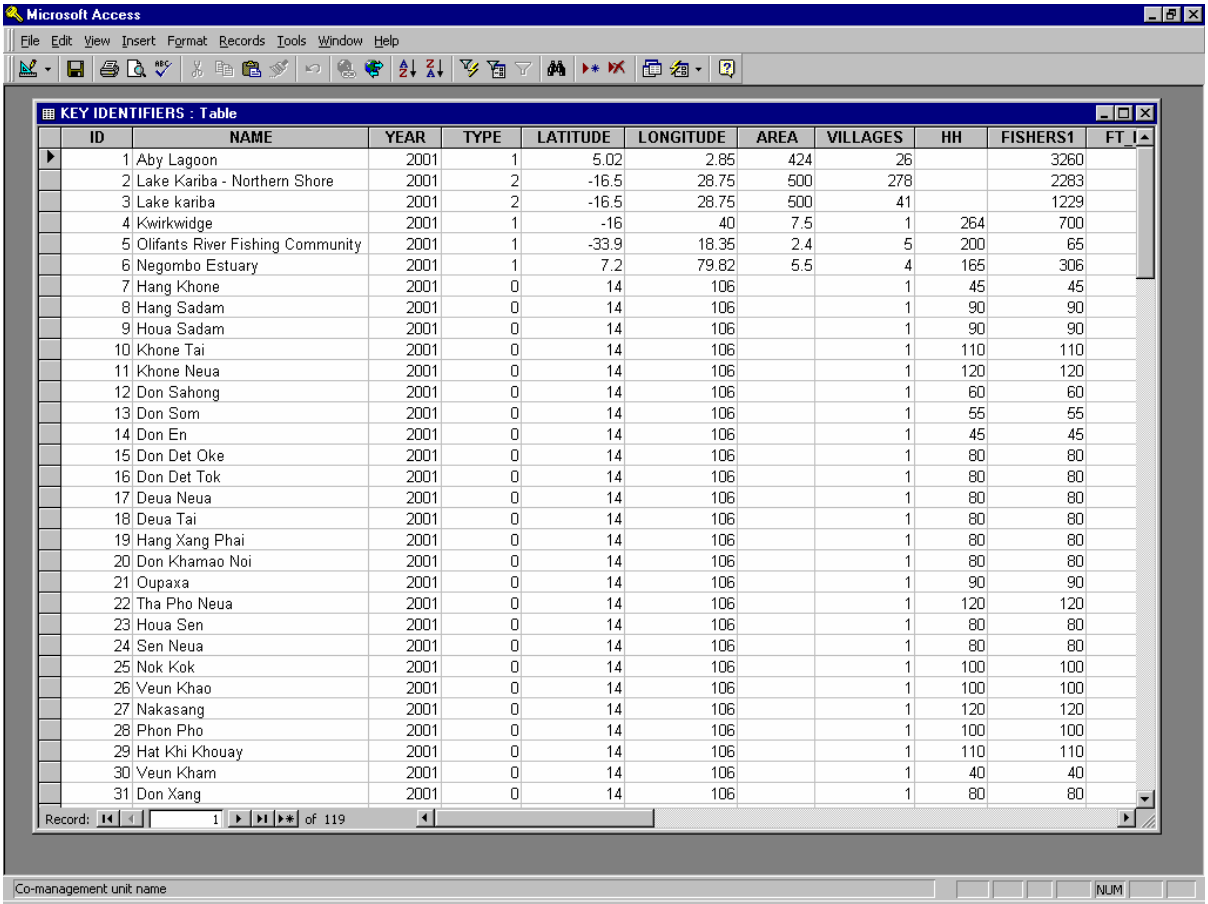


Figure 4.2 The IMA_DATABASE main menu listing the 10 tables of variables corresponding to the IAD research framework groups of variables.

These tables correspond to the same categories of variables and factors described in Annex II based upon the IAD framework with an additional table (REFERENCES) containing the reference details of the source material.

The data are structured in each table in the standard format (Figure 4.3) with each row (record) containing all the data for a particular management unit. The fields (column headings) correspond to the attributes (variables) measured for each management unit.



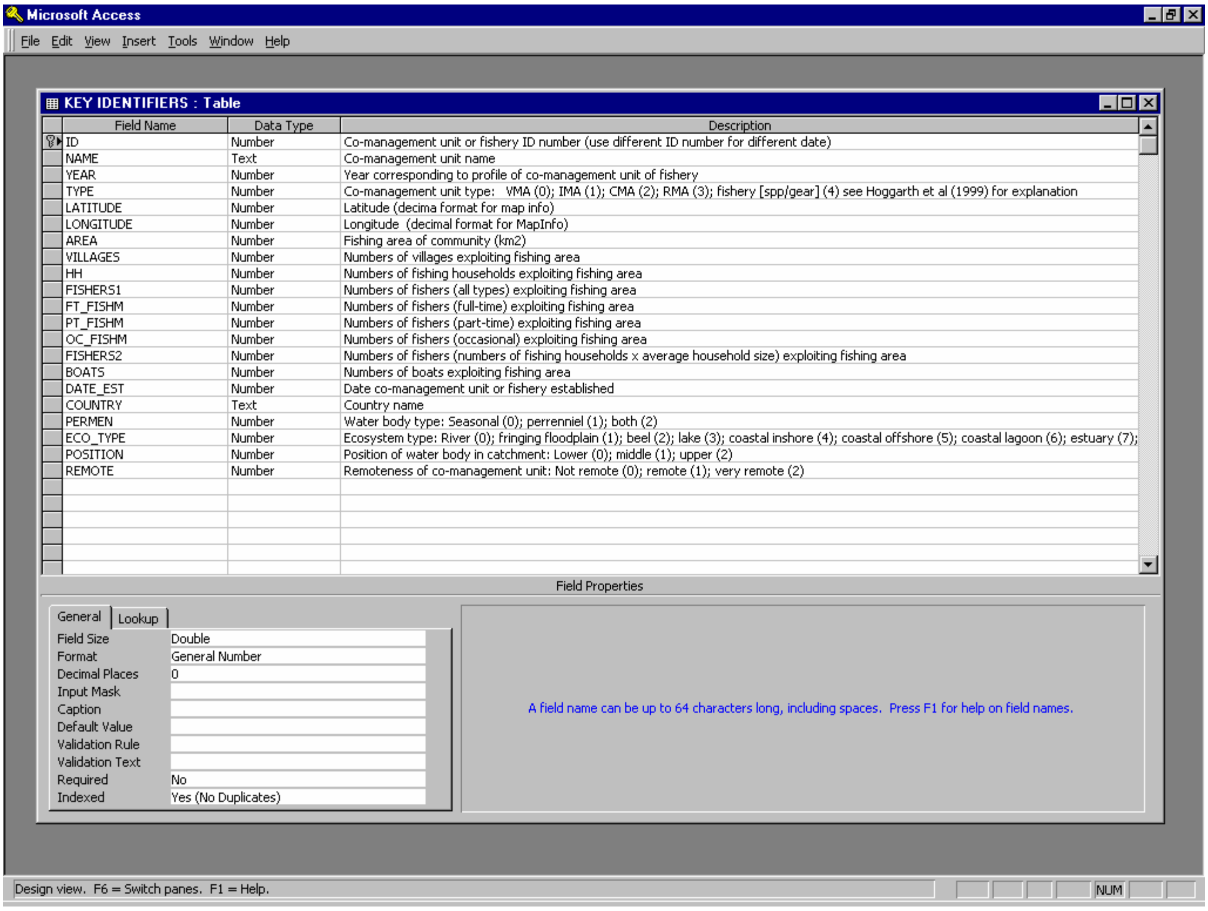
ID	NAME	YEAR	TYPE	LATITUDE	LONGITUDE	AREA	VILLAGES	HH	FISHERS1	FT_I
1	Aby Lagoon	2001	1	5.02	2.85	424	26		3260	
2	Lake Kariba - Northern Shore	2001	2	-16.5	28.75	500	278		2283	
3	Lake kariba	2001	2	-16.5	28.75	500	41		1229	
4	Kwirkwidge	2001	1	-16	40	7.5	1	264	700	
5	Olifants River Fishing Community	2001	1	-33.9	18.35	2.4	5	200	65	
6	Negombo Estuary	2001	1	7.2	79.82	5.5	4	165	306	
7	Hang Khone	2001	0	14	106		1	45	45	
8	Hang Sadam	2001	0	14	106		1	90	90	
9	Houa Sadam	2001	0	14	106		1	90	90	
10	Khone Tai	2001	0	14	106		1	110	110	
11	Khone Neua	2001	0	14	106		1	120	120	
12	Don Sahong	2001	0	14	106		1	60	60	
13	Don Som	2001	0	14	106		1	55	55	
14	Don En	2001	0	14	106		1	45	45	
15	Don Det Oke	2001	0	14	106		1	80	80	
16	Don Det Tok	2001	0	14	106		1	80	80	
17	Deua Neua	2001	0	14	106		1	80	80	
18	Deua Tai	2001	0	14	106		1	80	80	
19	Hang Xang Phai	2001	0	14	106		1	80	80	
20	Don Khamao Noi	2001	0	14	106		1	80	80	
21	Oupaxa	2001	0	14	106		1	90	90	
22	Tha Pho Neua	2001	0	14	106		1	120	120	
23	Houa Sen	2001	0	14	106		1	80	80	
24	Sen Neua	2001	0	14	106		1	80	80	
25	Nok Kok	2001	0	14	106		1	100	100	
26	Veun Khao	2001	0	14	106		1	100	100	
27	Nakasang	2001	0	14	106		1	120	120	
28	Phon Pho	2001	0	14	106		1	100	100	
29	Hat Khi Khouay	2001	0	14	106		1	110	110	
30	Veun Kham	2001	0	14	106		1	40	40	
31	Don Xang	2001	0	14	106		1	80	80	

Figure 4.3 The KEY IDENTIFIERS table illustrating the data structure.

Management unit **ID** (serial number) forms the primary key among the tables to query the database or create reports. A number of queries have been constructed containing subsets of the explanatory and dependent for model development based upon the hypothesis matrix.

Detailed descriptions of all the variables (fields) including units of measurement are available within the *design view* of each table as illustrated for the KEY IDENTIFIER table in Figure 4.4 below.

The IMA database is a significant project output. It is freely available at http://www.fmsp.org.uk/ where it may be periodically updated as further data becomes available:



Microsoft Access

File Edit View Insert Tools Window Help

KEY IDENTIFIERS : Table

Field Name	Data Type	Description
ID	Number	Co-management unit or fishery ID number (use different ID number for different date)
NAME	Text	Co-management unit name
YEAR	Number	Year corresponding to profile of co-management unit of fishery
TYPE	Number	Co-management unit type: VMA (0); IMA (1); CMA (2); RMA (3); fishery [spp/gear] (4) see Hoggarth et al (1999) for explanation
LATITUDE	Number	Latitude (decima format for map info)
LONGITUDE	Number	Longitude (decimal format for MapInfo)
AREA	Number	Fishing area of community (km2)
VILLAGES	Number	Numbers of villages exploiting fishing area
HH	Number	Numbers of fishing households exploiting fishing area
FISHERS1	Number	Numbers of fishers (all types) exploiting fishing area
FT_FISHM	Number	Numbers of fishers (full-time) exploiting fishing area
PT_FISHM	Number	Numbers of fishers (part-time) exploiting fishing area
OC_FISHM	Number	Numbers of fishers (occasional) exploiting fishing area
FISHERS2	Number	Numbers of fishers (numbers of fishing households x average household size) exploiting fishing area
BOATS	Number	Numbers of boats exploiting fishing area
DATE_EST	Number	Date co-management unit or fishery established
COUNTRY	Text	Country name
PERMEN	Number	Water body type: Seasonal (0); perrenniel (1); both (2)
ECO_TYPE	Number	Ecosystem type: River (0); fringing floodplain (1); beel (2); lake (3); coastal inshore (4); coastal offshore (5); coastal lagoon (6); estuary (7);
POSITION	Number	Position of water body in catchment: Lower (0); middle (1); upper (2)
REMOTE	Number	Remoteness of co-management unit: Not remote (0); remote (1); very remote (2)

Field Properties

General | Lookup

Field Size	Double
Format	General Number
Decimal Places	0
Input Mask	
Caption	
Default Value	
Validation Rule	
Validation Text	
Required	No
Indexed	Yes (No Duplicates)

A field name can be up to 64 characters long, including spaces. Press F1 for help on field names.

Design view. F6 = Switch panes. F1 = Help. NUM

Figure 4.4 Descriptions of the variables belonging to the KEY IDENTIFIERS table shown in the table *design view*.

5. Evaluation of Previous Statistical Approaches

5.1 Introduction

Few attempts have been made to develop quantitative approaches that help to evaluate the sustainability of fisheries in an interdisciplinary manner or to identify factors contributing to successful co-management (Pomeroy et al, 1997; World Bank, 2000; Pitcher, 1999). These studies use multivariate approaches, focusing on a wide range of attributes from many disciplines, e.g. technological, social, economic, and ecological. While results from these approaches have, in some case, provided valuable insights concerning the fisheries under study, concerns arise surrounding the appropriateness of some of these approaches for the objectives in mind, and the statistical validity of the implementation process and subsequent interpretation.

This chapter reviews and highlights areas of concern in recent methodological approaches, identifying limitations in the methods of implementation and presents some alternative and more appropriate statistical procedures for studying the impact of a range of attributes of the types identified in Chapter 3 on fisheries outcomes.

Section 5.2 describes the three most important studies where multivariate[1] approaches have been used to evaluate fisheries and/or identify factors contributing to sustainability. For each study, detailed consideration is given to both the statistical approaches employed and the data collection procedures undertaken. On the basis of these reviews, alternative, and arguably more appropriate, methodological approaches for data from these studies are considered in Section 5.3. A summary of the major statistical concerns is presented in Section 5.4, together with some concluding remarks.

5.2 Evaluation of Previous Approaches

There have been two major studies aimed at understanding factors contributing to successful co-management of fisheries resources. The first, described by Pomeroy et al (1997), was a study led by the International Centre for Living Aquatic Resources Management (ICLARM), to evaluate the impact of community based coastal resource management (CBCRM) projects in the Philippines. The second was a study conducted by the World Bank (2000) concerning coastal resources management in the Pacific Island Region. Both studies were based on the perceptions of coastal communities concerning changes in a range of attributes, e.g. socio-cultural characteristics, management processes and ecological indicators.

The study of factors influencing the sustainability of fisheries has also arisen as a component of a more general multi-disciplinary technique called “Rapfish”, developed at the Fisheries Centre at the University of British Columbia (Preikshot & Pauly, 1998; Pitcher & Preikshot, 2001). It is primarily aimed at evaluating the sustainability of a set of fisheries. The development of this system (Pitcher, 1999) has been motivated by the practical limitations of earlier evaluation systems which used stock assessments and ignored other important aspects (social, technological, economic, etc), which are likely to have some bearing on the ultimate sustainability of the fishery.

Rapfish on the other hand is described as a rapid appraisal technique to evaluate the sustainability status of fisheries by using easily scored fisheries attributes from many disciplines, i.e. technological, social, economic, ethical and ecological.

The methodological approaches underpinning these three studies are examined in detail below.

[1] The term “multivariate” is used here to include also multiple regression techniques although in statistical terminology, the term “multivariate” is restricted to situations where there are many “response” (Y) variables, rather than to situations where there are several explanatory (X) variables.

5.2.1 *Study 1 - Community-Based Coastal Resources Management in the Philippines*

Data Collection

Recognising the need to carry out a quantitative evaluation of the impact of over 100 CBCRM projects in the Philippines between 1984 and 1994, a multi-disciplinary team led by ICLARM undertook a study at six sites between November 1995 and February 1996. These six sites were stratified as being "successful" or "less successful" with respect to implementation and sustainability of project material and organisational interventions. One site within each stratum type was selected from each of three municipalities and at least 30 respondents interviewed at each site. Half of these respondents were chosen to be members of the project beneficiary association.

Perceptions of CBCRM project impacts were measured by showing each respondent a ladder-like diagram with 15 steps and explaining that the first step indicated the worst scenario and step 15 the best scenario with respect to the following 10 indicators:

1. Overall well-being of the household
2. Overall well being of the resource
3. Local income
4. Access to resources
5. Control over resources
6. Ability to participate in community studies
7. Ability to influence community affairs
8. Community conflict
9. Community compliance with resource management
10. Amount of traditionally harvested resource in the water

Each respondent was asked to consider each of the above indicators in turn and specify where the indicator was on the ladder before the CBCRM project, where it is today and where it is perceived to be in 5 (or 10) years time, as well as reasons for any perceived changes. Thus the data on impact indicators were scores on a 1-15 scale given by 200 respondents from the six sites.

Through a literature review, variables likely to influence peoples' perceptions of project impacts were identified and corresponding data gathered during the interviews. There were nineteen such explanatory variables (Table 5.1):

Table 5.1 Variables used in the Philippine Study

Variable Category	Variables
Social	Age
	Years of formal education
	Household size
	Years resident in community
Occupation	Years of fishing experience
	Job other than fishing in the past?
	Willingness to change from fishing to another occupation?
Income	Income from sources other than fishing?
	Fishing most important source of income?
	Fishery provides over half the respondent's household income?
	Household receives income from outside the household?
Resource	Resource in bad condition in the pre-project period?
	Ecological knowledge[1]
Cooperation	Potential for community members to work together
	Potential for fishers to work together
	Respondent member of then project sponsored association
Project	Respondent had an influence on project planning?
	Influence on post-implementation activities?
	Attended project-training activities?

[1] as determined by the number of factors they cited as contributing to a healthy marine resource.

Statistical Analysis

In the Philippines study, several statistical methods were used, namely paired t-tests, correlation analysis, principal component analysis, stepwise multiple regression procedures and chi-squared tests.

Study of changes in perceptions from past to present:

Paired t-tests were used to compare the respondents' perceptions of pre-project to present day changes for each of the 10 indicator variables. While this analysis approach is reasonable, attention is concentrated entirely on results of tests of significance. No comment is made on the magnitude of the differences in mean scores from past to present e.g. that the mean increase ranges from 2 units for the amount of traditionally harvested resource in the water to 3.7 units for community compliance with resource management. It would also have been valuable to examine the proportion of respondents who perceive an increase for each indicator. More importantly, all respondents have been regarded as a random sample when clearly the sample was stratified by site and by other socio-economic variables. Ignoring the structure in the data limits the interpretation.

Study of correlations

In the next stage of the analysis, correlations between each of the 10 indicators and each of the 19 explanatory variables are examined and again the emphasis is on significance tests. Little can be learned from this analysis since it only demonstrates whether each correlation coefficient is significantly different to zero. The significant correlations are all very small, with magnitudes ranging from 0.17 to 0.28. There is also no indication that any scatter plots have been examined to assess whether spurious correlations have arisen, for example due to the presence of one or more outliers.

What specific values were used to represent the indicators is not explicitly stated. We presume that the correlation analysis was based on the present-post differences in the perception scores. Such differences result in a limited range of values, as do many of the explanatory variables that correspond to binary (yes/no) responses. The correlation analysis is thus further limited by the small range of discrete values (0, 1, 2, etc) taken by the data.

Data reduction

The next stage of the analysis is appropriately done and involves a principal component analysis carried out on the 10 indicators to achieve a reduction in the number of dimensions being used as indicators. The first three principal components are interpreted sensibly as comprising three new indicators capturing 66% of the variation in the data. These indicators are used in turn in a stepwise regression analysis to explore their dependence on the selected 19 explanatory variables. The scores for the three principal components are also summed to give an overall score of perceived impact. This is harder to interpret. A simpler, more readily interpretable overall measure could have been the simple total of the original 10 indicators, or a weighted total if participatory discussions had revealed a rank ordering reflecting the importance of the 10 indicators.

Multiple Regression procedures

The stepwise regressions identify a few variables significantly influencing each of the four scores but the overall predictive power is very low (20% to 43%). This suggests wide variation in the data being used. Again further study of the suitability of the chosen models, e.g. via an analysis of residuals (i.e. the unexplained elements of the regression) may have revealed a clearer understanding of the extent of validity of the fitted models. As with the t-tests, the analysis here ignores the data structure imposed by the method of sampling. Further analysis involved categorizing the indicator changes as being positive or negative and examining the association between this binary categorization of the indicator changes and explanatory variables found significant in the regression analysis. The use of chi-squared tests for this purpose is reasonable but allows only pairs of variables to be examined at a time.

Despite some of the analyses limitations outlined above, a few useful findings concerning the six sampled villages emerge from this study. Perceptions of project success by project staff and beneficiaries vary because they use different criteria. Fishers generally perceived that CBCRM projects were a success and felt a sense of empowerment and more information with which to make decisions and improve their lives. Early and continued participation of beneficiaries in project planning and a positive attitude towards community cooperation, led to a positive evaluation of CBCRM project impacts.

5.2.2 Study 2 - Management of Coastal Resources in Pacific Island Countries

Data collection

Factors that contribute to the successful management of coastal resources were also studied in a World Bank sponsored survey conducted in 1998-99. The survey focused on coastal countries in five Pacific Island countries, namely Fiji, Palau, Samoa, Solomon Islands and Tonga (World Bank 2000). Thirty-one sites among these countries were included, with 6-8 focus groups (2-6 respondents per group) being interviewed at each site. The 31 sites were divided into 12 focus sites (2-3 per country) and for in-depth analysis, 19 supplementary sites were chosen, selected purposively to cover a range of conditions believed to influence management success. On average, 6 focus groups were interviewed at each focus site and three at each supplementary site. The groups at each site were chosen so that one-third were village elders. In total, 133 focus groups were interviewed.

Data were collected at three levels: (i) on fisheries and environmental agencies via national questionnaires; (ii) community level information at each of the 31 sites; and (iii) focus group perceptions at the "people" level. As in the study by Pomeroy et al (1997), data at level (iii) were collected using a baseline independent method whereby information on trends over time were gathered from community perceptions of changes in coastal management success and in factors (e.g. community conflict, habitat condition) that may influence this success. The process involved asking community respondents to state their perception of trend according to one of the categories listed below which were then coded on a five-point scale as indicated.

Perception trend	Code Value
Improving a lot	5
Improving a little	4
Stable	3
Declining a little	2
Declining a lot	1

The "perceptions of success" were measured on the basis of the following indicators:

(a) CPUE	-Trends in perceived catch per unit of effort for three key resources
(b) HABITAT	-Trends in the condition of habitats for three habitats identified by each group;
(c) THREAT	-Trends in threats to the site, later classified as pollution; siltation/ sedimention/deforestation; destructive fishing; mining; overfishing; or other.
(d) COMPLIANCE	-Assessment of compliance at the time of the survey for 5 management rules.

While (a), (b), (c) were measured on the 5-point scale, (d) was measured on a 4-point scale with "4" indicating full compliance and "1" indicating no compliance.

Statistical Analysis

Exploratory data analysis

The initial analysis of the data in the World Bank Study (World Bank, 2000), involved exploratory data analysis techniques applied to the four success indicators and over a hundred potential explanatory variables. Different types of correlation coefficients (Pearsons, Cramer's V, Spearman's rank correlation coefficient) were calculated between success and explanatory variables to take account of differing types of data, interval-scale, ordinal and categorical data. Additionally, descriptive statistics and graphs were produced to study patterns in the data. Such exploratory work is always valuable at the initial stages of data analysis to get a "feel" for the data and to identify any potential problems (e.g. outliers, data errors, etc) and this is a positive aspect of the work here.

Comparing success indicators across attribute indicator categories

The dependent variables, i.e. the focus groups perception of success for each of the four indicators, were analysed using descriptive procedures and non-parametric tests. The purpose of the latter was to assess how each indicator of success (e.g. CPUE trend) varied across the indicator categories (e.g. resource categories for CPUE, such as shellfish, reef fish and trochus). Non-parametric tests were employed on the grounds that the data follow highly non-normal distributions. The particular tests used were the Kruskal-Wallis test (for comparing two or more groups) and the Mann-Whitney U-test (for comparing two groups). In applying these tests, it was recognised that the resulting data are not independent because (i) a single focus group may provide multiple measures on a single indicator category, e.g. five responses to both wrasse and emperor fish, both of which fall in the "reef fish" category; and because (ii) each focus group provides their perception of CPUE trends for more than one indicator category.

The first issue was overcome by considering at most *one* indicator measure per indicator category, and referring to the resulting data as being "semi-independent". No discussion is presented concerning the second issue, but the question of non-independence may not arise if each focus group can be assumed to have given independent assessments of their perceptions for each indicator category. It seems reasonable to suppose that they did.

There are limitations with the statistical approach here apart from non-normality and possible non-independence. One limitation is that the Kruskal-Wallis and Mann-Whitney U tests ignore the data structure. These tests are therefore very limited in their interpretation. In particular, the overall variability residing in the data are affected, not only by the different indicator categories, but also by variation amongst the focus groups. If the data set were complete, it would have been possible to allow for this additional source of variation by using the non-parametric equivalent of the two-way analysis of variance, i.e. the Friedman's test. In this particular situation the Friedman's test is not possible because the data matrix, comprising 133 rows for the 133 focus groups, had missing cells. This is because the columns of this matrix correspond to all of the indicator categories identified by the focus groups, but since each focus group was asked to identify (and then give responses to) only three categories for each indicator variable, several empty cells resulted.

A second limitation is that the non-parametric tests employed here proceed by producing an overall ranking of the data, combined across all the indicator categories. This process does not yield useful results since the full data set only contains values from 1 to 5.

Thus the use of non-parametric tests is limited. They apply only to simple data structures or to situations where there are no missing cells. They also have low power, i.e. the tests are unable to identify significant differences unless such differences are substantial. So the finding, for example, that there were no significant differences between perceptions of the men, women and the elderly, is open to some doubt.

Study of factors influencing success indicators
In this component of the analysis, tables of correlation coefficients between the four indicators of success and a large number of explanatory variables are presented. Three tables are presented corresponding to correlations with site characteristics, external factors and process factors. There is little that can be learnt from these tables as already highlighted in Section 5.2.1 for the Philippines Study.

Multiple regression analysis procedures are used to explore the influence of ten explanatory variables on each of the four success indicators. The explanatory variables used were the following:

- An index of last years government official visit to site;
- Percent of income from coastal resources and tourism;
- Whether the site had experienced a natural disaster;
- Study team's assessment of the quality of site leadership;
- Measures (on an ordinal scale) of the inability of local leaders to exclude outsiders;
- Whether pollution threats were identified at the site;
- Ratio of village population size to site size (persons per km^2);
- Number of distinct ecosystems identified by the study team;
- Degree of inequality and involvement of user groups in coastal resource management;
- Country (4 dummy variables used to represent the five categories).

In addition, dummy variables were used to capture the different indicator categories, e.g. specific resources for CPUE.

In the report, three difficulties encountered are highlighted:

(i) The multi-level structure of the data (country, site, focus group and specific resource, habitat, threat or management rule for each success indicator);
(ii) The ordinal nature of some of the dependent and explanatory variables;
(iii) The endogeneity of some of the explanatory variables, e.g. whether government visits to sites causes success or if the visit took place because the site was successful or because they were having problems.

To overcome (i), a correction was applied that allows the standard errors to be calculated on the basis of stratified, clustered random sampling. What this correction is, or how correcting for standard errors helps in selecting an appropriate model is not made clear.

In addition, dummy variables are used to control for some of the variation within the lowest level of the data hierarchy, i.e. between specific resources, habitats, threats and rules. This approach does not really help in dealing with multiple levels, particularly since all focus groups do not score the same set of resources, habitats, threats and rules. Combining the responses for a particular category (e.g. CPUE for three key resources) into a single measure, say by summing the responses over the three resources, could have led to a more readily interpretable summary measure.

The ordinal nature of the dependent variables are dealt with by using an ordered probit model to check the robustness of ordinary least squares regression estimates. Using a Probit Model for binary data is a well known statistical technique, but is generally used when the pattern of response between the dependent and explanatory variable is expected to be sigmoidal in shape. It is highly inappropriate for the data being dealt with here, and specially so when the response is ordinal.

Reference is made to an Ordinal Probit Model where regression coefficients are given for 4 variables called “cut 1”, “cut 2”, “cut 3” and “cut 4”, indicating the use of a proportional odds model instead. If this is the case, the interpretation in terms of the significance of regression coefficients is not appropriate. However, we believe that the analysis merely amounts to using a set of dummy variables to correspond to different divisions of the 5-point scale of each response variable since elsewhere reference is made to “a single equation ordinary least squares (OLS) or ordered probit model”.

In the report, categorical explanatory variables are dealt with by creating dummy variables for use in a multiple regression model. We do not see the necessity for doing this. Firstly, the creation of dummy variables is unnecessary since currently available statistical software allow classification (factor) variables to be included directly into a general linear modelling procedure. Multiple linear regression is a special case of this more general model. Secondly, using dummy variables treats the factor levels as being nominal, thus losing the ordinal nature of the corresponding explanatory variables.

The discussion of results subsequent to using dummy variables to replace ordinal explanatory variables, implies some lack of understanding of the interpretation of regression coefficients corresponding to the dummy variables. The view is expressed that if the ordinal explanatory variables could be regarded as continuous variables, then the associated dummy variables would be expected to have coefficients of the same size. There is no discussion of how the regression coefficients could be interpreted if this was not the case.

Although much effort has been made to ensure that results from the regression models are valid and can be interpreted meaningfully, the analyses reflect a limited knowledge of general statistical methodology, and in particular about the application of general linear modelling procedures. The interpretation of results is entirely based on the significance of individual regression coefficients, some of which are dummy variables. The interpretation fails to recognise that the regression coefficients associated with dummy variables represent differences in means of the response variable for the factor level represented by the dummy variable and the factor level of the omitted dummy variable.

There is also no attempt to determine the best fitting model via some kind of stepwise regression procedure. All the interpretation relies on the significance of regression coefficients from the full model with several variables declared as non-significant. Dropping these from the model one by one, and adding previously dropped variables into the regression at a later stage, would alter the significance probabilities. Investigations of this type have to be carried out with great care to avoid getting inconsistent conclusions. The interpretation of results from the analysis as presented, where just one model is fitted, is therefore less useful.

Use of a Principal Component Analysis
The final component of the analysis involved grouping the large number of explanatory variables, 64 in all, into the five obvious categories, i.e. economic, ecological, ethnic, technological and social) and carrying out a principal component analysis (PCA) on the variables in each group. A scree plot is used to determine the optimal number of principal components to be extracted. This usually resulted in the extraction of 2 to 3 principal components per category. The components loadings are used to interpret each of the principal components and this appeared to have been done sensibly.

We have just two comments concerning this analysis. The first is that the number of observations being used in the analysis has not been made clear. Most variables appeared to be site level variables, and we therefore assume that each principal component analysis involved 31 rows of data for the 31 sites and did not involve several measurements from results of several focus group discussions within a site.

Our second comment is that although a reduction in the original number of variables was achieved within each set (social, economic, etc), the analysis did not proceed any further beyond an attempt at regressing these factors against the five indicators of success and finding difficulties with the interpretation. The value of the PCA is therefore questionable.

5.2.3 Study 3 – The Rapfish Studies

Data collection
In Rapfish, the data comprise a number of attributes from each of several disciplines, chosen to yield maximum *a priori* discriminatory power between the fisheries under consideration. Examples are given in Pitcher & Preikshot (2001) of relevant attributes to use within five disciplinary areas, namely ecological, economic, sociological, technological and ethical. Some of these attributes reflect the status of the fishery at the time of data collection, while others relate either to changes in the status of a fishery over time or a judgement of the direction in which changes are taking place at the time of data recording.

Generally all attributes used in the application of Rapfish are scored on a 3 or 4 point ordinal scale. Scores for each fishery are determined from available literature, both peer-reviewed and ‘grey’ literature, and/or based on interviews or correspondence with experts on each fishery. For some of the social and economic attributes, the information can also be drawn from the CIA world factbook (CIA, 1995). All scores are carefully reviewed after a pilot analysis.

The Rapfish method is described as being flexible about the definition of fisheries included in the analysis, e.g. it is able to deal with a set of fisheries or the trajectory in time of a single fishery, or both. It is also possible to compare fisheries from individual fishing communities, or to compare a group of fisheries of a particular type in one setting, e.g. lakes in one country, with those of another setting, e.g. lakes in another country.

Statistical Analysis
A multivariate technique, namely multidimensional scaling (MDS) is used in Rapfish. The aim of this procedure is to describe the dissimilarities among n fisheries by a set of coordinate values in an n-1 dimensional Euclidean space. Most applications of MDS hope for a two-dimensional solution to capture the information contained within the $n \times n$ matrix of dissimilarities since the corresponding coordinates can then be plotted on a graph to depict the positions of all fisheries relative to one another. Rapfish aims to do the same. Results reported from the application of Rapfish show a two-dimensional representation using the first two MDS axes.

MDS is essentially an exploratory tool to show graphically the “distances” between the entities of interest, starting with a matrix of dissimilarities. When the dissimilarities satisfy the metric inequality $d_{ik}^2 + d_{kj}^2 \geq d_{ij}^2$ for any three elements i, j and k, the MDS procedure is described as being metric. Non-metric MDS arises when this inequality is not necessarily satisfied for all i,j,k.

Many papers have been published to describe the Rapfish technique (Pitcher 1999; Pitcher &

Preikshot 2001), and to show its application to different data sets (Preikshot & Pauly 1998; Preikshot *et al* 1998). Attempts are made in these papers to justify the approach and to validate the choice of MDS options from those available in the software package (SPSS) used for the analysis. We review below various features of the Rapfish technique, paying attention to both the appropriateness of the methodologies used and the implementation procedures.

Choice and scoring of attributes
First, since Rapfish aims to evaluate the sustainability of a fishery, it is clear that each attribute must be an indicator of sustainability. Of the attributes chosen by the Rapfish developers, only some can be clearly identified as being indicators of sustainability, e.g. those which represent judgements of the directions in which change is occurring. However, many of the chosen attributes do not appear to be directly linked to sustainability. For example, Table 1 shows 12 technological attributes reported in Pitcher & Preikshot (2001). The question arises whether every attribute listed here gives an indication of sustainability? Using *vessel size*, *pre-sale processing* and *trip length* for example as sustainability indicators is questionable.

The second key feature of the Rapfish methodology is that for each of the attributes chosen for the analysis, it must be possible to say, prior to any investigation of the data, how the attribute affects sustainability in terms of whether high attribute values demonstrate “good” or “bad” effects. This is dealt with by scaling each attribute so that the extremes of its range of values correspond to “good” and “bad” with regard to sustainability (Table 5.2). There are some difficulties with this.

Table 5.2. Example of a set of technological attributes from Pitcher & Preikshot (2001)

Technological Attribute	Scoring	Good	Bad	Notes
Trip length	Days	Low	High	Average days at sea per fishing trip
Landing sites	0; 1; 2	0	2	Are landing sites dispersed (0); somewhat centralized (1); heavily centralised (2)
Pre-sale processing	0; 1; 2	2	0	Processing before sale, ex.gutting, filleting: none(0); some(1); lots(2)
Use of ice	0; 1; 2; 3	3	0	None (0); some(1); sophisticated (2); live tanks (3).
Gear	0; 1	0	1	Gear is passive (0) or active (1)
Selective gear	0; 1; 2	2	0	Device(s) in gear to increase selectivity? Few(0); same(1); lots(2)
Power gear	0; 1	0	1	Is gear power-assisted? no(0); yes(1)
FADS	0; 0.5; 1	0	1	Are FADS: not used (0) ; bait is used (0.5) ; used (1)
SONAR	0; 0.5; 1	0	1	Is SONAR used? not(0) ; sounders are used(0.5); yes(1)
Vessel size	0; 1; 2	0	2	Aver. length of vessel: < 8m (0); 8-17 m (1); > 17 m (2)
Catching power	0; 1; 2	0	2	Have fisherman altered gear and vessel to increase catching power over past 5 yrs? No(0); somewhat (1); a lot/rapid increase(2)
Gear side effects	0; 1; 2	0	2	Does gear have undesirable side effects? no(0); some (1); a lot (3)

First, it can happen that an attribute is thought to affect sustainability in some way and yet the direction of this effect may not be clear *a priori*. A judgement of which end of the scale represents “good” cannot be made unequivocally for all attributes without reference to the fishery of interest and the community using the fishery. Moreover, the effect may not be monotonic and it could happen that what is “good” or “bad” for sustainability occurs somewhere in the middle of the range of values of the attribute. For example, amongst economic attributes listed in Pitcher & Preikshot (2001), a high price per tonne of landed product is listed as “good”. In considering sustainability in a poor fishing community, is this necessarily the case? Here, a moderately high price may motivate more people to take up fishing, thereby exploiting the resource and lowering sustainability. On the other hand, a very high price or a very low price could both lead to less exploitation and hence to a high level of sustainability. Thus price could well be an example of a variable with a non-monotonic relationship with sustainability.

Second, Rapfish requires that each attribute be scored “good” or “bad” on its own, ignoring the effects of other variables. However, the effect of a particular attribute on sustainability may be mediated by or through other attributes (see Section 6.6.1). This latter problem, in statistical jargon, can be expressed as difficulties arising due to multicollinearity.

Rapfish methodology appears to assert that if a variable cannot be easily scored with the extremes of its range clearly corresponding to “good” and “bad” for sustainability, then that variable is unsuitable for inclusion in the attribute set. While this undoubtedly leads to an easier problem to solve, there must be a chance that some important variables will have been excluded. The analysis should be able to cope with such variables, which could be nominal.

A different approach could be to identify one or more variables as *outcomes* or *response* variables, i.e. those that are clear indicators of sustainability. Other attributes, which possibly have an indirect influence on sustainability, may be regarded as *explanatory* variables. This would entail a different statistical procedure, one which recognises this distinction. The MDS procedure adopted in the Rapfish approach treats all of the variables on the same footing. Implicit in the method is an underlying latent response representing sustainability but it is not observable or measurable. A procedure that recognises one or more of the attributes as outcomes, effectively implies that these variables are proxy indicators of sustainability. Ideally, the alternative approach would differ from Rapfish in another important respect: it would *model* the effects of explanatory variables on outcomes rather than insist on some prior, and perhaps dubious, scoring of "good" and "bad". In effect, it would allow the *data* to determine this orientation of attribute scales.

A third feature of the attributes proposed in Rapfish is that most are scored on a 0 to 2 scale. Recognition of the data type of each attribute, e.g. whether nominal, interval scale or ordinal, is also important since this has a bearing on the type of dissimilarity measure to be constructed from the raw data prior to the application of multidimensional scaling. Some of the Rapfish attributes are essentially on a nominal scale of measurement while others are clearly ordinal. A few of the attributes form interval scale measurements.

Despite the different types of measurements involved, Rapfish uses Squared Euclidean distances. A better alternative is to consider a measure which allows for the attributes to be of different data types. Such a measure has been proposed by Gower (1971). This is designed to give a dissimilarity measure between any two objects on the basis of a mixture of data types. Some software packages, e.g. Genstat, S-Plus, have the facility for constructing dissimilarities for mixed data types.

Use of multidimensional scaling

The Rapfish procedure involves several steps when applying multidimensional scaling to evaluate the status of a group of fisheries. First a *squared* Euclidean distance matrix is constructed using the attribute scores and they are then normalised to standard normal variates. Pitcher (1999) bases the justification for this on a simulation study. Squared Euclidean distance is chosen from a set of 5 possibilities, i.e. Euclidean, Squared Euclidean, Chebychev, Minkowski and Eucliean^2-ratio. However, the diagrams resulting from the simulation (Pitcher (1999)) show little difference between Euclidean distance and *squared* Euclidean distance.

The five distance measures considered are all ones that would generally be used when the attributes are on an interval scale of measurement. In looking at fishery attributes, there is a mixture of data types, typically ordinal, nominal and interval. Hence other dissimilarity matrices which recognise the mix of data types can be more useful. The choice should be made independently of any subsequent analysis procedures. This is particularly true when the analysis involves MDS since MDS is performed on a dissimilarity matrix consisting of measures of "distance" between the objects.

Steps in Rapfish also involve creating a series of additional pseudo fisheries for inclusion with the "real" fisheries when MDS is performed. These are of three types. The first involves the construction of two fisheries, one "good" and one "bad", from the extremes of all attribute scores. This is of course subject to the allocation of "good" or "bad" to the extremes being unambiguously meaningful. The two fisheries created are used to identify the horizontal direction of the first MDS axis, the purpose being to relate all other fisheries along this axis. While this is a good idea in principle, including additional pseudo fisheries can have a large unknown impact on the final coordinates that identify the first two MDS axes. For example, imagine MDS applied without the "good" and "bad" fisheries to give a two-dimensional representation. If all of the "real" fisheries are far from being "good" and are relatively close in their attributes to those of the "bad" fishery, then introducing the "good" fishery may alter the final configuration substantially.

One way to overcome this problem and to check whether or not the configuration has changed to something less meaningful is to derive a simple measure of the performance of each fishery (say in terms of a total score across all attributes) and plotting this measure against the coordinates of the first MDS axis. A monotonically increasing plot will give confidence that the inclusion of the "good" and "bad" fisheries has not had a serious impact. An alternative is to repeat the ordination after omitting the "good" and "bad" fisheries and observing whether there has been a substantial change in the resulting distances between the fisheries.

The second set of pseudo fisheries, created during the application of Rapfish, consists of two simulated fisheries called *Mid-Range Reference Points*. These are constructed so that one point has half the attributes scored as “bad” and the other half as “good”. The second point forms a mirror image of the first point, with the first half of attributes scored “good” and the second half scored as “bad”. There are of course many ways in which such a pair could be constructed, but any such pair is said to be suitable. The resulting two points are said to provide a reference direction for the vertical dimension (Pitcher 1999), i.e. the second MDS axis. There is no explicit explanation of how or why these reference points should necessarily produce the vertical axis of the final ordination. However, via a simulation of three trajectories, Pitcher demonstrates that a fishery with large changes in the scores of individual attributes, but little change in the overall status of the fishery, produces a trajectory in a direction orthogonal to the first MDS axis. This is better understood if one can assume that the “overall status” referred to by Pitcher is in fact a total of the scores across all attributes.

The third set consists of 20 simulated fisheries, constructed from random scores allocated to the attributes. They are said to establish the size of meaningful differences on the ordination (Pitcher 1999). There is no explanation of what this interpretation actually means or why it is important to include these 20 random fisheries. More than 20 is said to improve the ‘statistical rigor’. This suggests that the author supposes that adding a set of simulated fisheries will improve the analysis in some way. To do this (say) for achieving an increased sample size is highly inappropriate. However in Pitcher & Preikshot (2001) there is a slightly clearer justification for the inclusion of the random reference points. These are said to act as anchors for the MDS distances in order to compare the variation among one group of fisheries with another group of fisheries. However, the possibility of distortion to the ordination, caused by the inclusion of a large number of hypothetical fisheries, has not been considered.

The overall purpose behind including several sets of pseudo additional fisheries seems to be to assist with the interpretation of the resulting 2-dimensional representation of the MDS coordinates. There is serious concern however in the inclusion of these as a routine part of the Rapfish technique. The representation can change each time additional fisheries are brought in. The interpretation becomes very dubious if there are many more simulated fisheries included in the ordination than the number of “real” fisheries. It should be noted that MDS is essentially an exploratory tool to look graphically at the “distances” between a set of objects. The theoretical development of MDS makes no attempt to interpret the position of the objects as “good” or “bad” in relation to their axes. The emphasis is on ensuring that the dissimilarities are well represented by a fewer number of dimensions. Changes in measures of “goodness-of-fit”, e.g. STRESS values (Kruskal 1964) or SSTRESS (Takane *et al* 1977) are used to decide on the appropriate number of dimensions. Rapfish tries to over interpret the main function of MDS by introducing simulated fisheries, and implies that a 2-dimensional representation will be appropriate with STRESS values of 0.25 or lower. Kruskal (1964) however suggests that STRESS values of 0.05 can be regarded as good and 0.20 as poor! Rapfish pays little attention to either the appropriateness of the dissimilarity matrix used or to the most suitable number of dimensions.

As indicated above, a *squared* Euclidean measure is used for calculating dissimilarities amongst the fisheries, although there seems little reason for choosing this measure over Euclidean distance. The latter satisfies the metric inequality, so classical MDS can be used. The advantage is that there is then an exact algebraic solution to creating a ‘distance’ map of the fisheries, provided by using *metric* MDS. Using *squared* Euclidean distance and the more approximate non-metric MDS procedure is therefore not justified. It is also very unusual to use a squared Euclidean distance in practice since this make the “distance” between the units even more separated on the MDS two-dimensional representation.

Pitcher’s 1999 paper, which describes the Rapfish technique in considerable detail, also dismisses the use of Principal Component Analysis (PCA) as producing arched, biased plots, and settles in favour of non-metric MDS. However, had a metric approach been used with Euclidean distance, the PCA analysis and a plot of the second principal component versus the first principal component would have produced exactly the same distance map as that produced via metric MDS. A further advantage in using metric MDS arises when assessing which of the fisheries attributes have the largest influence on the first MDS axis and this is discussed in the following section. Since metric scaling is also fairly robust to departures from Euclidean distance (Sibson 1979), metric MDS could have been used initially. After the analysis however, examination of the results (e.g. eigenvalues of the XX' matrix) could have revealed whether non-metric MDS would have been of advantage.

Of course, the above argument in favour of metric MDS assumes that a dissimilarity matrix based on Euclidean distance is appropriate. This is not necessarily the best option for a mixture of data types. Had a different distance measure been adopted, then using non-metric MDS may well be the best approach.

Examining the importance of fisheries attributes in the ordination
Pitcher & Preikshot (2001) suggest several approaches for examining which of the attributes have the greatest influence on the first MDS axis. They refer to this axis as the sustainability axis, having suggested that the axes be rotated so that the first MDS axis is aligned with the line joining the "good" and "bad" (simulated) fisheries.

The first analysis proposed is a multiple regression with the "sustainability" axis as the dependent variable and the normalised attributes as the independent variables. Pitcher & Preikshot suggest that significant regression coefficients identify those attributes that bear a relationship to the sustainability axis, but give less emphasis to this technique on the grounds that the non-parametric nature of the MDS technique implies that the results do not transfer to other analyses, presumably to those based on other data sets. We do not see that the use of non-metric MDS is a problem here, nor do we see the so-called non-metric MDS as being non-parametric! Pitcher's 1999 paper also refers to Rapfish as using an ordination technique that makes no distributional assumptions, but we would like to point out that even metric (or classical) multidimensional scaling makes no distributional assumptions!

The second proposed method of analysis involves a study of the correlations between each attribute and the MDS axes. Many correlations are mentioned here, e.g. canonical correlations and multiple regression, together with a statement that "the correlations cannot be interpreted singly, for they determine the MDS axes jointly". This is ambiguous when the interpretation given appears to indicate a Pearson's correlation coefficient between two variables.

The third proposal is to consider the "leverage" of each attribute on the ordination and is based on successive repeats of the ordination method, each time dropping one attribute in turn from the analysis. The method is described in greater detail in Pitcher (1999) using as an example, data from 18 fisheries in the east coast of Canada (Pitcher & Power 2000). The statistic used to assess the importance of each attribute is the sum of squares of the differences between the x-values (and then the y-values) of ordinations performed with and without the attribute. This is referred to, rather inappropriately, as a standard error %. The % is used only for the x-ordination and we therefore believe that it merely symbolises the fact that each fisheries status along the "good" to "bad" axis can be represented as a percentage if "bad" is taken as being 0% and "good" is taken as being 100%.

The results are presented as a bar chart with two sets of bars on either side of a vertical line, the bars to the right representing the attributes importance along the x-axis and the bars to the left representing its importance along the y-axis. The analysis is repeated for each fishery to show the influence of each fishery in the final ordination. Further graphs are produced to show changes to the position of each fishery when attributes are dropped in turn. We regard this analysis as a severe over-interpretation of a set of data for use in MDS, which is only of value as an initial exploratory tool for the purpose of reduction in the dimensionality of a data set.

Comparing groups of fisheries by kite diagrams
Pitcher 1999 produces kite diagrams as a means of comparing average scores of one group of fisheries with the average scores of another group of fisheries in a multidisciplinary fashion by first drawing a polygon with k sides for k disciplines to represent the "perfect" fishery, i.e. one which scores 100% on the first MDS axis. Here the MDS scales are assumed to be re-scaled so that "good" is 100% and "bad" is 0%. He then puts in points to represent the average score, over various attributes, that each fishery gets in each discipline along the line joining the centre of the polygon ("bad") to the vertex ("good") representing that discipline. Finally, the points corresponding to each fishery are joined to make irregular polygons within the original polygon. This does produce a graphical illustration for comparing two (or more) groups of fisheries, but there are two serious limitations.

First, only one MDS axis is represented in the kite diagram. It is unusual to get a good representation of a fishery along a single ordination axis. It would be better to use a simpler and more easily understood measure, such as the total of all scores given to an attribute, if a single summary statistic is to be used in the kite diagram.

Second, as Pitcher himself demonstrates, taking an average loses much of the information about the individual fisheries within the group being represented. He uses an example to show that the variation of the individual fisheries within each group can be quite different for any single discipline. Having recognised this limitation, it is surprising how much emphasis is given in Pitcher's 1999 paper to this diagrammatic representation.

Again, we feel that the data are being over-interpreted without adequate attention to the validity of the MDS procedure in terms of the distance measure used, the correct number of dimensions needed for producing a good representation of the data and the objectives of the analysis. Note also that the same information as represented in the kite diagram can also be shown graphically by a multiple bar chart which is easier to comprehend for a visual comparison of the fishery groups across the different disciplines.

Analysis of rankings

Pitcher (1999) also proposes another method to compare a group of fisheries in situations where there is uncertainty about the original attributes. The ordination is performed as before, but the scores for the first MDS axis are replaced by ranks rather than percentage status values. There is no attempt to obtain an overall ranking but a correlation matrix between the disciplines is presented. It is not clear whether rank correlations are being used here, but it would seem not since there is a mention that the highest correlation, between the Social and Ethical fields, has a coefficient of determination of only 46%. It appears therefore that Pearson's correlation has being used, whereas a more appropriate measure for ranked data would have been Spearman's rank correlation coefficient.

Review of the application of Rapfish to real data sets

Initial developments of the Rapfish technique and its application to real fisheries have been reported in Preikshot & Pauly (1998), Preikshot *et al* (1998) and Pitcher *et al* (1998). In these papers, the method is referred to as an interdisciplinary multivariate method for rapid appraisal of the status and health of fisheries but it is essentially the Rapfish methodology at an earlier stage of its development.

The general concerns of Rapfish as discussed above are mirrored in these papers. With regard to the application of multivariate techniques and interpretation of results, the following problems were identified:

(i) Euclidean distances are used as the distance matrix for MDS when many of the attributes are scored on a scale of 0,1,2. Most of the attributes are ordinal. Some are nominal. Only a few are quantitative measurements but all attributes are treated as interval scale data and normalised to z-scores.

(ii) All attributes are treated alike in the ordination, making the implicit assumption that they are all equally important in assessing the fisheries under consideration.

(iii) It is further assumed that the direction of positive characteristics can be identified in relation to the two ordination axes. The theoretical base of the MDS technique does not justify such a claim.

(iv) Relationships between the two axes and the attributes used in MDS appear to be judged on the basis of simple correlation coefficients or coefficients of a multiple regression equation without attention to possible interactions between the attributes themselves.

Other positive and negative aspects of the individual papers are discussed below.

Preikshot & Pauly (1998) attempt to compare 17 small-scale tropical fisheries by contrasting attributes from ecological, economic, social science and technological attribute sets. They also create hypothetical fisheries A and B to reflect "Malthusian overfishing" effects (resource depletion with an increase in the number of participants) through early, young, mature and old stages. The exact method of scoring these 8 hypothetical fisheries with respect to a listed set of 24 attributes is unclear. They are merely said to be scored with declining relative and absolute economic standards, collapsing social structures and decreasing use of selective gears.

MDS is applied to each attribute set (ecological, social, economic, and technological) in turn to produce a 2-dimensional ordination. The reasons for not requiring a third dimension are appropriately justified, but the S-stress values quoted are quite high, ranging from 0.22 to 0.30.

Cluster analysis is used to objectively produce 3-4 groupings of the fisheries for each of the 4 attribute sets and these groupings are shown on each ordination graph. Correlations between each attribute in a given set (technological, ecological, economic or social) and each of the ordination axes are used in the interpretation. Key attributes which distinguish between the fishery groups are identified. Although the methodological limitations listed in (i) to (iv) above are still of concern, the general approach provides a reasonable descriptive tool for comparing the fisheries. What is problematical is the way in which the relative positions of the hypothetical fisheries are interpreted to identify four cluster groups as "favourable", "fishery decline", "environmental decline" and "unfavourable". This component of the interpretation is less convincing, particularly in view of the authors' own recognition of the absence of attributes that are time-related.

Preikshot *et al* (1998) use the same attribute set as in the above paper but apply the methodology to a set of 32 African lakes. Some of the fisheries were the same as ones used in Preikshot & Pauly (1998). Some were from the same location but in different time periods. Regarding the time repeats as presenting additional ***independent*** cases for inclusion in the analysis is inappropriate. Three additional fisheries from the Philippines, Belize and Thailand were also included for global comparison, as well as hypothetical "good" and "bad" fisheries. These "good" and "bad" fisheries are used to rotate the ordination axes so that the "good" fishery appears in the upper left quadrant. This pre-supposes that (a) each attribute scale can clearly identify which extreme corresponds to "good"; (b) including the two hypothetical fisheries does not alter the relative positions of the "real" fisheries. Neither of these can be justified; (b) will certainly alter the true ordination although the degree of distortion cannot be determined without further analysis. There has been no attempt to study this aspect.

An additional ordination is included, based on carrying out an MDS on the co-ordinates for each fishery from the four attribute ordinations. The value of producing this analysis, based on results of the previous ordinations, and subsequent interpretation, are highly questionable.

The analyses procedures adopted in Pitcher *et al* (1998), applied to 26 fisheries worldwide, are similar to the above, with the inclusion of an additional ordination. Here 20 "random" fisheries are created in the analysis, in addition to the "good" and "bad" fisheries. This further distorts the true distances between the real fisheries of interest. Again there is no attempt to determine what effect the inclusion of 22 hypothetical fisheries has on the true ordination. The 20 "random" fisheries are depicted on the ordination with a cross to show 95% confidence limits, based on the mean scores of the random fisheries in the direction of the ordination axes. It is unclear how the presence of the cross aids in interpreting the health of the fisheries.

The "good" and "bad" fisheries are said to help in rotating the axes so that the "good" fishery always occupies the top left quadrant and "bad" occupies the bottom right quadrant. However a further ordination without these two fisheries, or some other alternative analysis approach, is needed to reach confidence that the ordination is not unduly affected by their inclusion.

Whereas in the two previous papers (Preikshot & Pauly, 1998; Preikshot *et al* 1998) the effect of each attribute on the MDS ordinations is studied on the basis of correlations, in Pitcher *et al* (1998) this is said to be done using "loadings estimated using multiple linear regression with an intercept of zero" with untransformed scores on the variables. What exactly these "loadings" are is unclear, but they possibly refer to the regression coefficients of the multiple regression equation relating scores for each ordination axis in turn to attribute scores. This approach is questionable since again (as with correlations), no account is being taken of possible associations among attributes.

The analyses procedures adopted in each of the above papers are very similar, but there is some over-interpretation of the results emerging from applying MDS to real data. There appears to be little recognition that MDS is essentially an exploratory tool.

5.3 Improved Methodological Approaches for Data from Previous Studies

5.3.1 The Philippines Study

In the Philippines study, the simple forms of analysis concentrate on t-tests and the study of correlations. The former is applied correctly, if simple random sampling can be assumed, but the interpretation is limited to just the significance levels. More information could be obtained by a study of the magnitude of the differences in the 10 indicator variables from past to present to assess which indicators have resulted in the greatest change due to co-management activities.

Chi-square tests to look at the effect of explanatory variables, one at a time, on the direction of perceived change in key indicators could be extended to log-linear modeling procedures so that interactions among all explanatory variables could be studied simultaneously.

The more advanced techniques applied, namely principal component analysis and multiple regression, although appropriate in relation to the objectives, have again been conducted under the assumption of simple random sampling. The analysis method could be improved, thereby increasing the trustworthiness of the conclusions, by recognising the data structure, e.g. by taking account of the sample stratification by site and by other socio-economic variables. Further analysis to explore the validity of the fitted regression models could also lead to a better understanding of factors affecting indicators of the success of co-management schemes.

5.3.2 The World Bank Study

Similar comments apply to the statistical analyses procedures undertaken in the World Bank study. Their study of factors influencing success indicators can be much improved by adopting a general linear modelling procedure which allows categorical and interval-scale explanatory variables to be included directly in the model (without conversion to dummy variables) via the use of standard statistical software. Moreover, the approach, based on an interpretation of regression coefficients alone, is considerably limited since the regression model used involved all potential explanatory variables, including those that had little effect on the response indicator. Since the explanatory variables are themselves usually correlated, variable selection procedures are needed to identify the subset of variates that contribute significantly to the regression, i.e. those that explain a significant amount of the variation associated with each success indicator. Variates in this subset identify the factors influencing the success indicator of interest.

The World Bank Study, quite correctly recognises the difficulties that arise due to the data structure being hierarchical and the non-independence of observations when the same focus group give their perceptions of success indicators with respect to more than one resource, habitat, threat or rule. Difficulties with non-independence could have been overcome by asking each focus group to specify which is the most important of the three indicator categories they mention. Results from just this category could then have been used in the more formal analyses procedures.

Alternatively, it would have been reasonable to assume that each indicator category was given an independent assessment by each focus group. An analysis could then be done to take account of the variability between the perceptions of different focus groups. The data matrix would have many missing observations, but the use of general linear modelling procedures would have been appropriate here. These procedures are very flexible in their ability to handle a wide range of data structures. They are also quite robust to slight departures from non-normality. Any serious non-normality could have been handled by a suitable transformation, e.g. to log values.

5.3.3 Rapfish Approaches

Approaches used in Rapfish aim at assessing the sustainability status of a fishery as well as examining factors that affect the sustainability status. Many suggestions have been made in Section 5.2.3 for improvements and more appropriate alternatives to procedures used by Rapfish techniques. Here we highlight the fact that the analyses procedures addressing Rapfish aims are based on an initial multi-dimensional scaling (MDS) procedure using a squared Euclidean distance measure, although the analysis would have had a clearer interpretation if a (non-squared) Euclidean measure had been used. This would have provided a measure of the proportion of variation attributable to the first two MDS axes, thereby providing an assessment of the degree to which the sustainability status of different fisheries can be judged from the position of each fishery on the MDS plot.

The use of the first MDS axis as providing an overall measure of sustainability for examining factors influencing sustainability is very questionable. First there is no measure of the degree to which this axis captures the essential features of sustainability from the data. Secondly, all variables, including explanatory variables, are used in the MDS ordination. A better approach would be to clearly identify a set of outcome variables as proxy indicators of sustainability and use only these in the MDS ordination. Alternatively, each proxy indicator could be used as the response variable in turn to study its dependence on a range of potential explanatory variables. This would then be similar to approaches undertaken in the World Bank and Philippines studies where the methodological approaches was sound despite having been applied in a simplistic manner.

5.4 Summary and Conclusions

In this final section, the main statistical limitations concerning the three studies under discussion in this chapter are summarized and some overall conclusions are given. We focus on the statistical analyses procedures since the data collection methodologies were relatively sound. It should be noted however that the Philippines Study (Section 5.2.1) and the World Bank Study (Section 5.2.2) benefit by giving more attention to primary information sources and peoples' perceptions. Examples of the application of Rapfish on the other hand depends on expert opinion and secondary sources of data, and this aspect is emphasized by describing the data as comprising "easily scored attributes".

Statistical procedures applied in the Philippines Study were approximately suited to address the different objectives, but were limited because of the lack of attention to the data structure (e.g. data were drawn from six villages) and the high dependence on tests of significance in the interpretation of results. Each technique appeared to have been applied in a semi-automatic sort of way and did not extend beyond the first stage of analysis to further detailed exploration of the data.

In the World Bank Study, the reporting of methodological approaches undertaken were, in general, extremely clear. The description of the full data set was also excellent, as was their recognition of the need to commence analyses investigations by conducting exploratory data analysis procedures. It is clear however that the researchers could have benefited by some knowledge of modern approaches to statistical analyses. Recognition of the hierarchical nature of the data structure was a positive aspect of the study, but it wasn't surprising that dealing with this was found to be difficult, given that statistical software with capabilities for dealing with complex multi-level data are only just beginning to come into use.

Disappointingly however, there was a lack of awareness of capabilities in statistics software that have been in use for several years. We refer here to procedures for model selection when fitting general linear models involving both classification factors and regressor variables. For example, the interpretation of results concerning the study of factors affecting success indicators appeared to be based solely on the significance of the regression coefficients in one overall multiple regression model. This is an over-simplified approach which does not necessarily identify the correct set of attributes affecting the success indicators.

It is a great pity that there are some limitations in the data analysis approaches because the study has been extremely well done with appropriate sampling procedures and good participation of relevant stakeholders at all stages of the survey. The reporting also has been very meticulously done. The study has clearly generated an extremely good database of well-documented information. Unfortunately there is no mention of data archiving activities, so whether the data is available and accessible to other researchers is unclear.

A critique was presented in Section 5.2.3 to highlight a series of shortcomings in procedures adopted in the Rapfish studies from a statistical point of view. Our main concerns regarding the attributes themselves can be summarised as follows:

- No distinction is made between explanatory attributes and outcomes (response attributes);
- It may be unrealistic to determine *a priori* whether the effect of an explanatory attribute on sustainability is "good" at one end of its range of values and "bad" at the other;
- The prior assessment of the effect of each attribute is made with no regard for possible interactions with other attributes.

The choice of the distance measure for use in multidimensional scaling is made from a set of five possibilities, all of which apply to data on an interval scale of measurement. There are other candidates that are more suited for a mixture of data types. However, in view of many of the attributes being on an ordinal scale, the choice of a distance measure, assuming all the attributes are interval-scale, should not have serious implications in the application of MDS. Our concerns are in terms of the lack of justification for using a *squared* Euclidean distance and non-metric scaling in preference of the more commonly used Euclidean distance. Use of a squared Euclidean distance can over-emphasise the distances between fisheries that are only slightly distinct from each other on a Euclidean distance measure.

The choice of distance measure and corresponding use of non-metric scaling also has implications for the approaches used in studying the influence of fisheries attributes on the sustainability status of fisheries. Rapfish advocates the use of the first MDS axis, aligned with the line joining the "good" and "bad" (simulated) fisheries, to be the dependent variable in a multiple regression. There are two problems with this.

Firstly, the same attributes that are used in generating the first MDS axis are then used as the explanatory variables. Secondly, the approach essentially claims that the first MDS axis captures a large proportion of the variation in the set of attributes used in the ordination. There is no meaningful summary measure that can be calculated to determine this proportion when non-metric scaling is used. Had Euclidean distance been used, the first MDS axis would coincide with the first principal component and this would allow a judgement concerning the degree to which the reduction to a single ordination was appropriate. Rapfish offers no suggestion of the way in which the suitability of the single ordination can be assessed.

We have also highlighted various other limitations and lack of clarity in the use and application of regression analyses, correlation analyses, kite diagrams, etc. Overall, there is considerable over-interpretation of the data in the use of Rapfish and a number of limitations in the statistical approached used have been identified.

The three studies discussed in this chapter increase in complexity from the Philippines study to the Rapfish studies, but the trustworthiness of their conclusions are least with Rapfish. Rapfish approaches have serious limitations, are less transparent and do not appear to provide a methodological approach that can be readily re-produced by other researchers. All three studies use relatively large data sets but there appears to be little evidence of archiving activities or making these data accessible to other users via, for example, a web reference in the documentation. Preikshot and Pauly (1998) provide a web-address for just the table of attributes used but not for the actual data from each fishery. It is of course possible for individuals interested in the data to contact the authors of the relevant reports individually. We are very grateful to David Preikshot for supplying a set of data used in his PhD thesis which involved 54 fisheries scored on 28 attributes. This was used in the very initial stages of our own modelling work to explore a few possibilities. It should be noted however that the data analyses work reported in Chapter 6 are based solely on the profiled data described in Chapters 3 and 4.

6. Development of Methodologies for Data Analysis

6.1 Introduction

The suitability of any statistical technique when analysing a set of data depends first on the objectives of the study and a clear definition of the questions that the study intends to answer, and secondly, on the way the data were collected with respect to sampling procedures. The objective here is to identify outcomes indicative of co-management performance and model these to determine the way in which changes in co-management outcomes would be influenced by multi-disciplinary measures or attributes associated with the fishery. The model-based approach also allows key conditions for successful co-management to be identified and these would be suitable for inclusion in future monitoring programmes.

This chapter discusses two suitable approaches of model development of co-management performance and illustrates the application of these models to the case study data described in Chapters 3 & 4. These two model based approaches were selected on the basis of a review of the merits of application of alternative methodological approaches. In Section 6.2, we provide a brief discussion of a number of possible approaches and highlight their advantages and limitations.

In Section 6.3, we discuss the initial stages of data analysis which include data scrutiny and checking procedures, the creation of new variates and reasons for this, how the data were prepared for analysis, exploratory data analysis procedures, procedures for reduction in the number of cases and/or variables, and selection of outcome variables for analysis. Difficulties encountered at each of these stages are also highlighted.

Section 6.4 includes the first of our model development approaches, i.e. the use of general linear modelling techniques to identify attributes affecting co-management outcomes. This is followed by a discussion of the development and use of Bayesian network models in Section 6.6.

6.2 An Overview of Possible Model-Based Approaches

Our discussion here focuses on approaches that could be adopted in a situation where the main objective is to determine the set of factors (including categorical, nominal or continuous variates) that affect management outcomes or performance of a fishery (e.g. sustainability or equity). We also look at the manner in which such outcomes would be affected by changes in key attributes. It is appropriate for this purpose to use of some form of modelling technique to investigate and determine the subset of factors that have a significant influence on each outcome variable. In other words, using of some sort of generalisation of a regression model would be appropriate to identify factors that affect management performance outcomes. Possibilities include the fitting of general linear models (GLM)[#], logistic regression models, Bayesian network models, proportional odds models and multi-level models. The choice would depend on the nature of the data structure and the type of outcome variable being modelled, e.g. interval scale, binary or categorical.

For example, general linear models are applicable when the response is a quantitative variable. Its suitability stems from recognizing that it fulfils the project aim of identifying key conditions and attributes that contribute to co-management performance. There is just one limitation associated with using this modelling technique, i.e. it requires any outcomes describing co-management performance to satisfy certain assumptions. We shall return to this point in our more detailed description of the model in Section 6.4, but note for the moment that the GLM technique is very powerful and is widely used because it provides a simple mathematical model equation to describe, often quite complex systems, to a good degree of approximation. It is essentially an extension of standard multiple regression models to a more general set of explanatory variables which include categorical variates

[#] General linear models deal with normally distributed data. Subsequent references in this report to GLMs should not be confused with statisticians' use of GLM to represent ***generalised*** linear models for data from other distributions (e.g. binomial, Poisson, gamma, etc).

as well as quantitative variates. It is a very well developed statistical technique and is found to work well in a wide variety of situations in many areas of application. This is the first of our model-based approaches and it is described more fully in Section 6.4.

Logistic regression models on the other hand, are used when the response of interest is binary, e.g. success/failure, present/absent, etc. These ideas were used implicitly in our Bayesian network model developments described in Section 6.6. The benefits of these network models are discussed more thoroughly in Chapter 7.

Proportional odds models are used when the number of category levels for the response extends beyond two levels to three or more ***ordered*** categories. Given that many of the outcome variables identified in the hypothesis matrix (Table 3.2) are ordered on a three-point scale (e.g. food security, participation in management, equity, compliance with rules and regulations), it seems appropriate to use proportional odds modelling. However, there are some difficulties associated with the application of these models.

First, the methodology involves grouping the categories into binary sets in different ways. Thus, if the response variable has four category levels 1, 2, 3, 4, there are three binary sets, namely the set made up of 1 versus 2,3,4; the set made of 1,2 versus 3,4; and the set made of 1,2,3 versus 4. The analysis looks at the probability of a co-management unit falling in one group of a binary set relative to the probability that it falls in the second group of that same set. There is then the assumption that this ratio of probabilities on a logarithmic scale are the same, irrespective of which binary set is being considered and for all explanatory variables included in the model. This is quite a strong assumption and it has been found to be violated in many practical situations. We have considered this assumption for the set of fisheries attributes and outcomes relating to this study, and found that the assumption was far from plausible.

There are further difficulties associated with the use of proportional odds models. The method not only requires the frequency of cases in each of the category cells of the response variable to be sufficiently large, it also requires non-empty cell categories across combinations of the response and other attributes used during the modelling process. In the type of work being considered here, model development will always be based initially on such a large number of explanatory variables that these requirements will not be met. For these reasons, proportional odds modelling was rejected as a suitable methodological approach to pursue.

Multi-level models extend the ideas of general linear models to situations where the data structure is hierarchical, i.e. where information is collected at several levels. An example of this was seen in the World Bank study described in Chapter 5 where information had been collected at country level, site level and focus group level. This approach takes account of the correlation structure between units at one level because they occur within units at a higher level.

In the work presented here, data were collected at just one level, i.e. co-management unit level, so the need for multi-level modelling did not arise. However, it is important to consider this approach as a possibility if data were to be collected at different levels.

One other general approach also needs to be mentioned. This is canonical correspondence analysis (CCA), which has been widely used by ecologists in a quite different setting, but with data structures that are formally similar. In this analysis, a set of response variables is modelled by deriving new variables from the explanatory variables which best explain the variation in the responses. In ecological applications of CCA, the responses are usually the abundances of a number of species, measured at a number of sites, with a set of environmental variables as explanatory variables. The idea is to analyse the impact of the environmental variables on the species abundances. In our setting, the responses would be the outcome variables, instead of sites we would have fisheries, and in place of environmental variables we would have attributes of the fisheries.

In CCA, the effect of the explanatory variables is measured in terms of its effect on an ordination of the response. This can be thought of as a sort of ordination like MDS. Typically the output from CCA is a plot rather like the ordination plot from MDS, but with the explanatory variables appearing on the plot. CCA and related methods are described by Jongman *et al* (1995). Standard statistical package generally do not include CCA, but specialised software packages for this analysis are available. Of these, the most popular amongst ecologists is CANOCO.

There are two major difficulties with this approach for analysing fisheries outcomes and attributes. One is that an ordination of outcome variables or an ordination of attributes should produce a meaningful summary which can be readily interpreted. Although the attributes shown in the hypothesis matrix (Table 3.2) have been grouped according to the IAD framework, the actual variables within each group are still too diverse in their nature to lead to a meaningful summary. The same is true for the set of outcome variables, which range from resource related variables to those describing food security, empowerment, compliance, etc. It would have been possible to include variates of just one type of outcome, e.g. the eight variables describing equity, but this was inappropriate for two reasons. In the first place, four of these equity variates were trend variables, four were static variables and combining these would not be meaningful. Secondly, all were scored on a low, medium, high basis and this was inappropriate for the application of CCA.

In the light of this review of likely candidates for statistical methods, and taking account of features of the data available for the present study, we have chosen to develop two complementary approaches: general linear models and Bayesian network models. A more detailed rationale for this choice will emerge from further discussion below.

6.3 Initial Stages of Data Analysis

Before either approach could be applied, it was first necessary to assemble the data into an Access database (see Chapter 4), keeping in mind the need for data to be subsequently transported to a suitable statistical package for analysis. Particular attention was given to coding of missing values and the naming of variables. The data were then imported into the statistics software package SPSS for initial data scrutiny and checking procedures, and for initial stages of variable screening. These are described in Sections 6.3.1 and 6.3.2.

Some attention to data reduction (variables as well as cases) was also necessary since the list of all potential variables (see Annex II) affecting management performance outcomes was substantially large and unmanageable for direct use in appropriate statistical analyses procedures. Hence some form of dimension reduction was also desirable at the initial stages of analysis. Principal components analysis (PCA) is the “classical” method of dimension reduction, and this approach was considered. Cluster analysis of variables, using distance (or similarity) measures more appropriate for mixed data types, was also considered. These approaches to data reduction are discussed in Sections 6.3.3 and 6.3.4. Finally, exploratory data analysis procedures undertaken are described in Section 6.3.5.

6.3.1 Data Scrutiny and Checking

When data are assembled from a number of fisheries which vary substantially from each other, and which are largely based on secondary sources of data, various types of errors in the data are inevitable and these have to be corrected before the full data set is ready for analysis. Any inconsistencies found in the data also need to be resolved. The data were therefore first listed and scrutinized. Simple summary statistics (for quantitative variates) and frequency tables (for qualitative variates) were produced and then examined for any inconsistencies and data errors. In collaboration with the Principal Investigator, and in some cases, by communication with the original profilers, these queries were dealt with and corrected in both the master database on Access and in the SPSS file used for initial exploratory analysis.

In certain cases, decisions had to be made concerning specific data values. For example, the number of gears for two of the fisheries had been recorded as ≥ 30 and ≥ 20. Here we preferred to make an *ad hoc* decision to replace these two values by 30 and 20 respectively rather than declare them as missing observations in the data set. A few variables were also omitted from the final data set because no data were available for these variables, e.g. secci depth, bi-limiting nutrient concentration, optimal threshold and macro/political status, while others were omitted because they were needed only for mapping purposes, e.g. latitude and longitude, water body name and district.

6.3.2 Initial Screening of Variables for Analysis

The initial screening process involved considering variables in each attribute set (resource, market, technological, environmental, etc) in turn, and examining each for their suitability. The full list of variables is given in Annex II, but all variables could not be considered for analysis for a variety of reasons. Some of the reasons were the following:

- Difficulties with interpretation;
- Very few (≤ 5) non-missing observations;
- Not applicable to most of the fisheries co-management units
- No variation in the recorded values, e.g. YEAR_VAR, POP_GROW, WAR.
- Only 1 or 2 observations different from the remaining set with identical values;
- Only available for Laos data with all values identical, e.g. GRADIENT;
- Too many multiple response answers, e.g. GR_BAN_N.

The variables omitted from the analysis are listed in Annex VI. In total 60 explanatory variables and 19 outcome variables were discarded from further consideration. Since the major reasons for omissions were the non-availability of the information or non-applicability, it is unlikely that inclusion of these variables in any future monitoring programmes would serve any useful purpose.

The large number of missing values, leading to a very patchy data set, was a serious difficulty faced during statistical model developments. The problem of multiple missing values can, in principle, be addressed by model-based methods of missing value imputation (Schafer 1997, Little and Rubin 1987). However, most of these methods are robust only when the fraction of missing data is not too large, which is not the case with the present data set. Also, with many variables, as we have in here, there is a significant computational overhead, especially when attempting to fit a variety of statistical models to the data. It was therefore decided not to pursue this option. Instead, analyses were carried out with the maximal complete set of data available for the variables under consideration.

The variables that could be considered for data analysis procedures were identified according to whether they were categorical (classification) variables or interval-scale quantitative variates since this information was relevant for the statistical analyses. In what follows we will be referring to both explanatory variables and response variables as “variables” when both groups are being considered, but where a distinction has to be made, response variables may be referred to as “outcomes” and explanatory variables as “attributes”. Within the set of explanatory variables, where needed, categorical variables will be referred to as “factors” and interval-scale measurement variables as “quantitative variates”.

6.3.3 Dimension Reduction

For some of the modelling approaches attempted, the number of variables had to be considerably reduced, even after the screening process described in *6.3.2.* To be useful, most statistical models should be parsimonious and not overloaded with redundant variables. Replacing the original set of variables with a smaller set is called “dimension reduction” and is reasonable to attempt in cases where there are possible redundancies among the variables. These redundancies would occur, for instance, when two or more variables are highly correlated and can be regarded as measuring essentially the same thing. Often, such variables can be regarded as “proxies” for some unobservable latent variable.

Statistical methods for dimension reduction are exploratory and do not lend themselves to formal tests of significance. Decisions concerning which variables to include and which to set aside are judgements arrived at by careful consideration of the contextual meaning of the variables aided by exploratory statistical analysis. Two statistical methods were tried: variable-clustering and principal components analysis (PCA).

The idea of clustering variables is similar to the more familiar clustering of cases, except that a more appropriate measure of “distance” is used. In fact it is more usual to think of “similarity” between two variables, the converse of distance. It is natural to base this on some measure of correlation between variables. Because the data types were mixed, some being measurements on an interval scale while others were ordinal or binary, a similarity measure derived from rank correlation was thought to be suitable. The square of Spearman’s rank correlation was the measure used. The package S-PLUS 6 (Insightful Corp., 2001) was used for this analysis; the S-PLUS function for variable clustering is *varclus*, which is part of the *hmisc* library.

This method was applied separately to sets of variables in attribute or outcome groups. To illustrate the method, we present the analysis for one set of attributes selected from the Decision-Making Arrangements group of variables. An outcome variable EQUITY (distributional equity among community members) was included with a view to having a prior look at how it might depend on the attributes in this group. The dendrogram (Figure 6.1) below summarises the results.

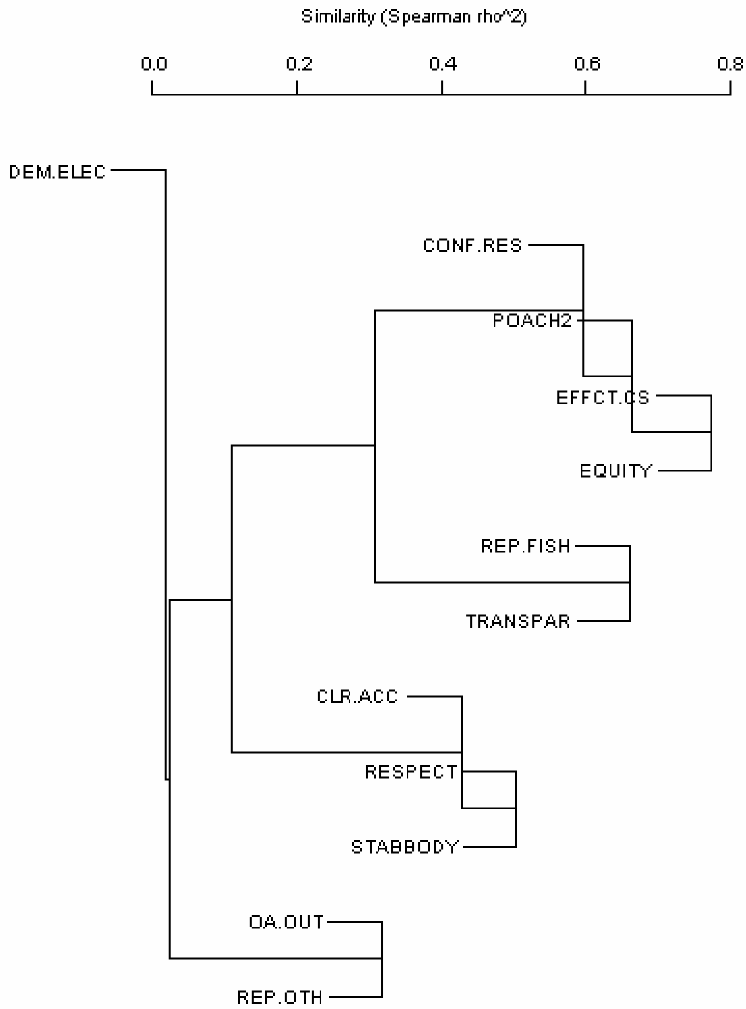


Figure 6.1 Dendrogram illustrating similarities among variables

It can be seen that, for example, the variables REP_FISH (representation of fishers on the decision-making body) and TRANSPAR (transparency) are closely related, and probably contain similar information. In the interests of parsimony, only one of these variables was retained for the network models described in Section 6.5. In some cases, variables were retained for modelling even though they were closely related statistically. This occurred when the contextual meanings of the variables were different and model interpretation would benefit from retaining them all. For example, the three variables CLR_ACC (clear access rights), RESPECT (respectability of the decision-making body) and STABBODY (stability of the body) were all retained in spite of being quite closely related to each other.

With some of the groups of variables examined, it was possible to gain further insights into the complex relationships between them by using PCA. Given the varied data types (especially with ordinal variables taking values 0, 1, 2) we should not perhaps expect great success with this approach (which generally works best with measurement variables). However, as an exploratory tool, it was found to be useful, at least in some cases, to further explore possible relationships. As an example, PCA was tried on the variables EQUITY, RESPECT, STABBODY, CLR_ACC, REP_FISH, DEM_ELEC, CONF_RES, EFFECT_CS and POACH2. The first two components accounted for 85.5% of the variance. A biplot (Figure 6.2) of the first two components is shown below.

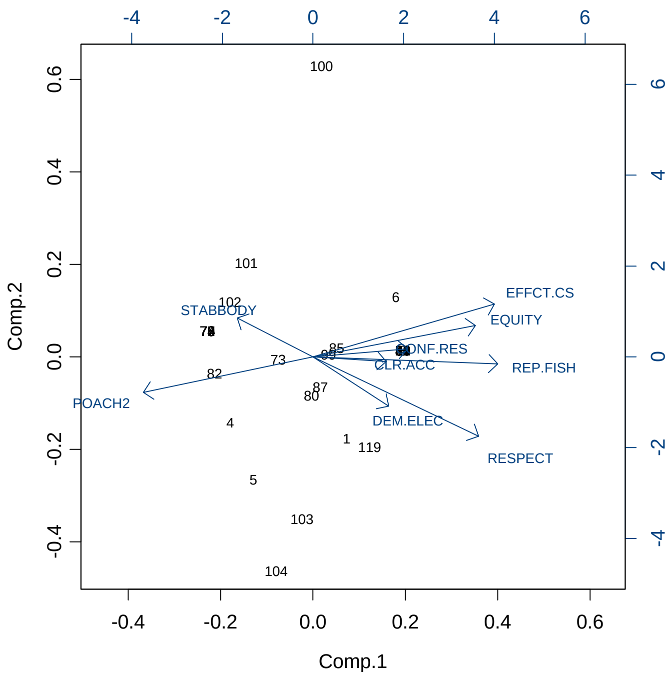


Figure 6.2 PCA Biplot

Biplots like this are very useful summaries of PCA because they simultaneously represent the data points and the variables. Their interpretation is extensively described by Gower and Hand (1996), but for our purposes it suffices to note that the length of a vector represents the variance of the corresponding variable and that the angle between two vectors is a measure of the correlation between the variables (a small angle indicating a high correlation). The numbers on the plot are the ID numbers of the fisheries in the database. (Note the direction of the STABBODY variable is unexpectedly opposite to that of RESPECT, but this is because of the way numeric codes were assigned to the former variable, 0 representing "stable".)

Taken together, these two exploratory tools, variable clustering and PCA with biplots, were found to be very helpful in selecting sets of variables for inclusion in models, especially the network models described in Section 6.5 below.

6.3.4 Subset of Cases used for Analysis

The data set contained 119 cases (fisheries) from 13 countries. The distribution of cases by country is shown in Table 4.1 in Section 4.2. Note that more than half of the cases were from one country, Lao PDR. Initial inspection of the data revealed that these 64 fisheries were relatively homogeneous with respect to most variables and the inclusion of all of these would bias some of the statistical analysis. It was therefore decided, at least for some of the analysis (in particular for the network modelling described in Section 6.5) to select a subset of the Lao cases for analysis and set the remainder aside.

The procedure adopted for this selection process was as follows. A cluster analysis was performed on the 64 Lao cases, based on variables without too many missing observations. This analysis produced ten clearly defined clusters. One case was selected from each cluster, the choice being made according to cases with the least amount of missing data. The idea is that the ten cases could be regarded as representing the general pattern of variation in the Lao fisheries without losing any significant amount of information.

6.3.5 Exploratory Data Analysis

Following data checking, cleaning and reduction, exploratory data analyses using graphical and data summary procedures were undertaken. Such exploratory and descriptive methods of analysis are essential at the first stage of data analysis since they form a valuable tool for identifying important features of the data and further scrutiny of the data for any unexpected patterns or extreme observations. They are also useful for getting a preliminary idea of the behaviour of the data and the distributional patterns exhibited by individual variables. For example, it was clear that the levels of some of the categorical variables needed to be collapsed because of insufficient numbers of observations within some of the original set of category levels. The following variables were re-coded following this initial examination.

Description of variable	Name of variable	Code for category level	Description of category level
Ecosystem type	ECOTYPE3	1	Rivers
		2	Beels
		3	Lakes
		4	Reefs
		5	Others
Type of gear	GEARTYPE	1	Gillnets
		2	Hook& line and speargun
		3	Liftnets, bagnets, castnets, seines
		4	Traps and other types
Date co-mgt unit established	DATE	1	≤ 1900
		2	> 1900

Further variables were re-coded as necessary during the modelling work described in Sections 6.4 – 6.6. In particular, several variables were reduced to binary responses in developing network models. The particular variables involved are identified in Section 6.6.

6.4 Method 1 - General Linear Models

In this section, we describe the first of the modelling approaches undertaken in this research project. The approach uses a general linear model (GLM). We begin with a description of the model in Section 6.4.1 and briefly outline its associated assumptions. The choice of outcome variables and explanatory variables are then discussed in Sections 6.4.2 and 6.4.3, followed by a description of the model development process and methods of model validation in Section 6.4.4. An example is used to illustrate the process. The results of the model fitting procedures are given in Section 6.4.5 and discussed. Some conclusions are presented in the final section 6.4.6.

6.4.1 The General Linear Model

It is common in research investigations to use multiple linear regression techniques to explore the dependence of a key quantitative response variable (y) on one or more measurement variables (the explanatory variables) that are believed to influence y. Often this is the sole aim, but sometimes there is also interest in using the model equation as a predictive tool.

Multiple linear regression modelling generally deals with just quantitative explanatory variables. However, in practice, there is often a mix of different data types and must be dealt with. The appropriate model is then the general linear model (GLM). This is essentially a more general version of the model used in a multiple linear regression analysis. The aims of model development remain the same, i.e. as a predictive tool or to model, via a series of potential explanatory variables, the variation in y. In a GLM, a mixture of data types can be included, e.g. quantitative measurement variates, binary responses and categorical variables. It must be recognised however that variables, which contribute to explaining the variation in y, are not necessarily implying causation. Non-statistical considerations will help in determining whether or not causality is likely.

To illustrate the form of the model equation for a GLM, we consider a situation where the aim is to study the influence of two explanatory variables x_1 and x_2, and two categorical variables P (with 3 levels) and Q (with 4 levels) on a response variable y when measurements on y, x_1 and x_2 are made on n co-management units. The model equation is then the following.

$$y_{ijk} = \mu + \beta_1 x_{1i} + \beta_2 x_{2i} + p_j + q_k + \varepsilon_{ijk}, \quad i=1,2,\ldots n; \quad j=1,2,3; \quad k=1,2,3,4.$$

In this equation, μ represents a constant, similar to the intercept in multiple linear regression, while ε_{ijk} represents the residual component and reflects the random (or residual, or unexplained) variation in y after the effect of x_1, x_2, P and Q have been taken into account. The parameters β_1, (and β_2) give the change in y for a unit change in x_1, (and x_2,) when all other explanatory variables are held constant. The parameters p_{ijk} and q_{ijk}, show changes in the overall model constant in accordance with changing the levels of P or Q respectively. We draw attention to the fact that when the model is fitted, one level of p and one level of q are set to zero. In SPSS, p and q are set to zero for their last category level, i.e. when j=3 for p and when k=4 for q.

We also note here that the model carries some assumptions that need to be checked for their validity at the data analysis stage. The assumptions strictly relate to the residual components ε, but practically they require that the y values are independent of each other, have a constant variance, and follow a normal distribution. It is this last assumption that restricts GLMs to quantitative measurement variates. Although inferential procedures associated with GLMs are quite robust to small departures from normality, fisheries co-management performance measures such as equity, compliance, etc, are very clearly non-normal because they are measured just on a three-point scale. Our GLM modelling therefore needs to be restricted to genuine measurement data such as the catch per unit area (CPUA) or the catch per unit effort (CPUE).

The variance homogeneity assumption and the assumption of independence are both very important to ensure the validity of model-based results. Independence would normally be assured by collecting the data according to some well-defined random sampling procedure. For very practical reasons, this appears not to be the case in the present study (nor was it in the previous studies reviewed in Chapter 5). Strictly, this imposes certain limitations on the interpretation of the results of the analysis, but in the absence of obvious causes of dependence, it is reasonable to proceed as if the data had been properly sampled. On the other hand, it is both feasible and important to check the validity of the variance homogeneity assumption for each model investigated. This is possible through a *residual* *analysis*. This analysis involves looking at a series of plots where the residuals are plotted in different ways. The most useful is a plot of residuals versus fitted values – which should show a random scatter if the assumptions underlying the model are reasonable. In the modelling work below (Sections 6.4.4 and 6.4.5), each fitted model was therefore further investigated for the validity of model assumptions by conducting a residual analysis. For the data set used in this research, the residual analysis was also valuable for identifying outliers, i.e. observations far removed from the pattern exhibited by the remaining data.

6.4.2 The Outcome Variables

The hypothesis matrix (Table 3.2) lists a range of outcome variables (see columns labels), which potentially describe co-management performance. Although the number of outcome variables listed appears to be only 22, some of these could be measured by more than one indicator variable. For example, the sustainability of the resource could be measured by resource abundance or biomass, catch variability, viability of stocking, stewardship, and/or ecological knowledge of fishers.

Annex II gives the full list of outcome variables, 61 in all. Of these, some (19) had to be discarded during the initial screening process (Section 6.3.2), leaving 42 variables. Of these, we chose three key quantitative variables to illustrate the general linear modelling approach. Only quantitative variates could be considered in view of the GLM assumption that the response variable should follow a normal distribution. The three variables for analysis were chosen from the first three groups of outcome variables, i.e. the Production/Yield, Sustainability/Biodiversity, and Wellbeing groups. The chosen variates were: CPUA – the catch per unit area in tonnes km^{-2}; CPUE – resource abundance or biomass in tonnes per fisher per year; and HHINCOME – household income from fishing in $ per year.

6.4.3 The Explanatory Variables

The hypothesis matrix identifies for each outcome variable, the set of attributes that are expected to have a direct influence on the selected outcome. These are indicated by a Y in Table 3.2. Except those that were disregarded in the initial screening process, all others were considered for analysis. These attributes were of different types, categorical, binary or quantitative. Some comments are made below about the way in which these different types of data are treated in the GLM and how this affects the interpretation of some of the results.

For example, when the categorical attributes are nominal (e.g. type of ecosystem, or type of co-management), their inclusion in the model allows a test of whether the mean values of the outcome differ significantly across the different levels of the factor. So for example, if the catch per unit effort (tonnes/fisher/year) CPUE (say) is being modelled, and the model includes type of co-management (MANG_TYP) which has three levels, i.e. *government, co-management, self-managed*, then the overall significance level for MANG_TYP, obtained via the modelling process, indicates that the mean CPUE differs across the different co-management categories.

When a particular categorical variable considered for inclusion in the model is ordinal (e.g. level of ecological knowledge or wealth variation among fishers, recorded as *low, medium, high*), there is a choice to be made. The categorical variable can either be regarded as a quantitative variate (1 d.f. in the corresponding analysis of variance (anova) table which results from the GLM), or it can be regarded as a nominal variable (d.f. = number of levels-1). The former poses some difficulties. First, it assumes that the effect of the ordinal variable is a monotonic increase or decrease. Secondly, most of the ordinal variables in the profiled data set were scored on a 0,1,2 scale. So even if the effect was linear, the number of levels can be too low to identify this linearity. Moreover, it assumes that the "distance" from the "low" category to the "medium" category is the same as the "distance" from the "medium" category to the "high" category. We have therefore initially regarded all ordinal variables as nominal since this accounts for the total effect of such variables. Our procedure has been to determine the best subset of attributes (Sections 6.4.4 and 6.4.5 below) affecting the response variate (y) of interest and then investigate whether the main contribution from the ordinal variables in the model was due to the linear effect. If this was found to be the case, the model was refitted with just the linear component. However, we have found that for purposes of interpretation and reporting, regarding the ordinal explanatory variables as nominal was the most effective in the majority of cases. A binary variable (only 2 categories) can also be included in the model as nominal or as a quantitative variable, but the choice is less crucial here since the results of the tests of significance will be identical in either case. Some care is needed however in the interpretation of the corresponding model parameters since this can vary according to the software package being used.

6.4.4 Model Development

We discuss below, our approaches to model development for each of the chosen 3 key outcome variables, i.e. CPUA, CPUE and HHINCOME. As previously indicated, the starting point was the Hypothesis Matrix (Table 3.2) which identified the set of attributes which potentially can have a direct influence on each outcome variable.

In view of the patchy nature of the data, it was clear that any attempt to model all the variates simultaneously would result in very few or zero cases being available for analysis because only cases for which all variables have non-zero records in common with the outcome would enter into the model. A second stage screening of variables was therefore carried out at the start of the model development process with the aim of identifying the subset of attributes suitable for analysis. The justification for this is first discussed.

Criteria for selection of attributes

The GLM analysis is dependent upon the ability to estimate the unexplained residual variation (σ^2) in the outcome variable. For this purpose, once various explanatory variables have entered the model, a sufficient number of degrees of freedom (df), i.e. independent pieces of information, must remain. A rough rule of thumb is to have between 12 and 20 df, although in many practical situations, values down to about 8 d.f. may be acceptable if the findings are reasonably clear cut. A consequence is the need to have a sufficient number of cases for analysis, recognising that (a) each factor uses up (k-1) df where k is the number of factor levels, and (b) each quantitative variate takes up 1 df.

The model development involves a series of stages where potential attributes are added or dropped from the model to identify the most appropriate subset which best describes the variation in the outcome variable. To ensure an adequate number of residual df at each of these stages (residual df decreases as more attributes are included), it was decided that only those attributes having at least 15 non-zero values in common with the outcome variable being modelled, would be considered for inclusion in the analysis. It was further decided that in the case of categorical variables, at least two non-zero cases must result within at least two category levels. Imposing these conditions resulted in the selection of the attributes listed in Table 6.1 for each of the outcome variables. Only attribute names are given. Full descriptions of these attributes appear in Annex II.

For each of the outcome variables considered in this section, i.e. CPUA, CPUE and HHINCOME, the number of attributes selected for model development were still too many to enable all to be included simultaneously. Therefore the approach adopted was to consider the attribute groups (Table 6.1) in turn and first investigate which of the attributes in each set had an influence on the outcomes. The process is illustrated using the following four attributes corresponding to the set of key identifiers which possibly influence CPUA. The analysis was carried out using SPSS version 10.

PERMEN	-	Waterbody type: Seasonal (0), perennial (1), both (2).
ECOTYPE	-	Ecosystem type: Rivers(1), beels(2), lakes(3), reefs(4), others(5).
VILLAGES	-	Number of fishing villages.
FISHERS1	-	Number of fishers of all types.

<u>Stage 1</u>

Initially, a backward elimination procedure was adopted, whereby all 4 attributes were first included in the model with the intention of dropping one by one in turn if they were unimportant (as judged by a corresponding test of significance). The primary output (from SPSS) considered at this stage was the analysis of variance table whose main components are shown in Table 6.2.

The reference to Type III in the column of mean squares (MS) indicates that the probability levels (last column) reflect the importance of each attribute when the remaining 3 attributes are already included in the model. The attribute VILLAGES appears to be the least important attribute, so this was dropped from the model and the model re-fitted. The resulting probabilities for the remaining attributes were then 0.017, 0.453 and 0.420 for ECOTYPE, PERMEN and FISHERS1 respectively. At the next step, PERMEN was dropped and the model re-fitted giving probabilities of 0.015 and 0.536 respectively for assessing the significance of ECOTYPE and FISHERS1. Since FISHERS1 was still non-significant, ECOTYPE alone was fitted giving a significant probability of 0.013 (Residual df=25; R^2=39%).

Table 6.1 Attributes chosen for GLM Modelling

	Outcome Variables		
Attribute Type	CPUA	CPUE	HHINCOME
Key Identifiers	PERMEN, ECOTYPE, VILLAGES, FISHERS1	DATE, POSITION, PERMEN, ECOTYPE, VILLAGES, HH, FISHERS1	ECOTYPE, PERMEN, REMOTE
Resource	PRIM_PRO, BARRIERS, TL	PRIM_PRO, ALLOC2, TL, BARRIERS	MICR_BHR
Environmental	ENV_ALL, LAND_USE, TEMP	ENV_ALL, WAST_MAT, POLLUTN, LAND_USE, SUBSRTAT, TEMP, SILT, DEPTH, FLD_SEAS, DRY_SEAS.	-
Technological	GEARTYP2, SELECTIV, HARM_GR, PASS_GR, HAB_ALT, FISH_DEN, GEARS	GEARTYP2, SELECTIV, HARM_GR, PASS_GR, FADS, HAB_ALT, GEARS, FISH_DEN, BOAT_DEN, PRES_TEC.	EXPLOIT, GEARTYP2, SELECTIV, HARM_GR, PASS_GR, FADS, GEARS, PRES_TEC, FISH_DEN.
Market	-	-	INFRASTR, FEES, MRKT_RUL, MRKT_ORI, VAL_PAR
Community Characteristics	PURPOSE, ALT_LIVL.	PURPOSE, ALT_LIVL, DIFF_OCC, EDU_YRS	-
Decision-making arrangements	GR_RESTR, GR_BAN, BAN_DRIV, SIZE, SCIENCE, RES_AREA, RES_PROP, RES_MONS, NUMB_RES, RULE_YRS, AVLB_RES, INST_YRS	MAN_PLAN, MAN_OBJS, GR_RESTR, GR_BAN, BAN_DRIV, BAN_LIGHT, CLS_SEAS, SIZE, SCIENCE, AVLB_RES, RES_AREA, RES_PROP, RES_MONS, NUMB_RES, RULE_YRS, INST_YRS	OA_OUT, CTRL_OUT
Exogenous	-	NGOSUPP, DISASTER	-
No. of attributes	35	51	20

Table 6.2 An example of an ANOVA table for CPUA.

Attribute type	d.f.	Type III MS	F	Sig. Prob.
ECOTYPE	4	1526.9	1.81	0.177
PERMEN*	1	338.8	0.40	0.536
FISHERS1	1	313.4	0.37	0.551
VILLAGES	1	0.13	0.00	0.990
Residual	16	845.6		

* only 1 d.f. since there were no data corresponding to the 'seasonal category

Stage 2

At the next stage, attributes discarded at a previous stage, namely VILLAGES and PERMEN, were brought back into the model to assess whether the removal of FISHERS1 would now indicate their importance. This was not found to be the case. So ECOTYPE alone was considered from the set of variables listed under *key identifiers* as the only variable contributing significantly to variation in CPUA.

It is important to note that when there are more than three discarded variables at the start of this stage, different numbers of variables need to be returned to the model in different orders to determine whether a particular combination of variables would jointly explain a substantial component of the variation in the outcome variable. Several iterative procedures are needed before being satisfied that the final selection is the best subset of variables.

Stage 3
Similar procedures as above were carried out for each of the other attribute sets. However, ECOTYPE was usually included with attributes of each set because any model not including ECOTYPE was believed to have little meaning. Many of the fisheries attributes considered within this study are quite specific to the type of ecosystem and therefore ECOTYPE was considered in all the models. Unsurprisingly, it was also a highly significant factor in all the models explored.

Stage 4
The final set of attributes selected from each attribute set were finally considered together and stages 1 and 2 repeated.

In the actual analysis, several alternative models were developed. Each was subjected to a residual analysis and further investigations were made. Further details are provided in the results section 6.4.5 below.

6.4.5 Results from General Linear Modelling

Catch per unit area (CPUA)

In the analysis of CPUA as a key outcome variable, three cases arose as outliers, due to very high CPUA values, in many of the initial models explored. These were Hamil Beel and Dum Nadi Beel in Bangladesh (which were both stocked with fish), and Dano Lamo in Indonesia for which the area of the resource is likely to have been significantly underestimated. These cases had a serious impact on model results and were therefore excluded from the analysis.

The initial modelling of CPUA took place separately for variables within each attribute set. The set of attributes identified as contributing significantly to variation in CPUA, i.e. ECOTYP, PRIM_PRO, GEARTYPE, FISH_DEN, HARM_GR, BAN_DRIV, SIZE and NUMB_RES, were then considered together to investigate their combined effect. Interactions between these effects were also investigated although in general, the non-availability of cases within all two-way combinations of the category levels did not enable any significance testing to be carried out.

Some further modelling was also carried out using attributes identified as being important during the development of the Network Models (Section 6.5), within the Decision-Making Arrangements attribute set. These were attributes that had been scored as 1 (indicating an indirect effect through compliance) or 14 (indirect effect via exploitation intensity) in the hypothesis matrix. The attributes explored were MANG_TYP, RESPECT, STABBODY, CLR_ACC, OA_COMM, SELF_FIN, REP_FISH, CONF_RES, POACH2, EFFCT_CS, LEGIT, DEM_ELEC and LOC_BODY.

The modelling exercises above gave rise to a number of alternative models. The results from these models are summarized in Tables 6.3a and 6.3b and show that the full set of attributes contributing significantly to the variability in CPUA are the following:

ECOTYPE	– Ecotype system: Rivers/flood plains(1), beels(2), lakes(3), reefs(4), and other(5).
PRIM_PRO	– Primary Production in g/C/m^2/year: low(0), medium(1), high(2).
GEARTYP2	– Type of gear: Gillnets(1), Hook&line or speargun(2), Liftnets/bagnets/castnets/seines(3), traps and other gear types (4).
HARM_GR	– Whether destructive fishing practices were evident: No(0), Yes(1).
BAN_DRIV	– Whether there was a ban on fish drives: No(0), Yes(1).
SIZE	– Whether there were landing size restrictions: No(0), Yes(1).
NUMB_RES	– Number of reserves.
MANG_TYP	– Type of management: Govt(1), Co-managed(2), Self or traditional(3).
OA_COMM	– If open or restricted access: Open(1), Restricted(2).
FISH_DEN	– Fisher density (fishers km^{-1} yr^{-1}).

Table 6.3a shows an overall summary of the seven models that clearly explained variability in CPUA. All models included ECOTYPE. Some included fisher density in addition. The associated probabilities reflect the importance of each model attribute in the presence of the other attributes in the model.

Table 6.3b shows the extent and direction of the effect of each attribute. For categorical variables, changes from a base level are shown for each other category level, the base level being given the value zero. This base was chosen to be the last or first level according to which was easier for interpretation. Although ECOTYPE was a highly significant factor in all the models, it was not included in results of Table 6.3b since it acts as a stratification variable whose effect must be eliminated before exploring the effect of other attributes.

Table 6.3a Model summaries for CPUA

Model	Attribute Description	Attributes in model	Prob. for sig.	Residual d.f.	Residual M.S.	Adjusted R^2
1	PRIM_PRO, i.e. Primary Production (g/C/m^2/year), with ecotype and fisher density	ECOTYPE PRIM_PRO FISH_DEN	0.000 0.014 0.033	12	36.2	85%
2	GEARTYP2, i.e. Type of gear, with ecotype and fisher density	ECOTYPE GEARTYP2 FISH_DEN	0.000 0.006 0.004	16	33.3	85%
3	HARM_GR, i.e. Destructive fishing practices, with ecotype and fisher density	ECOTYPE HARM_GR FISH_DEN	0.000 0.000 0.013	13	28.1	88%
4	BAN_DRIV, i.e. Ban on fish drives, with ecotype.	ECOTYPE BAN_DRIV	0.000 0.000	18	25.7	89%
5	SIZE, i.e. landing size restrictions, and NUMB_RES, i.e. number of reserves, with their interaction, and with ecotype..	ECOTYPE SIZE NUMB_RES SIZExNUMB_RES	0.000 0.000 0.001 0.013	14	12.1	93%
6	MANG_TYP, i.e. Type of management and OA_COMM, i.e. if open or restricted access, with ecotype and fisher density.	ECOTYPE MANG_TYP OA_COMM FISH_DEN	0.000 0.005 0.018 0.043	17	32.6	85%
7	LOC_BODY, i.e. Local decision making body, and OA_COMM, i.e. if open or restricted access, with ecotype and fisher density.	ECOTYPE LOC_BODY OA_COMM FISH_DEN	0.000 0.001 0.015 0.011	18	30.8	90%

The effect of quantitative variates (NUMB_RES and FISH_DEN) is shown in Table 6.3b in terms of the corresponding model parameter, i.e. the "slope" in standard multiple regression models. This reflects the increase in CPUA (negative values imply a decrease) for a unit change in the attribute.

The results in Table 6.3b are indicative of the way in which a number of attributes can affect CPUA. For example, a fishery with a high level of primary production is likely to have a CPUA that is 20 t km^{-2} yr^{-1} higher than a fishery with low primary production. Using nets can give 16 t km^{-2} yr^{-1} higher CPUA compared to using Gillnets. Banning destructive fishing practices or banning fish drives can increase CPUA by about 20 t km^{-2} yr^{-1}.

Table 6.3b Changes in CPUA from a base level of each significant attribute

Model	Attribute	Attribute Levels	Changes from base level	n
1	PRIM_PRO, i.e.	Low	0	7
	Primary Production	Medium	5.6	7
	(g/C/m^2/year)	High	20.8	4
	(with ecotype and fisher density)			
2	GEARTYPE2, i.e.	Gillnets	0	10
	Type of gear	Hook & Line or Speargun	–2.5	9
	(with ecotype and fisher density)	Nets	16.4	3
		Traps or other	–0.91	3
3	HARM_GR, i.e.	No	19.8	11
	Destructive fishing practices?	Yes	0	9
	(with ecotype and fisher density)			
4	BAN_DRIV, i.e.	No	0	19
	Ban on fish drives	Yes	23.6	5
	(with ecotype)			
5	SIZE, i.e. landing size	No	0	19
	restrictions, and	Yes	15.5	3
	NUMB_RES, i.e. number of reserves, according to SIZE.	"Slope" for size=No	–0.57	-
		"Slope" for size=Yes	-2.90	
6	MANG_TYP, i.e.	Govt.	0	6
	Type of management	Co_mgt	15.4	5
	And	Self/Trad.	12.4	15
	OA_COMM, i.e. if open or restricted	Open	0	11
	access.	Restricted	6.4	15
	(with ecotype and fisher density)			
7	LOC_BODY, i.e.	Absent	0	6
	Local decision making body and	Present	15.0	20
	OA_COMM, i.e. if open or restricted	Open	0	11
	access.	Restricted	6.4	15
	(with ecotype and fisher density)			

The "slope" coefficient for the number of reserves depends on whether or not there are landing size restrictions. In the absence of landing size restrictions, the number of reserves has no effect ("slope" = - 0.57 is non-sig). However, if there are landing size restrictions, then results of Table 6.3b indicate that an increase in the number of reserves by 1 unit can lower CPUA by approximately 3 t km^{-2} yr^{-1}. However, it is important not to place too much emphasis on these results since about 50% of the co-management units entering this analysis had zero values for NUMB_RES and three had very high values.

Catch per unit effort (CPUE)
Preliminary analysis of CPUE demonstrated very quickly the need to use the log-transformed values for both CPUE and for fisher density. As for CPUA, the type of ecosystem was included in all models investigated for CPUE. ECOTYPE contributed significantly in explaining much of the variability in log CPUE across the different co-management units. Since this was expected, it was regarded as a stratification variable in the analysis, and the effect of other attributes on log CPUE was investigated after allowing for variability due to ECOTYPE.

Modelling procedures were carried out in a similar manner to those undertaken for CPUA. Results for the final, most promising set of models, are shown in Tables 6.4a and 6.4b. The full set of attributes contributing significantly (but not necessarily simultaneously) to variation in log CPUE are the following.

ECOTYPE – Ecotype system: Rivers/flood plains(1), beels(2), lakes(3), reefs(4), and other(5).
GEARTYP2 – Type of gear: Gillnets(1), Hook&line or speargun(2),

Liftnets/bagnets/castnets/seines(3), traps and other gear types (4).
PURPOSE – Whether predominantly for subsistence or commercial purposes.
GR_RESTR – Gear size restrictions: No(0), Yes(1).
Ln(FISH_DEN) – Log of Fisher density (fishers km^{-1} yr^{-1}).
MAN_PLAN – Whether a management plan exists: No(0), Yes(1)
MANG_TYP – Type of management: Govt(1), Co-managed(2), Self or traditional(3).
EFFCT_CS – Effectiveness of enforcement measures: Low(0), Medium(1), High(2).
CONF_RES – Effective conflict resolution mechanism: No(0), Yes(1).
POACH2 – Incidence of poaching: Low(0), Medium(1), High(2).
OA_COMM – If open or restricted access: Open(1), Restricted(2).

It is clear from results of Tables 6.4a and 6.4b that models which do not include fisher density are less good at explaining a substantial proportion of the variability in ln(CPUE). They were however included because they do contribute independently to a component of the variability. It is relevant to note here that ecotype alone explains only 30% of the variability as expressed by the adjusted R^2. So apart from CONF_RES, the attributes in models 4, 5 and 7 do indicate a substantial contribution.

Table 6.4a Model summaries for CPUE

Model	Attribute Description	Attributes in model	Sig. Prob.	Residual d.f.	Residual M.S.	Adjusted R^2
1	GEARTYP2, i.e.	ECOTYPE	0.000	18	0.317	92%
	Type of gear, with	GEARTYP2	0.010			
	ecotype and log of fisher density	Ln(FISHDEN)	0.000			
2	PURPOSE, i.e.	ECOTYPE	0.001	14	0.303	93%
	For subsistence or commercial, with	PURPOSE	0.003			
	ecotype and log of fisher density	Ln(FISHDEN)	0.000			
3	GR_RESTR, i.e.	ECOTYPE	0.000	22	0.405	90%
	Gear size restrictions, with	GR_RESTR	0.014			
	ecotype and log of fisher density	Ln(FISHDEN)	0.000			
4	MAN_PLAN, i.e.	ECOTYPE	0.000	29	1.726	53%
	Management plan exists? with ecotype.	MAN_PLAN	0.000			
5	MANG_TYP, i.e. type of management, and	ECOTYPE	0.007	22	1.160	63%
		MANG_TYP	0.039			
	EFFCT_CS, i.e. effectiveness of enforcement measures, with ecotype..	EFFCT_CS	0.010			
6	CONF_RES, i.e.	ECOTYPE	0.014	29	2.402	36%
	Effective conflict resolution mechanism	CONF_RES	0.027			
	with ecotype.					
7	POACH2, i.e.	ECOTYPE	0.000	28	1.536	59%
	Incidence of poaching, and	POACH2	0.014			
	OA_COMM, i.e.	OA_COMM	0.002			
	if open or restricted access, with ecotype.					

On the other hand, ECOTYPE with log of fisher density explains 88% of the variability in log CPUE. This demonstrates that the contribution from other attributes included in the first three models is in fact very little. Some caution therefore needs to be exercised in the emphasis given to these results, particularly because the findings in Table 6.4b are not generally consistent with what one would expect. In contrary to results for CPUA, the general findings here are more difficult to explain.

Table 6.4b Changes in CPUE from a base level of each significant attribute

Model	Attribute Description	Attribute Levels	Changes from base level	N
1	GEARTYP2, i.e.	Gillnets	0	10
	Type of gear, with	Hook & Line or Speargun	0.43	9
	ecotype and log of fisher density	Nets	1.37	5
		Traps or other	0.12	3
		“Slope” = -0.926		
2	PURPOSE, i.e.	SUBSISTENCE	0	10
	For subsistence or commercial,	COMMERCIAL	1.46	11
	with ecotype and			
	log of fisher density	“Slope” = -0.725		
3	GR_RESTR, i.e. Gear size	NO	1.80	13
	restrictions, with ecotype	YES	0	16
	and log of fisher density	“Slope” = -0.836		
4	MAN_PLAN, i.e.	No	3.02	23
	Management plan exists? with ecotype.	Yes	0	12
5	MANG_TYP, i.e. type of management, and	Govt.	0	5
		Co_mgt	-0.75	16
		Self/Trad.	0.981	10
	EFFCT_CS, i.e. effectiveness of	Low	1.87	10
	enforcement measures, with	Medium	1.05	6
	ecotype..	High	0	15
6	CONF_RES, i.e.	No	1.65	9
	Effective conflict resolution mechanism with ecotype	Yes	0	26
	.			
7	POACH2, i.e.	Low	0	20
	Incidence of poaching, and	Medium	1.43	9
		High	1.62	7
	OA_COMM, i.e.	Open	0	19
	if open or restricted access, with ecotype.	Restricted	1.63	17

Several of the models indicate that CPUE was lower in those cases where management interventions would be expected to give rise to higher CPUE. This may reflect the introduction of interventions designed to improve low CPUE, which have yet, or have failed, to have had their desired effect.

The models 1 and 2 are likely to reflect differences in gear efficiency. CPUE as a proxy of abundance or biomass is only comparable when gear or effort efficiency (measured by catchability q) is approximately constant. CPUE as a proxy of abundance or biomass is not therefore comparable across different gear types of between subsistence and commercial fisheries that are likely to employ gears of different efficiencies.

The distinction between response and explanatory variables is often not obvious. For example, CPUE might be expected to be low in response to high levels of poaching. However, if the total amount poached is small relative to the size of the stock, then a high CPUE (or catch rate) may encourage greater levels of poaching as predicted by Model 7.

Household income from fishing ($ per year) - HHINCOME
Attributes listed in Table 6.1 for household income from fishing were investigated for their effect on this outcome variable. Only one attribute was found to explain a significant amount of the variation in HHINCOME. This was INFRASTR, i.e. Market facilities/infrastructure with a probability value of 0.001 (residual d.f.=24) and an R^2 of 40%. However, further exploration of the data through residual analyses showed that this effect was caused only by a few management units with very high values for HHINCOME. Therefore little emphasis can be placed on this result.

The results here are not too surprising, given that the values reported in secondary sources for household income levels must be very approximate. Moreover, income data are known to have very skew distributions and if the data we have here are averages, they are likely to be poor estimates and are unlikely to reflect the true situation.

6.4.6 Conclusions

The data analysis approach undertaken here, i.e. the use of general linear modelling techniques, is quite powerful for identifying attributes that have a direct effect on quantitative outcome variables such as CPUA and CPUE. However it is important not to place too much emphasis on the results reported in Section 6.4.5 for a number of reasons.

First, the inferences drawn from the modelling procedure are based on assuming that the data are a sample selected through some probability based sampling procedure. The profiled data used in this study were selected purposively and consist of as many co-management units as possible that could provide data for the 258 variables identified as appropriate for describing each unit. The analysis is quite “global” with data from several countries, and the population to which the inferential procedures apply is ill-defined. Our aim in presenting some results was to demonstrate the methodological approach but models other than those developed in the previous section are possible within particular ecosystems or within a particular region.

The type of ecosystem in particular, features in our analysis only as a stratification variable. The emphasis is only on accounting for variability due to this source. Ideally, it would be of interest to derive models for each type of ecosystem. This would have involved a consideration of the interaction between ecosystem type and other factors considered for inclusion in the model. Unfortunately, the study of interactions was not possible due to the patchy nature of the data. The results reported here therefore correspond to averages across all ecosystem types, whereas ideally we would want to explore how the results vary from one type of ecosystem to another. This was not possible due to limited information available in the profiled data.

During the analysis, we also found that some of the results were quite sensitive to data from a few of the co-management units. For this reason, several potentially good models had to be discarded. It is therefore likely that with more information, many other attributes may emerge as being important, while some of the attributes identified in our analysis as important, may well become redundant.

There are further limitations. The analysis here is based largely on secondary sources. Although every effort was made by the Principal Investigator to ensure consistency in the coding of attributes, it is possible that the manner of allocation of codes to many attributes differed across the different management units. For a serious model development process concerning a particular ecosystem, region or country, primary data collection, with careful guidelines concerning the coding of attributes, is needed.

Also to be noted is the fact that the data screening process used to select smaller sets of variables for analysis was driven by the particular data set compiled for this project. A consensus of expert opinion concerning the importance of the variables under consideration could have helped in reducing the number of variables to a more manageable number for analysis purposes. Expert opinion would also help ensuring that those key variables, whose exclusion from the model would make the model meaningless, are always included.

Finally we need to emphasise that the general linear modelling approach undertaken was largely based on attributes that were identified as potentially having a ***direct*** influence on the outcomes (CPUA, CPUE and HHINCOME) chosen for analysis. Pathways of influence through secondary variables were not considered. This is a main feature of the Bayesian network modelling approaches described in the Section 6.6.

6.5 A Closer Examination of the Relationship between Catch Per Unit Area (CPUA) and Fishing Intensity

Unsurprisingly, fishing intensity, measured in terms of fisher density was shown in Section 6.4 to be an important determinant of catch per unit area, where catch comprises the catches of all species combined. Control of fishing intensity (effort) is one of the most basic, but often the most difficult to implement, management interventions for improving yield from a fishery. The relationship between CPUA and fisher density was examined further with an expanded dataset comprising the data assembled from the 119 case study sites described in Section 4, augmented with other estimates assembled from the literature and a database described by MRAG (1995) – see Tables A1 to A3 (Annex VII). Ecosystem was found to be an important covariate in determining CPUA. On the basis of data availability, relationships between CPUA and fisher density were, therefore, examined for floodplain river, lake and reservoir and reef-based ecosystems. This exercise was intended to build on the work described by Bayley (1988) using an updated dataset and an alternative model. Fishing intensity is measured as the number of different fisherman active during the year[1] divided by the surface area of the resource – the same standardization as that used for yield (CPUA).

Based upon data from various tropical, multispecies fisheries, Bayley found a unimodal trend of total yield with effort for both single fisheries and groups of similar fisheries with catch per unit effort (CPUE) decreasing with increasing effort. Bayley found, after testing all possible combinations of untransformed, log-transformed and square-root transformed variables, that the best fitting unimodal model took the form of a second-order polynomial (Equation 1) – an empirical variation of the logistic equation or Schaefer model with an intercept:

$$\ln Yield = ai^{0.5} + bi + c \qquad \textbf{Equation 1}$$

where yield in t km^{-2} yr^{-1} , i is fishing intensity (fishers km^{-2}), and a, b, and c are fitted parameters. Here, Equation 2, based upon the Fox (1970) model with an intercept, which has a pronounced plateau at high levels of effort, was also fitted to the data:

$$\ln Yield = i^{0.5}\exp(a + bi^{0.5}) + c \qquad \textbf{Equation 2}$$

Both models were fitted to the data using a non-linear least squared fitting method in SYSTAT for DOS software.

6.5.1 Floodplain Rivers

The model fits for the floodplain river data set were remarkably good (Figure 6.3 and Table 6.5). Fishing intensity explained up to 83% of the variation in CPUA (corrected $r^2 = 0.83$). Overall, a marginally better fit was achieved with the modified Fox model (Equation 2) than Equation 1. Fitting the data for floodplains from Africa and Asia to Equations 1 and 2 resulted in very similar curves, whose coefficients could not be distinguished at $P = 0.05$. Insufficient data were available to test for differences between Latin American floodplain rivers and those in other continents. A maximum sustainable yield of 132 t km^{-2} yr^{-1} (95% CI [1.9, 225]) or 132 kg ha^{-1} yr^{-1} is predicted at a fisher density of approximately 12 fishers km^{-2} (95% CI [9, 17]).

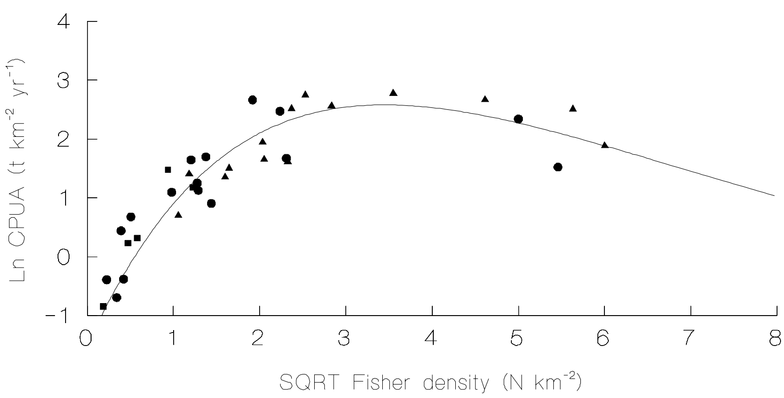


Figure 6.3 CPUA vs. fisher density for floodplain rivers (all continents). Curve is least squares fit of Eq. 2 to all 36 floodplain rivers (Table A1 – Annex VII). Floodplain rivers in Africa (●); Asia (▲); and Latin America (■).

[1] A proxy for the overall exploitation rate of a number of species caught by a variety of different gear types.

Table 6.5 Comparison of non-linear least squares fits to Equations 1 and 2 for floodplain-rivers, lakes and reservoirs and reef-based fisheries.

			Parameter Estimates			Upper 95% CI			Lower 95% CI			n	r^2	MSY	MSY	MSY	i_{MSY}	i_{MSY}	i_{MSY}
Model	**Ecosystem**	**Continent**	**a**	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**				**(upper)**	**(lower)**		**(upper)**	**(lower)**
Bayley	Floodplain Rivers	All	2.116	-0.280	-1.075	2.581	-0.202	-0.579	1.651	-0.357	-1.570	36	0.78	18.6	2133	1.4	14.3	41	5.3
	Floodplain Rivers	Africa	2.034	-0.290	-0.786	2.662	-0.182	-0.199	1.407	-0.398	-1.374	16	0.83	16.1	13834	0.9	12.3	53	3.1
	Floodplain Rivers	Asia	1.779	-0.218	-0.787	2.398	-0.132	0.124	1.159	-0.304	-1.698	14	0.82	17.2	60774	0.6	16.6	83	3.6
	Lakes & Reservoirs	All	1.340	-0.095	-0.507	1.614	-0.060	-0.124	1.067	-0.130	-0.889	143	0.61	67.9	45714	3.7	49.7	181	16.8
	Lakes & Reservoirs	Africa	2.283	-0.305	-1.153	2.822	-0.203	-0.615	1.744	-0.407	-1.690	97	0.56	22.6	9823	1.2	14.0	48	4.6
	Lakes & Reservoirs	Asia	1.221	-0.075	-0.385	1.652	-0.030	0.424	0.790	-0.121	-1.195	37	0.75	98.0	1.E+10	1.1	66.3	758	10.7
	Lakes & Reservoirs	L.America	2.299	-0.249	-1.891	4.656	0.157	0.485	-0.057	-0.655	-4.268	9	0.71	30.4	NA	NA	21.3	220	NA
	Reefs	All	0.070	-0.001	0.502	0.113	0.000	0.900	0.027	-0.002	0.103	79	0.13	5.6	NA	1.2	1225.0	3.E+11	45.6
Fox	Floodplain Rivers	All	1.171	-0.290	-1.511	1.435	-0.243	-0.940	0.907	-0.337	-2.082	36	0.80	13.2	225	1.9	11.9	17	8.8
	Floodplain Rivers	Africa	1.064	-0.311	-1.067	1.460	-0.237	-0.353	0.669	-0.384	-1.781	16	0.82	10.6	562	1.1	10.3	18	6.8
	Floodplain Rivers	Asia	1.122	-0.259	-1.706	1.609	-0.218	-0.181	0.635	-0.299	-3.230	14	0.79	14.2	3839	0.4	14.9	21	11.2
	Lakes & Reservoirs	All	0.714	-0.156	-1.013	0.991	-0.117	-0.504	0.438	-0.195	-1.522	143	0.64	44.8	2883	4.1	41.1	73	26.3
	Lakes & Reservoirs	Africa	1.385	-0.303	-2.005	1.681	-0.248	-1.264	1.089	-0.358	-2.745	97	0.61	17.2	815	1.4	10.9	16	7.8
	Lakes & Reservoirs	Asia	0.476	-0.113	-0.754	0.944	-0.067	0.263	0.009	-0.159	-1.771	37	0.76	88.8	1.8E+06	1.8	78.3	223	39.6
	Lakes & Reservoirs	L.America	1.105	-0.204	-2.214	2.445	0.026	0.645	-0.235	-0.433	-5.072	9	0.72	25.3	NA	NA	24.0	1479	5.3
	Reefs	All	-1.641	-0.043	0.100	-1.010	-0.027	0.619	-2.272	-0.059	-0.419	79	0.18	5.8	265	1.3	540.8	1372	287.3

6.5.2 Lakes and Reservoirs

Reasonable fits were also achieved with data from lakes and reservoirs (Table 6.5). Again, better fits were achieved with Equation 2 than Equation 1, but in both cases, the *b* parameter was significantly different at P=0.05) for African and Asian Lakes. The resulting curves (Figures 6.4 and 6.5) imply that much higher sustainable yields may be achieved in Asian compared to African lakes and can sustain much higher levels of fishing effort. This may reflect one or a combination of different factors including the common practice in Asia of stocking lakes and reserves to augment natural recruitment, a greater proportion of part-time fishermen in Asia compared to Africa, and natural differences in production.

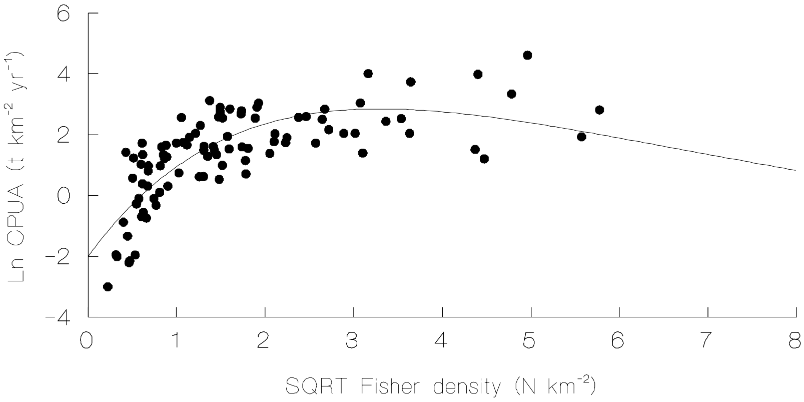


Figure 6.4 CPUA vs. fisher density for African lakes and reservoirs.
Curve is least squares fit of Eq. 2; *n* = 97.

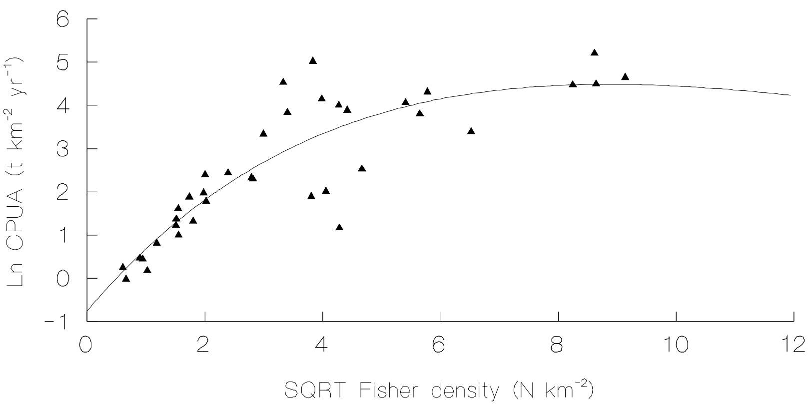


Figure 6.5 CPUA vs. fisher density for Asian lakes and reservoirs.
Curve is least squares fit of Eq. 2; *n* = 37.

6.5.3 *Reef-Based Fisheries*

A marginally better fit was also obtained with Equation 2 for the available data for reef-based fisheries (Table 6.5). Fisher density, however, explained only 18% of the variation in CPUA (Table 6.5 and Figure 6.6). It is likely that this poor fit largely reflects imprecise estimates of (i) fisher density that are based mainly on estimates of total population number rather than numbers of fishers; (ii) the surface area of the resource; and (ii) variation in the habitat covered by the term “reef”. The maximum sustainable yield for these systems is predicted to be in the order of 6 t km^{-2} yr^{-1} at 540 fishers km^{-2} (95% CI [287, 1372]).

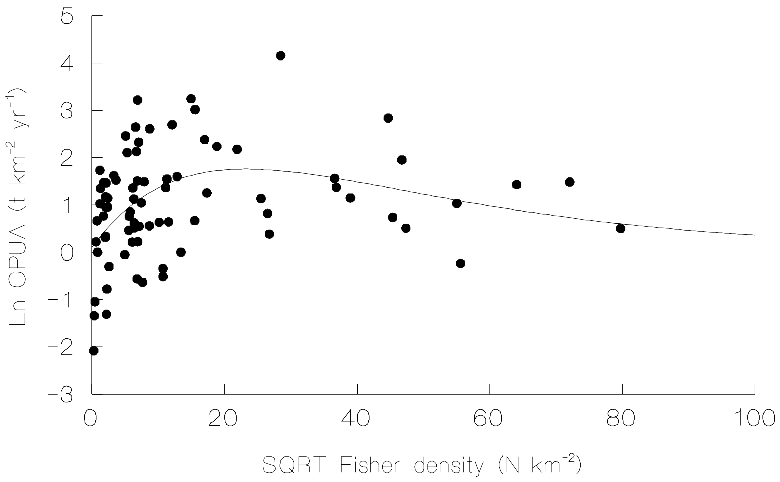


Figure 6.6 CPUA vs. fisher density for reef-based fisheries.
Curve is least squares fit of Eq. 2; *n* = 79.

6.6 Method 2 - Use of Bayesian Network Models

The overall objective of the GLM modelling in the previous section was to identify important sets of attributes which are associated with outcome variables. The idea is to gain insights into attributes of the fisheries which are associated with “success”, as measured by outcome variables.

This section addresses a different objective, namely to develop a methodology which could be used as a management tool to identify strengths and weaknesses, make predictions and to explore “what if” scenarios for a *particular* fishery. The approach we adopt here, Bayesian networks, has its roots in expert systems rather than statistical modelling. The general idea is to build models based on information contained in our database and propose this model as a tool. The presentation focuses on the *methodology* and makes no pretence at producing a definitive model. It is envisaged that, in practice, the method would be applied by building a model for a particular situation (country, region or type of fishery) based on data from that situation.

6.6.1 *Why Network Models?*

In our review of previous related work (Chapter 5), it was mentioned that some approaches, in particular those based on multidimensional scaling, make no distinction between explanatory and response variables. Indeed this was seen as a weakness of those methods. The statistical modelling of Section 6.4 addresses this issue and clearly defines and builds models for a response (outcome) in terms of sets of explanatory variables (attributes). Each explanatory variable in a model is seen as *directly* impacting on the response variable. With explanatory variables x_1, x_2, …, x_p, and response y, the situation can be represented by the following diagram.

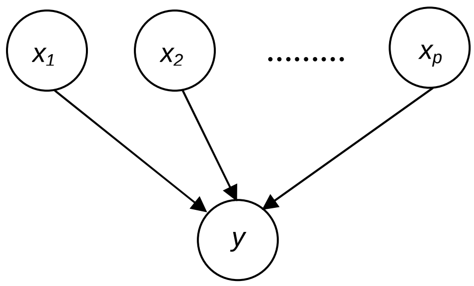


Figure 6.7 Explanatory variables directly impacting on a response variable

In reality, however, it can happen that the relationships between variables are not as simple as this model allows. The effect of one *x*-variable on the response *y* may be mediated through another *x*-variable, or through two or even more *x*-variables. It could also happen that some of the *x*-variables affect some of the others. Indeed, with datasets containing many variables, it is easy to envisage quite complex patterns of association. The roles of "response" and "explanatory" become blurred, with variables taking on each role in turn. In the simple example in Figure 6.8, variables *E* and *D* could be regarded as "responses", and *A* and *B* as "explanatory". But *C* seems to play both roles. It looks like a response with *A* and *B* acting as explanatory variables, and it is an "explanatory" variable for *E*.

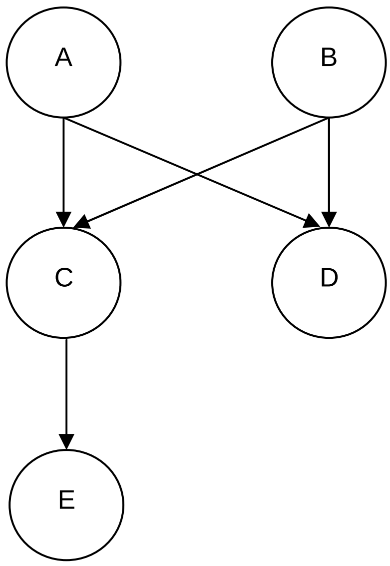


Figure 6.8 Indirect mediation of effects of explanatory variables

It is customary for statisticians to warn that a significant correlation (or regression model) between variables does not necessarily imply any *causal* relationship. In contrast, there is an important class of network models which deliberately set out to model patterns of causality. The arrows in the above diagram represent causal links. The causation does not have to be deterministic and can incorporate a degree of uncertainty. Indeed, in the network models we use here, the variables are modelled as random variables and the links are probabilistic. A link from *A* to *C* would be interpreted as meaning that the value of *A* affects the value of *C* by means of influencing the probability distribution of *C*.

Historically, these models evolved largely in the artificial intelligence (AI) community, and form the basis of *expert systems*. Generally they are not tools for statistical inference, as are the models of Section 6.4, but rather they are mechanisms for encoding probabilistic causal relationships and making predictions from them. Because of their AI background, it is not surprising that the current terminology of network models is quite different from statistical jargon, and is perhaps less familiar. Sometimes there is an exact correspondence between an AI term and a statistical one, the two terms being different names for the same concept.

6.6.2 Bayesian Networks

The general class of models that we will use consist of a number of *nodes* (random variables) connected by *directed* links. A node which has a directed link leading from it to another node is called a *parent* node and the second one is a *child* node. Cycles are not permitted: that is, it is not possible to start from any node and, following the directed links, end up on the same node. A model with these properties, after specifying the probabilities which govern the links, is called a *Bayesian belief network*, or just a Bayesian network (BN). Most of the currently available software for building and analysing BNs requires that the nodes are discrete, taking only a finite set of possible values, and we assume this to be the case in what follows. Continuous variables can be accommodated by grouping their values into class intervals. An introductory account of BNs is given by Jensen (1996) while a more rigorous and complete treatment is Cowell *et al* (1999).

To explain the basic ideas, consider the simple example of Figure 6.8. For simplicity, assume that all of the nodes are binary variables, taking values T or F (true or false). The probabilistic mechanism which governs the relationship between, say, *E* and its parent *C* is the *conditional probability distribution* of *E* given *C*. This can be expressed as a table:

	E	
C	*F*	*T*
F	p_{00}	p_{01}
T	p_{10}	p_{11}

The table of conditional probabilities for node *C*, which has parents *A* and *B* would have the following form:

		C	
A	*B*	*F*	*T*
F	*F*	p_{000}	p_{001}
F	*T*	p_{010}	p_{011}
T	*F*	p_{100}	p_{101}
T	*T*	p_{110}	p_{111}

A node with no parents (*A* or *B* in the example) would have just a *prior* probability table:

A	
F	*T*
p_0	p_1

The complete specification of a BN consists of

(a) the set of nodes,
(b) the directed causal links between the nodes,
(c) the tables of conditional probabilities for each node.

Early applications of BNs were in medical diagnosis and genetics, but recently there has been something of an explosion in their use, including environmental impact assessment, tracing faults in computer systems and software, robotics and many other areas.

Estimating the Conditional Probabilities

In practice, there are several possible ways of obtaining estimates for the conditional (and prior) probabilities. If sufficient data are available then cross-tabulating each node with its parents should produce the estimates. There are alternatives to deriving the probabilities from data, however. It is possible to use *subjective* probabilities or *degrees of belief*, usually encoded from expert opinions. In many of the early applications of BNs in medical diagnosis this was generally the approach that was used. There has been some recent research into developing systematic ways of *eliciting* prior beliefs from experts and building probability distributions from them (O'Hagan, 1998). In the present work, cross-tabulations of data were used as far as possible, but in a few cases the data were rather sparse and reasonable subjective measures were substituted.

Evidence and Updating

In the simple example of Figure 6.8, if the states of the nodes (i.e. the values of the variables) *A* and *B* were known, then it would be possible to use the rules of probability to calculate the probabilities of the various combinations of values of the other nodes in the network. This kind of reasoning in a BN can be called "prior to posterior", in the sense that the reasoning follows the directions of the causal links in the network. Suppose now that the state of node *E* were known. What could be said about the other nodes? The *updating algorithm* of Lauritzen and Spiegelhalter (1998) allows us to calculate the posterior probabilities of all other nodes in the network (and this works for *any* BN), given the known value at *E*, or indeed, given any combination of known nodes. In the jargon of expert systems, "knowing" the value of a node is called "entering evidence". This is "posterior to prior" reasoning and allows us to infer something about the states of nodes by reasoning *against* the direction of the causal links. The updating algorithm is a very powerful tool in BNs and enables us to make useful predictions and examine "what if" scenarios with ease. Various software packages are available which facilitate the construction of BNs and implement the updating algorithm. For this project, the program Netica (Norsys, 1998) was used. Examples of using the updating algorithm with this software are described in Section 6.6.4 below.

Conditional Independence

Consider a very simple network consisting of single parent node *X* with child nodes *Y* and *Z*, as in Figure 6.9.

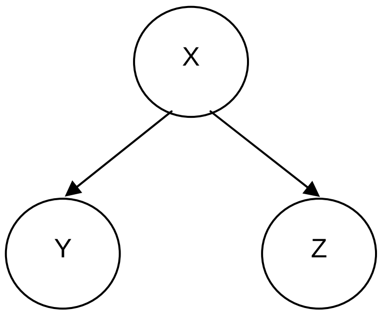


Figure 6.9 An example of a simple network

Knowledge of the state of *Z* would enable us to infer something about the possible states of *X* (i.e. calculate the posterior probabilities of *X*), using the updating algorithm, or in this simple case by using Bayes' rule from probability theory. From this we could estimate the probabilities of the states of *Y*. However, if the state of *X* were *known* then knowledge of *Z* would tell us nothing about *Y* in addition to the what we deduce form knowing the state of *X*. *Y* and *Z* are said to be *conditionally independent given X*. For another example, refer again to the example on Figure 6.8. If the state of *C* were known, then knowledge of the states of the nodes *A, B* and *D* would tell us nothing about the state of *E*, so *E* is conditionally independent of *A, B* and *D* given *C*. Also, *C* is conditionally independent of *D* given *A* and *B*.

Conditional independence is a fundamentally important property of BNs without which the updating algorithm would not work. It is not a property of the particular probability distributions of the nodes. In fact conditional independence has nothing at all to do with probabilistic interpretations but is a feature of causal relationships. It is also important at the stage of building a BN model because it implies that at any stage of development of the model, we can focus just on one node and its parents without having to consider the joint effect of all possible interacting nodes. This amounts to a great simplification in the model building process.

6.6.3 Building a Bayesian Network

Network construction, for all but the very simplest models, is an iterative process. The first step in constructing a BN is the *qualitative* stage of specifying the nodes and the causal relationships between them. To begin with, this is a tentative specification representing a hypothesis (or rather, a collection of related hypotheses) and will most likely be modified after closer investigation of the validity of the links. Usually we would start by focusing on a particular outcome or set of outcomes and then propose nodes representing immediate (proximate) causes. Then we decide whether there should be any causal links between the nodes representing these immediate causes and then look for causes of theses causes, if there are any, and so on. At each stage, we again insert any possible causal links between the nodes so far included. In principle, this process could be continued for several stages of causality, but a good model, just as with statistical models, should be parsimonious, and should aim to represent the main features of the patterns of causality the exist in reality. A model which attempts to explain everything will be impossible to interpret and of little practical use.

To illustrate the process with the fisheries data, we begin by building a model for the equity outcome. There are several outcome variables in the database which are measures of equity. The techniques outlined in Sections 6.3.2 and 6.3.3 were used to identify a single variable to serve as a measure of equity. According to these procedures, the variable DISTRIB (distributional equity among community members) was found to be a good overall measure of equity. Most variables used were ordinal (low/medium/high) and these were recoded to binary variables (grouping either “high” or “low” with “med”, depending on the observed frequencies) for the purposes of this analysis. To begin with, the selection of variables was guided by the hypothesis matrix (described in Chapter 3). The decision on whether or not to include an attribute variable as a candidate causal variable was based on a combination of judgement based on contextual knowledge and the statistical significance of a chi-square statistic calculate from a two-way contingency table cross-tabulating the outcome with the attribute variable. Of the variables initially thought to influence equity, associations with the following variables turned out to statistically significant: REP_FISH (representation of fishers on the decision making body), CONF_RES (conflict resolution), MANG_TYPE (type of management unit: government, co-management, traditional), DEM_ELEC (decision making body democratically elected), STABBODY (stability of the decision making body), RESPECT (respectability of the body) and GEARS (number of gears). It is important to stress that the chi-square tests used to get an initial idea of the relevance of these variables were based on simple two-way classifications, that is, assessing attribute-outcome associations one at a time. This simple analysis takes no account of the interaction of the effects of attributes on the outcome. The next step was to assess the *joint* effects of the attribute variables on the response. This was done using logistic regression (when the response was binary), or log-linear modeling for multi-dimensional contingency tables for categorical variables with more than two levels. (Appropriate log-linear models are equivalent to logistic regression when the response is binary and the explanatory variables are categorical (McCullagh and Nelder, 1989).) Details of the logistic regression modelling used appear at the end of this subsection.

A similar process was repeated for other variables until a pattern of associations was established. In many instances, repeated applications of this process revealed that the best representation of the associations between the variables was not direct but involved chains of association so that the effect of an attribute on the outcome variable was mediated through one or more of the other attribute variables. At this stage, the pattern of associations that we started with was re-assessed, taking account of the relationships established through the process described, and the entire sequence of steps was repeated. This iterative procedure led to the final model.

This process of building a network model is not derived from statistical tests of association alone, but involves judgements based on what is known of the context of the data. In other words, it is the product of a blend of expert knowledge of the domain with decisions based on statistical criteria. It happens that in the present case we have data which can help establish, or at least confirm, the associations which are expected. In some applications of BNs there is little or no hard data and the causal links, and their conditional probabilities, are derived by a process of elicitation from expert knowledge alone.

The result of this initial qualitative stage of model building resulted in the network shown in Figure 6.10. Note that nodes *Respectability* and *Stability* emerge as “outcomes” in the sense that they are influenced by other nodes but do not themselves affect any other nodes. *Management type* affects *Equity* through two pathways, *No. of gears* and *Fisher representation*. Also *Management type* significantly affects *Fisher representation* both directly and through the node *Democratically elected*. The effect of *Fisher representation* on *Equity* is mediated through *Conflict resolution*. From the way in which the model has been developed, it should be clear that there is no claim that it represents *the* definitive model. It reflects a blend of expert opinion with results from the data, but it is quite possible that other legitimate models could be proposed which are also consistent with the data.

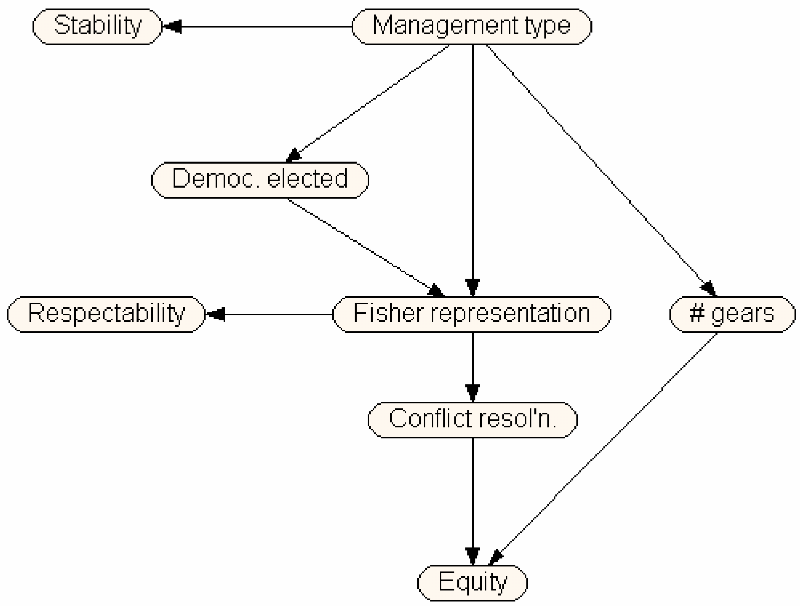


Figure 6.10 The initial qualitative stage of model development

Before elaborating this model further, we turn to the *quantitative phase* of model development. That is, we specify the conditional probabilities which govern the links between parent and child nodes. In the absence of data to guide this process, this would be done by a process of elicitation of expert opinions, as mentioned in Section 6.6.2, but here we have data on the variables represented by the nodes in the model and it is possible to use cross-tabulations to estimate the conditional probabilities. In the event, some of the estimated probabilities were based on quite small numbers of cases in the cross-tabulations which occasionally resulted in extreme estimates (0 or 1). When it was judged to be possible, but unlikely, that an extreme occurs, these probabilities were subjected to small adjustments (0.05 or 0.95, for example).

As examples of probabilities estimated in this way, Table 6.6 shows the conditional probabilities for the node *Conflict resolution* and Table 6.7 represents the conditional probabilities for the node *Fisher representation*.

Table 6.6 Conditional probabilities for *Conflict resolution*

	Conflict resolution	
Fisher rep.	No	Yes
Low	0.77	0.23
Med/high	0.06	0.94

Table 6.7 Conditional probabilities for *Fisher representation*

		Fisher representation	
Mg't. type	Dem. Elec.	Low	Med/high
Gov't.	No	0.95	0.05
Gov't.	Yes	0.95	0.05
Co-mg't.	No	0.91	0.09
Co-mg't.	Yes	0.11	0.89
Trad.	No	0.33	0.67
Trad.	Yes	1.00	0.00

Prior probabilities for nodes with no parents (only *Management type* in this model) were derived from simple frequency distributions of the variables.

With all of the probabilities estimated, the model can be represented as shown in Figure 6.11. The nodes are here shown as bars charts representing the probabilities (expressed as percentages) of the possible states. The probabilities displayed in the nodes are the overall *marginal* probabilities of the states of the nodes, conditional on their parent nodes. This representation of the model is produced by the Netica software and is an interactive interface enabling the user to enter evidence or modify the model in various ways (see Section 6.6.4 below).

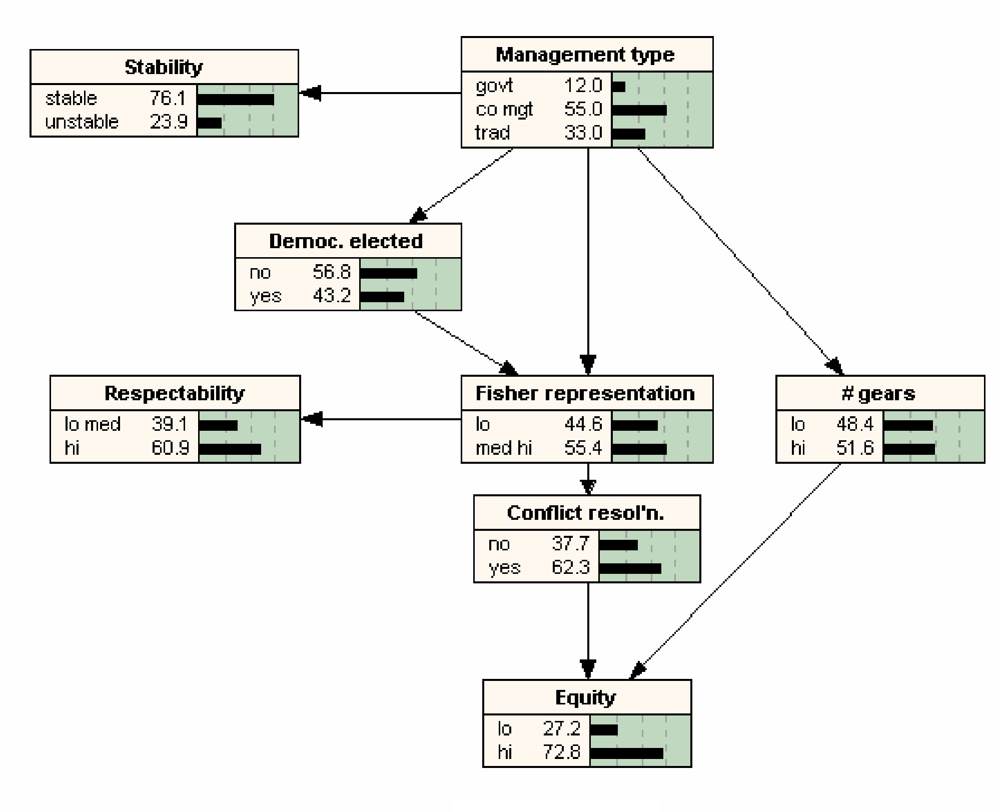


Figure 6.11 The initial quantitative stage of the network model development

One way of further developing this model is to try including other outcome variables. Proceeding with the qualitative development as explained above, we could, for instance attempt a model for the outcomes *Equity* together with COMPLY (*compliance* with rules and regulations) and CPUE_CHG (perceived *change in catch per unit effort*: declining or static/rising). This last variable is interesting as it appears to be a suitable proxy indicator for sustainability of the fishery. A possible model for these outcomes is shown in Figure 6.12. Here, in addition to the main outcomes *Equity*, *CPUE change* and *Compliance*, which have been placed at the bottom of the network, there are now three subsidiary outcome nodes: *Stability, Respectability* and *Poaching* (Low or Med/high). These appear on the left side of the network.

Interesting conclusions can be drawn from the qualitative aspects of the model, before considering probabilities. For instance, it is striking that *Fisher representation* appears to have a pivotal role in the model, in the sense that the effects of several variables on the outcomes are mediated through it.

Clearly, this process of elaboration could be continued so as to include even more outcome and explanatory variables. However, as mentioned previously, complexity is not a prerequisite of a useful model. Isolating the key factors and relationships between them should be the goal in building network models. There are undoubtedly other explanatory variables which could be added to the network in Figure 6.12, even including some which are not statistically significant according to the data. But it is more important to strive for a judicious blend of statistics and judgement based on knowledge of the domain so as to arrive at an economical representation which will be interpretable and useful for management purposes. In the present situation, with a large number of variables, a good strategy may be to construct several BNs, each one representing different important outcomes. For example, the network in Figure 6.12 does not model the *Compliance* outcome very well in terms of the potential attributes which probably affect it. It may be more sensible to build a separate model for this outcome. The main objective here is to describe the process of building BN models and not to construct the definitive model.

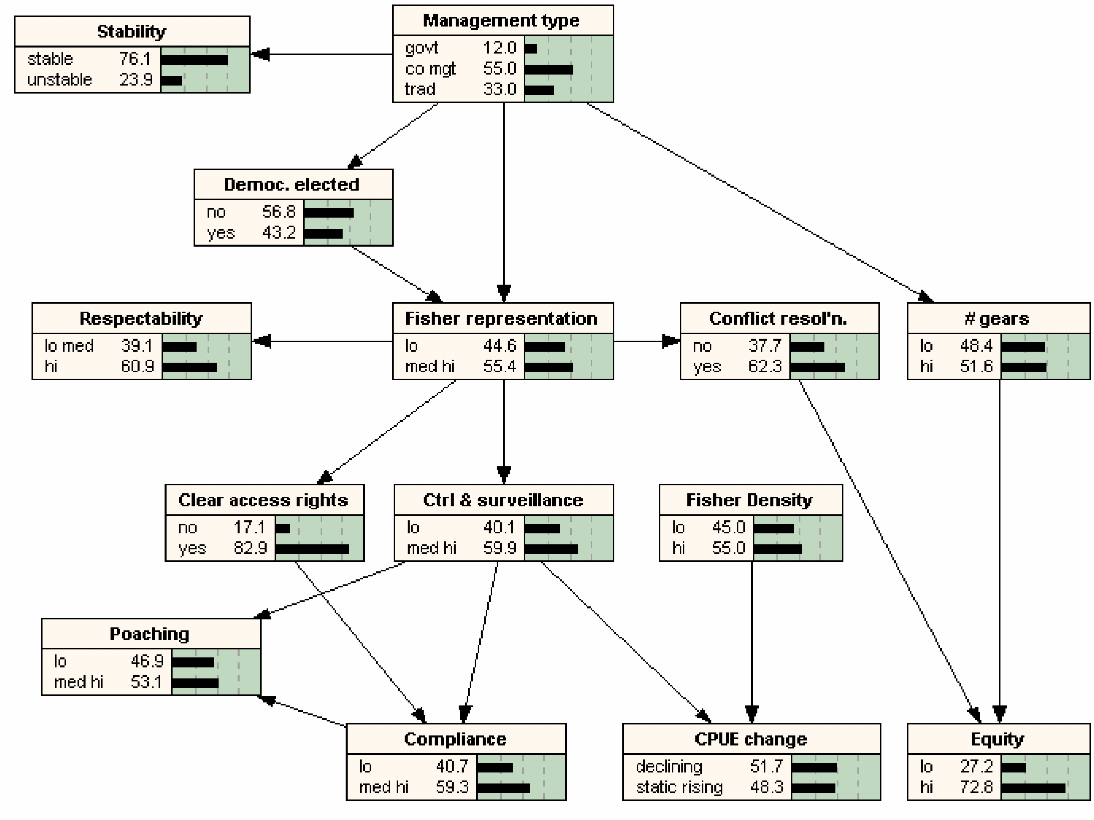


Figure 6.12 The final network model

Logistic Regression Models

As mentioned above, the statistical significance of the links in the BN shown in Figure 6.12 was tested by fitting logistic regression models to the data. An important consequence of conditional independence in BNs is that we only have to consider each node (and its parents) in turn, without having to worry about the joint effects of all the other nodes in the network.

A logistic regression model for a binary response y has three components:

(1) $y_1, y_2, \ldots, y_n$ are independent 0/1 random variables with p_i = probability that $y_i = 1$

(2) Explanatory variables forming a set of *linear predictors* η_i (for $I = 1,\ldots n$)

$$\eta_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik}$$

(3) The link between (1) and (2) is given by

$$\log\left(\frac{p_i}{1-p_i}\right) = \eta_i$$

The logistic regression model is a special case of generalised linear models (McCullagh and Nelder, 1989) and is fitted by a process of iteratively re-weighted least squares. These models are available in most serious statistics packages. S-PLUS 6 (Insightful Corp., 2001) was used for the computations here. A test of the effect of each explanatory variable is given by the *deviance*, a statistic which approximately follows a chi-square distribution.

The results for the nodes in the BN of Figure 6.12 are summarised in Table 6.8. In the network construction process, several links with other variables were also tested and found to be non-significant; these results are not presented. For each child node (response variable), where there are two or more parent nodes (explanatory variables), the deviance values for the parent nodes should be read sequentially: the deviance of the second is a measure of the variation accounted for *after* taking account of the first variable.

Table 6.8 Results of logistic regression analyses

Child node	Parent nodes	Deviance	d.f.	Signif., P
Equity	Conflict resolution	10.11	1	0.001
	# gears	4.98	1	0.026
CPUE chg.	Fisher density	7.13	1	0.008
	Ctrl & surveillance	6.29	1	0.012
Compliance	Clear access rights	19.10	1	<0.0001
	Ctrl & surveillance	13.08	1	0.0003
Poaching	Compliance	20.13	1	<0.0001
	Ctrl & surveillance	3.90	1	0.048
Ctrl & surveillance	Fisher representation	41.87	1	<0.0001
Clear access rights	Fisher representation	18.10	1	<0.0001
Fisher representation	Management type	12.67	2	0.002
	Democ. elected	20.89	1	<0.0001
Conflict resolution	Fisher representation	43.05	1	<0.0001
# gears	Management type	17.58	2	0.0002
Democ. elected	Management type	30.87	2	<0.0001
Respectability	Fisher representation	12.47	1	0.0004
Stability	Management type	7.13	2	0.028

6.6.4 Using a Bayesian Network

It has already been mentioned that purely qualitative features of a network model can lead to interesting conclusions. Indeed, the very process of constructing the model is itself a useful exercise in the elucidation of characteristics of the situation being modelled. However, it is the ability to "enter evidence" and use the updating algorithm which makes BNs powerful tools in decision making under uncertainty. We illustrate this process by entering evidence at various nodes in the model in Figure 6.12.

As a first example, we use the model to investigate the effect on the outcomes of *Management type*. The probabilities displayed in this node in Figure 6.12 are just the actual proportions of the three management types that occurred in the data. If we set this variable to, say "government", the resulting posterior probabilities in all nodes are updated with the result shown in Figure 6.13. Using the Netica software this is very easily achieved by simply clicking on the "government" state in the *Management type" node*. Compare the probabilities now displayed in the nodes with the overall average probabilities in Figure 6.12. We see, for example that the posterior probability of high *Equity* has changed from 73% to 58%. Note also the effect on the subsidiary outcomes: the probability of med/high *Poaching*, for example has changed from 53% to 78%. By successively entering the three possible management types, the effects on the main outcomes can be compared and these results are summarised in Table 6.9.

Table 6.9: Posterior probabilities of favourable (main) outcomes by management type

		Management type		
Outcome	Overall	Gov't.	Co-mg't.	Trad.
Equity (high)	73%	58%	80%	67%
CPUE change (static/rising)	48%	27%	50%	53%
Compliance (med/high)	59%	30%	62%	66%

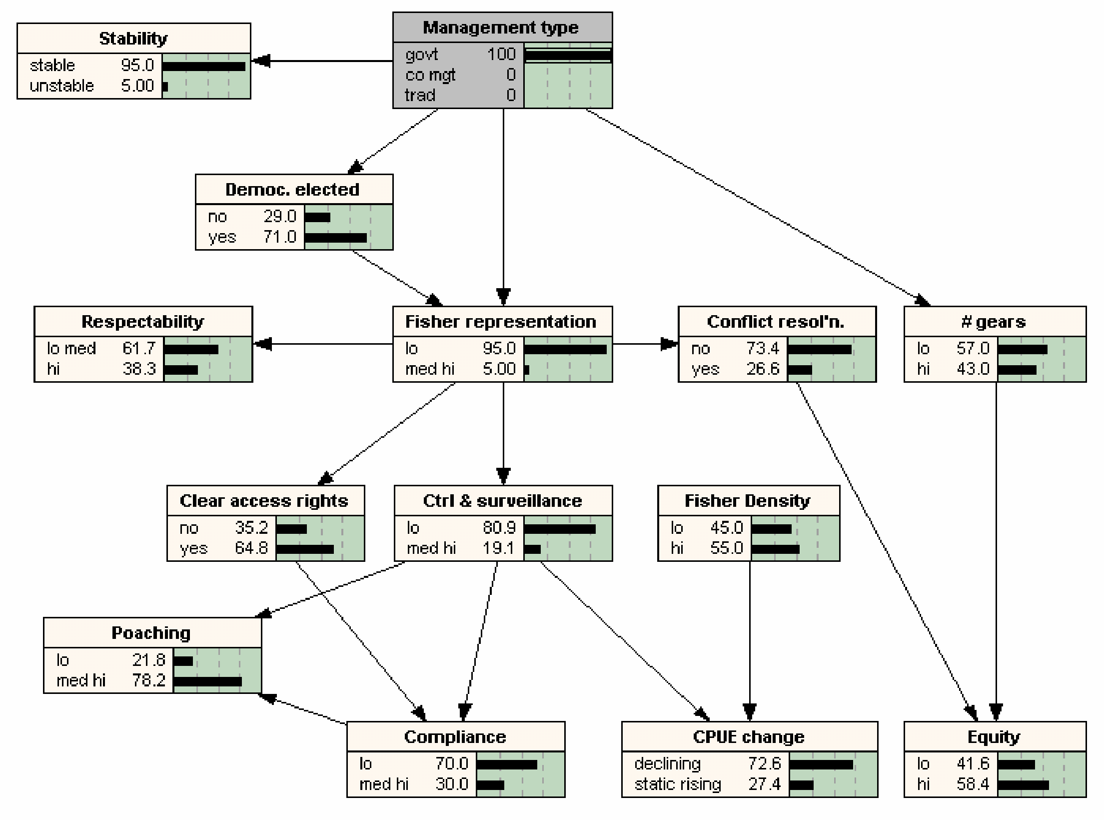


Figure 6.13 Exploring the effects of government management on management outcomes

In the same way we can obtain the posterior probabilities of the subsidiary outcomes and these are shown in Table 6.10.

Table 6.10 Posterior probabilities of favourable (subsidiary) outcomes by management type

		Management type		
Outcome	Overall	Gov't.	Co-mg't.	Trad.
Poaching (low)	47%	22%	49%	53%
Stability (stable)	76%	95%	66%	86%
Respectability (high)	61%	38%	63%	66%

Evidence can be entered into any node, or indeed any combination of nodes simultaneously, and posterior probabilities for all remaining nodes in the network obtained by updating. To illustrate this, we can examine the posterior probabilities resulting from setting all three main outcomes to their "favourable" states: med/high *Compliance*, static/rising *CPUE change* and high *Equity*. The resulting posterior probabilities could be obtained as in the previous example, but for the purposes of illustration, Figure 6.14 shows the result in a slightly different form. It gives what is called the *most probable explanation*. This is the configuration of states that are most likely to be conducive to favourable results in the three outcomes simultaneously. The bars in the nodes no longer represent probabilities, but the required favourable state of each node is indicated by 100%. The lengths of the bars for the other states in the same node now represent the relative importance of those states, in the sense that a high percentage (close to 100%) would indicate that the actual state is probably not critical. We are thus able to deduce which nodes are critical for favourable outcomes. For example, referring to Figure 6.14, we see that *Fisher representation* appears to be an important feature because the "low/med" state scores only 2.73 against the preferred state "high". Note also the *Management type* node, where although "co-management" is the state most likely to produce favourable outcomes, "traditional" fisheries score 83.5, which indicates that the corresponding posterior probabilities of the main outcomes would also be quite high.

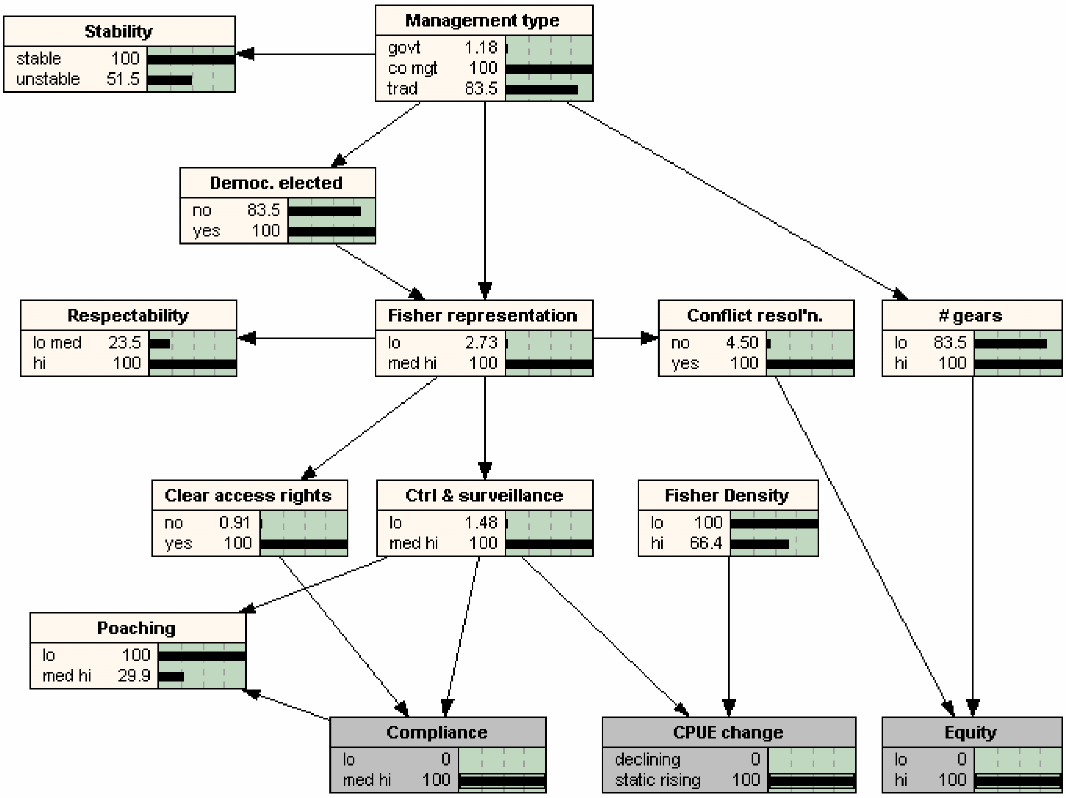


Figure 6.14 The configuration of states that are most likely to achieve favourable states in all three management outcomes simultaneously

An additional useful output from a BN is an analysis of what is called *sensitivity to findings*. The idea is to assess the relative impact of entering evidence in nodes on a given node of interest (or, in the present context, the relative importance of attributes to outcomes). This is accomplished by comparing the amount of uncertainty represented in the model before and after entering the evidence. Various statistics have been proposed for this measure, and there is a choice of two in the Netica software. We use what is called *mutual information*, a measure of entropy reduction. This analysis enables us to rank the importance of attributes on outcomes, as summarised in Table 6.11.

Table 6.11. Relative Importance of Attributes to Outcomes

Outcome	Important Attributes	Mutual info.
Compliance	Ctrl & surveillance	0.3427
	Fisher representation	0.2636
	Clear access rights	0.1377
	Management type	0.0357
	Democ. elected	0.0225
Equity	Conflict resol'n	0.0918
	# gears	0.0524
	Fisher representation	0.0490
	Management type	0.0221
	Democ. elected	0.0170
CPUE change	Ctrl & surveillance	0.1944
	Fisher representation	0.1276
	Fisher density	0.0967
	Management type	0.0185
	Democ. elected	0.0110

In reading this table, no meaning should be attached to absolute values of the mutual information, nor to comparisons between outcome nodes, but values between attributes affecting each outcome node can be compared.

Again it must be stressed that the conclusions drawn from the model can only be as reliable as the model itself. Since the emphasis here has been on describing the methodology, all of the above findings should be regarded as tentative.

One way in which the network modelling approach can be useful as a management tool is for assessing the strengths and weaknesses of a particular fishery. Assume that a model has been constructed which is thought to be a satisfactory representation of the fisheries in a particular domain (country, region or type of fishery, for example). Suppose that fragmentary data are available for a new fishery within the domain. This information could be entered as "evidence" into the appropriate subset of nodes in the model and the posterior probabilities could be used to investigate the likely states of the other nodes. This analysis could help identify priority aspects that need to be addressed in order to achieve a high chance of successful outcomes.

6.6.5 Conclusions

The methodology proposed in this section should not be seen as an alternative to more statistical analysis such as GLMs and multivariate analysis. BNs, as described here, are not tools for statistical inference but could be useful tools for management in an environment of uncertainties. A careful statistical analysis of data would serve as an important step in guiding the design of a network model. However, it has already been mentioned that with carefully thought out elicitation procedures, it is still possible to construct a meaningful network model from expert judgements alone.

An attractive feature of BNs is that they can be developed adaptively: as more cases (evidence) become available, improved estimates of the conditional probabilities can be derived. In AI jargon, this is called "learning" (Cowell *et al*, 1999). The qualitative structure (the nodes and links) can also change adaptively. These developments seem to be particularly appropriate to our present focus on adaptive co-management. Another development that may turn out to be important in adaptive management is the *dynamic BN*. The kind of model that has been described above can be regarded as a static snapshot view. A dynamic model incorporates the time dimension so that the model evolves. A dynamic BN consists of a series of snapshot models, one for each time period, with links between appropriate nodes at time t to nodes at time $t+1$. This may be useful for monitoring the performance of a fishery over time.

Experience has shown that it is quite feasible to train managers in the skills needed for constructing network models. As mentioned previously, the acquired discipline of analysing the qualitative relationships between variables can itself be a very useful exercise even without proceeding to the more quantitative aspects. The Netica software is very user-friendly and there are no great demands on pre-requisite knowledge to be able to use it. In addition to the analytical capabilities outlined above, it has facilities for designing and editing network models and for maintaining files of data ("cases" or "evidence" in the jargon). It is also inexpensive and a free version can be downloaded from the world-wide web (the only limitation is the number of nodes), and so is suitable for use in low-budget situations.

7. Conclusions & Recommendations

7.1 Introduction

This final chapter draws conclusions concerning the project activities and findings (outputs) and provides guidelines for field applications and recommendations for further work with reference to Phase II of the project.

7.2 Recommended Methods

Having considered a number of possible modelling strategies, we concluded that two complementary approaches for the analysis of data in support of adaptive co-management are appropriate. These are:

- GLM regression modelling for identifying and assessing the effects of key attributes on outcomes;
- Bayesian network modelling to construct tools for diagnosing strengths and weaknesses of particular fisheries management units and for exploring ‘what if’ scenarios.

The two approaches differ in that GLM modelling is a tool for statistical inference, enabling the estimation and testing of the effects of attributes on outcomes, and Bayesian networks model complex patterns of causality between several variables. There is also a difference in purpose of the two models in the sense that Bayesian networks are not particularly useful for statistical inference. The purpose of a BN is rather to serve as a management tool, or an expert system, for diagnosing strengths and weaknesses.

Application of both of these methods was preceded by an initial phase of data exploration and reduction using variable clustering and principal components analysis.

The rationale for these choices is as follows.

The general aim has been to propose sound statistical methods which would enable the identification of attributes which are important determinants of desirable outcomes and to assess their relative importance. The path to achieving this goal includes methods for exploring and reducing the complex data sets that arise from studies of fisheries co-management. We emphasise the importance of recognising *structure* in the data because of its role in the choice of appropriate statistical methodology. The manner in which the data were obtained, especially the sampling procedures that were used, imposes constraints on the validity of statistical analysis, a point which has been largely overlooked in previous studies. The nature of the variables, continuous, categorical, ordinal, etc., is crucial to the choice of method of analysis. An equally important characteristic of data is the distinction between what are sometimes called “hard” and “soft” data. Some variables are measurements or counts of observable phenomena and different observers would record essentially the same values in a given situation. Other variables are indicators of perception or opinion and, while equally valid as data, there are statistical methods which are better suited to their analysis than the more traditional approaches.

Some of the features of the data for the present study which influence and, to some extent, limit the choice of statistical methods are:

(1) Mixed data types, with many ordinal variables and both “hard” and “soft” data

(2) Many missing values with few variables being complete

(3) Large number of variables, with possible redundancies

(4) Multilevel data structure

(5) A mixture of “snapshot” variables and variables measuring change over time

(6) Complex patterns of dependency and causality between variables

The ways in which these features have been dealt with are discussed below, taking each point in turn.

(1) Mixed data types: To a large extent GLM models accommodate mixed data types, at least in the set of explanatory variables. “Soft” data in the form of categorised attitudes or perceptions are easily incorporated as explanatory variables in GLMs provided we ignore the ordinal nature of the categories. It would be easier to have these variables in the form of scores, preferably derived from a composite scoring scheme as described in section 7.5.2 below. The appropriate regression method for modelling categorical responses would be loglinear models or logistic regression. These methods have been reserved in our approach for designing BN models. The BN framework is particularly well suited to dealing with these variables.

(2) Many missing data values: The large number of missing data values has been problematic. It should be noted, however, that there are two kinds of “missing” data: *structurally* missing data, which occur when the variable in question is not defined in certain cases (e.g. FADs in beels), *accidentally* missing data, where there should be a values but, for whatever reason, they have not been recorded. Structurally missing data would have to be dealt with in any statistical approach, usually by limiting the domain of a particular phase of the analysis to the appropriate cases. It is more difficult to deal with accidentally missing data, and inevitably leads to a less than perfect analysis. In the present project, we have chosen subsets of variables for analysis in which the number of missing observations is as small as possible. It must be acknowledged that a more complete analysis, possibly using model-based multiple imputation procedures, would have been possible if there had been fewer missing data points. BN modelling, with the possibility of using quantities derived from both data and subjective expert judgements, is less vulnerable to this problem because of the possibility of blending data with expert judgements.

(3) Large number of variables: The problem of the large number of variables in the database has been addressed by first isolating the subset of variables which are relevant to a particular hypothesis and then using the dimension reducing techniques described in Section 6.3.3, namely variable clustering and principal components analysis with biplots. There are redundancies in the database, in many cases with several variables apparently measuring essentially the same thing.

(4) Multi-level data structure: Some variables are measures of attributes at the level of the management unit itself, others at the level of households and yet others at the level of individual fishers. The problem has been dealt with by aggregating low-level variables over higher levels, so that the unit of observation is the management unit. (This aggregation had already been done prior to the construction of the database.) This can be regarded as a necessary approximation, but it should be recognised that failure to take account of the hierarchical structure of data can lead to misleading conclusions (Goldstein, 1995). Further study, and data, would be called for if this aspect were to be thoroughly explored.

(5) Static and change variables: Several attributes in the database have been recorded both as “snapshot” observations, representing the current state of affairs, and also as perceptions of change. For example there are variables representing both CPUE and CPUE change over time (declining, static or rising). In several of the analyses presented here, it has been difficult to meaningfully combine both in the same model, and the emphasis has generally been on modelling the “snapshot” variables, especially in the GLM modelling. The “change over time variables”, however, are for the most part measures of *perception* (i.e. “soft” data) and would best be analysed in the appropriate framework. An example is CPUE change, which has been incorporated as an outcome in the BN model presented in Section 6.5. Further development of statistical analysis should recognise, and take account of, the difference between these two types of data.

(6) Complex causal relationships: Like any regression method, the GLM approach recognises a response, or outcome, variable and a number of explanatory variables. An essential feature of the model is that the joint effect of the explanatory variables is modelled *directly* on the response. That is, there is no scope for modelling intermediate pathways of causality. With GLMs it is possible to

assess the *interaction* of explanatory variables in the way they affect the response, but the joint effect is still modelled as a direct effect on the response. More complex patterns of causality cannot be accommodated in this model. The chief advantage of the GLM approach is that it is a powerful statistical procedure for testing and measuring these effects. On the other hand, the reason for exploring the use of BNs has been to propose a technique which *does* attempt to model these patterns of causality, which are intrinsic in the IAD and SL frameworks. Their ability to "learn" also makes BNs particularly appealing for our present focus on *adaptive* co-management. It has already been mentioned (Section 6.5) that a BN is not an alternative approach to statistical inference, but is rather an expert system which can be a useful tool for assessing the determinants of performance for a particular management unit. That is, potentially at least, it is a management tool rather than a statistical one.

7.3 Important Co-Management Attributes

Although the emphasis in this project has been on exploring and comparing different methodological approaches, it was hoped that the application of these methods to the "trial" dataset described in Chapter 4 would also reveal important factors affecting (co-)management success, and help identify important variables for inclusion in future monitoring programmes (Section 7.5.2).

7.3.1 Management Success Factors

The project had, at the PM stage, planned to identify key attributes for management success associated with all management outcome variables contained in the dataset. However, for the reasons described, identification of these factors was restricted to those associated with the six management outcomes selected. For the GLM modelling these were: production measured in terms of catch per unit area (CPUA), sustainability measured in terms of catch per unit effort (CPUE), and community well-being measured in terms of average annual household income per year. For the BN modelling, equity, compliance with rules and regulations, and changes in CPUE were included into a single network model to demonstrate the approach.

Important attributes contributing significantly to the variability in CPUA were identified as: Ecosystem type, annual primary production, type of gears employed, destructive fishing practices, bans on fish drives, landing size restrictions, numbers of reserves, management type, access restrictions and fisher density. For CPUE, ecosystem, gear and management type, gear and access restrictions, and fisher density were also found to be important in addition to: fishing purpose, existence of management plans, effective control and surveillance measures and conflict resolution mechanisms, and incidence of poaching. Fisher density was by far the most important explanatory variable explaining 88% of the variation in CPUE with ecosystem type (Section 6.4).

No reliable models of household income could be constructed, possibly reflecting low precision and accuracy in the estimates of household income. Because of their sensitivity to data from a few observations, several potentially good models had to be discarded. It is therefore likely that with more information, many other attributes may emerge as being important, while some of the attributes identified in our analysis as important, may well become redundant.

Further examination of the relationship between CPUA and fisher density using an expanded dataset has provided estimates of optimal fisher density and maximum sustainable yield by major ecosystem type. These estimates provide a useful starting point for iteratively refining adaptive management strategies aimed at maximising yield through effort restrictions (Section 6.5).

The results from the Bayesian network model suggest that the main factors affecting equity were (in order of the strength of their effects) effective conflict resolution, numbers of gears employed in the fishery, fisher representation, management type and democratically elected decision making body. The attributes influencing CPUE change were found to be effective control and surveillance, fisher representation, fisher density, management type and democratically elected decision making body. Those affecting compliance were found to be effective control and surveillance, fisher representation, clear access rights, management type and democratically elected decision making body. This last result should be regarded as tentative pending further investigation of attributes affecting compliance by means of another BN model focusing on this outcome.

Results derived from the BN model should be seen as indicative of the kind of finding that is possible with this approach rather than definitive results that are generally valid. As explained in Section 6.6, a BN model is a tool for investigating particular cases and not a mechanism for deriving generally applicable statistical results.

7.3.2 Limitations of the Results of the Analysis

The results described above should be treated with caution for the following three reasons.

First, inferential procedures used in the GLM modelling, in particular, assume that proper random sampling procedures have been followed in obtaining the data. This is not the case with the case-study dataset. Management units have been selected more or less opportunistically. Randomness means that different observations are statistically *independent*, and this assumption is clearly violated with the present data. A consequence is that, for example, significance levels (*p*-values) derived from GLMs and logistic regression are likely to be incorrect. They should be regarded only as very rough guides to the true state of affairs.

Second, the problem of missing data also has implications on the validity of the analysis. It would have been preferable in some instances to have included additional explanatory variables in regression models, especially when there was a chance of interacting effects. On occasion, this was not done simply because there were insufficient data points common to all required variables.

Finally, it has already been noted that the database consists of management units of very different types, and from different ecosystems. In some of our analysis, for the purposes of developing a methodology, these have frequently been analysed together. Separate analyses for each group of fisheries are likely to yield more useful results.

In the light of these difficulties, our chief focus has been on methods rather than results. Further development and application of the proposed methods will be more fruitful in a more limited domain, fisheries of a particular management type in a particular region, for instance. This is not the only scenario for application of these methods, however. With sufficient data, and proper sampling procedures, it would be possible to use the GLM approach to make comparisons between different domains (regions, for example). On the other hand, BN modelling appears to be best suited to development for a particular class of management units.

7.4 Other Project Outputs

The project succeeded in delivering its other planned output. The case study database is a significant output that will be made freely available at http://www.fmsp.org.uk where it may be periodically updated as further data becomes available providing a basis to generate further insights into factors affecting (co-)management performance. Whilst not originally defined as a planned output at the PM stage, the review of previous statistical approaches (Chapter 5) is also regarded as an important output given the significance of its findings, particularly with respect to the *Rapfish* technique. A draft paper has been prepared on the basis of this review that will be submitted for publication shortly.

7.5 Recommendations for Field Applications and Further Work

Recommendations for field applications of the proposed methods and further research are outlined below:

7.5.1 Sampling Requirements

The case study data we have used were drawn from studies carried out in several countries and therefore our sampling procedure for selection of co-management units can be described as being purposive. Although strict random sampling is not always crucial, the “global” setting to which our results may tentatively apply is inappropriate for recommendations at a local level. Our data collection approach was merely intended to demonstrate the general approach to model-based inferential procedures.

In real field applications, we recommend that the population of interest is clearly identified at a regional or national level and our modelling approaches applied to data from all, or an appropriately selected sample of management units within that region or country. The relevant sampling unit for this work must be a fisheries management unit with a clear specification of what the unit consists of in terms of its community members and fisheries sources.

7.5.2 Variables for Inclusion in Future Monitoring Programmes

Because of the limitations described in Section 7.3.2 it is difficult to prescribe a definitive list of attributes for inclusion in future monitoring programmes on the basis of the analysis described here. However, we recommend that the attributes identified in Chapter 6 as being important in determining outcomes be included. Consideration should also be given to excluding those variables we found to be redundant or unhelpful for a variety of reasons (Annex VI). A pilot or frame survey employing PRA techniques may provide a more efficient means of establishing the range of potentially important model variables and hypotheses for testing.

A common problem encountered when profiling the management units was the need to assign a single value to inherently multivariate or multi-dimensional variables (Section 4.3). For example, the variable *Gear Type* (Group I) allows only one gear to be recorded whilst, in reality, several gears may be used in the fishery. In this case, the most important gear in terms of catch weight was recorded. This problem could be overcome by adding additional variables to record other important gears in order of importance (eg *Gear Type 1*, *Gear Type 2*, *Gear Type 3*…etc) particularly when the focus of analysis is at a more local scale, and when many other attributes are likely to be constant and can be excluded. Another way might be to score gears according to important attributes or characteristics such as their catchability, habitat destructiveness, by-catch...etc. Selecting additional variables from those remaining should, therefore, be undertaken judiciously taking into consideration available resources and local conditions. Other, alternative variables should also be considered.

For example, many variables such as *Representation in Rule Making* are currently ‘scored’ in a subjective manner with three point ordinal scales eg low (0); medium (1); high (2). Explicit guidance notes for scoring these variables need to be developed to make these subjective assessments more objective. These guidance notes could be used to generate ‘composite scores’ for the attribute where the attribute score is the sum of scores assigned to a number of attribute indicators. For the attribute *Representation in Rule Making* these indicators may include the presence or absence of a forum for discussion and dialogue, the involvement of women in decision-making and whether the decision-making body has been democratically elected or not. In the example below (Table 7.1), representation in rule making is lowest at site 3 and highest at site *n*. This type of approach is commonly employed in marketing research and was adopted for elements of the World Bank (1999) study.

Table 7.1 Example of the calculation of a composite score for *Representation in Rule Making*

Attribute Indicators		**Site 1**	**Site 2**	**Site 3**	**Site n**
Forum for discussion	Yes (1); No (0)	1	0	0	1
Women involvement	Yes (1); No (0)	1	0	0	1
Democratically elected body	Yes (1); No (0)	0	1	0	1
Representation in rule making – composite score		**2**	**1**	**0**	**3**

This approach has the added advantage that it will reduce the total number of potential model variables without loss of any valuable information. Because all the case-study variables employed in this project were either scored or checked by the Principal Investigator, the absence of more explicit guidance notes should not have biased the results presented here significantly. Indeed, the composite score approach was implicitly, but less formally, employed in the allocation of scores to these variables. However, any remaining subjectivity included in the variable scores may preclude unbiased comparisons with additional observations scored by other workers.

7.5.3 Data Collection

The validity of results from the application of our recommended model-based approaches depend, of course, on the reliability of the data being used. We strongly recommend that primary data be used where possible in using these models. Since many of the variables of interest depend on the perceptions of fishers and other stakeholders, we recommend that primary data are collected through an approach similar to that adopted by Pomeroy *et al* (1997) where a 15 rung ladder was used to score attributes on a 0 to 15 scale. This is particularly beneficial for scoring outcome variables such as CPUE change or changes in the well-being of households, because the resulting variable, suitably aggregated to the co-management unit level, can then be regarded as a quantitative variate suitable for use in general linear models. The more specific requirement that the aggregated variable follows a normal distribution, is also satisfied through this approach because of a basic theorem in statistics (the Central Limit Theorem) which says that an average (mean value) over a sufficient number of observations gives rise to a normal variable.

7.5.4 Data at Different Hierarchical Levels

Our fourth recommendation relates to the need to distinguish between various hierarchical levels at which the data may be collected. Some of the variables in our case study data set, for example, involved variables such as household income, number of months fished per year and depth of reserve, which were aggregated over households or fisheries sources (lower levels of the hierarchy), to the co-management unit level – at a higher level. This aggregation was necessary because the model-based approaches developed in this project assume that all data reside at a single level. If this is not the case, then other modelling approaches, e.g. multi-level modelling techniques, are needed.

Some care is also needed in avoiding any confusion with regard to a stratification variable being considered as a variable at the higher level. For example, our case study data came from different countries and different types of ecosystems. Although the data could be considered as arising from within each country or within each ecosystem, neither country, nor ecosystem type can be regarded as making the data hierarchical since there were no specific variables that were measured at the country level (e.g. type of government) or at the ecosystem level (e.g. size of the river, beel, lake or other).

7.5.5 Selection of Outcomes and Attributes

Procedures for selection of outcome variables and explanatory attributes for use in modelling requires some step-by-step guidelines and we aim to provide these in this section. The first step in this process is the preparation of a list of all potential variates that are believed to have an affect, directly or indirectly, on management outcomes (e.g. sustainability or equity), and a list of all variates that could be regarded as proxy indicators of sustainability. The latter set comprises the outcome variables and should be clear indicators of whether the performance of a fishery is good or bad, e.g. catch per unit effort, household income from fisheries. A selection of attributes from each of these lists is then needed, to give subsets of variates which can be measured relatively easily by a fisheries scientist or other person who has a good understanding of the processes concerning the fishery of interest, and knowledge of the underlying environmental and resource conditions.

The next step would involve a consideration of the chosen set of outcome variables, and select those explanatory variables thought to have a possible influence on each chosen outcome. This step again requires expert opinion and was adopted in our work here through the development of the hypothesis matrix in Table 3.2. Although not done within this project, we have realised retrospectively, that this step could have been followed by an identification of the relative importance of each attribute within the explanatory set of variables in terms of its potential effect on the chosen outcome variable. A simple ranking exercise would have been adequate for this purpose. It would also have been very useful to have given careful consideration to the ease with which each attribute and each outcome could be measured in the field. This would then lead to a much reduced, and more manageable set of variables for analysis purposes.

7.5.6 Data Cleaning and Exploratory Analysis

The data collection stage must naturally involve collecting information on variables identified from above as appropriate for investigating and identifying the way in which changes in co-management outcomes are influenced by a host of multi-disciplinary attributes associated with the community and with the fishery sources comprising the management unit.

The data would then normally be computerised using appropriate database software (e.g. Access) and checked for possible errors and other oddities. Simple data summaries in the form of summary statistics and graphical procedures are recommended at this stage. Any suspect data has to be checked with the original source and corrected or some decision made whether to discard the erroneous value(s).

The next stage is exploratory data analysis. Such analysis procedures form a key component at initial stages of data analysis and are strongly recommended. This step is very important in understanding the behaviour of the data, identifying patterns of association between different variables, identifying odd observations (outliers) and determining whether any scored attributes demonstrate sufficient variability to be appropriate for inclusion in the modelling procedures. Errors in the data may also emerge at this stage and must be dealt with in an appropriate manner.

7.5.7 Data Analysis

Initial stages of modelling require further screening of attributes to ensure that the attributes share a sufficient number of cases in common with the outcome variables being modelled. Our guideline has been to ensure that at least 15 cases are available for both. However, the total number of cases, i.e. co-management units, included in the analysis must be considerably more during the model development process since the greater the number of variables in the model, the greater is the number of sampling units needed for analysis. A very rough guideline for the GLM approach is to have at least 25 cases more than the total number of quantitative attributes plus the sum of the number of category levels corresponding to each classification variable. For example, if GLM modelling is to be undertaken with 2 quantitative variates (e.g. fisher density and the number of reserves) and 2 qualitative factors (e.g. ecosystem type – 5 levels and gear type – 4 levels), then about 36 cases will be needed for a sensible application of GLM modelling with just the main effects of each of these attributes. However, if two-way interactions between the attributes are also to be investigated (i.e. ecotype by fisher density, ecotype by gear type, etc), then many more cases are needed (e.g. about 75 cases) to minimize the chance of empty cells within the two-way categories identified by these interactions.

For the Bayesian network models, the sample size requirements are based on ensuring, as far as possible, that all category combinations corresponding to each node and its parents have sufficient numbers of cases so that the relevant conditional probabilities can be calculated to give meaningful results. BNs are less vulnerable to missing data provided reliable expert judgements are available which can be suitably encoded.

Both modelling approaches recommended in the work here are quite advanced techniques, made more complex by the missing data. Although the final set of results reported may appear straightforward, they were the result of many months of hard work by experienced statisticians. We therefore strongly recommend the involvement of well-experienced and qualified statisticians in the application of the methodological model-based approaches described in this report.

7.5.8 Model Validation and Sensitivity Analysis

A commonly used technique for checking the adequacy of statistical models in general is *cross-validation*. The idea is to fit the model to a subset of cases in the dataset, use the fitted model to predict outcomes for the remaining cases and then compare the predicted with the actual values. A model which succeeds in predicting outcomes with low error can be regarded as performing well. A variant of this method omits *each* case, one at a time, fits the model to the remaining cases and again compares predicted with actual outcomes for the omitted case; the entire procedure is repeated for each case. Although this latter method appears to be fairly computer-intensive, there are computational "tricks" which achieve the required comparisons in an efficient way.

In practice it would be important to assess the extent to which a BN depends on the evidence encoded in it. The Netica software has provisions for carrying out a closely related analysis, namely *sensitivity to findings*. This provides a quantitative assessment of the extent to which each node is affected by entering evidence into a given node. Ideally, an approach along the lines of the cross-validation described above would be used. However, in BNs validation and "learning", that is, the adaptive development of a model as new observations become available, are activities that overlap to a large extent.

In the present study, opportunities for rigorous validation have been rather severely limited by the problem of missing data. In spite of this, it is strongly recommended that in future work which follows our proposed methodology, serious consideration is given to model validation.

7.5.9 Updating Models

Each of our proposed approaches can be adapted to deal with further data that may become available over time. How this is done depends on the regularity of updating the database. We consider each approach in turn.

GLMs: Additional information that becomes available on an *ad hoc* basis would probably be best accommodated by repeating the analysis from scratch. If, however, it is anticipated that data are to be collected at regular intervals (the same set of variables, of course), then it would be possible to incorporate the time dimension in the analysis. Eventually, given sufficient time, this would enable the estimation of trends. The methods of analysis would have to be extended to cope with correlated data structures. There are various statistical approaches to dealing with this situation (Diggle, Liang and Zeger, 1994).

BNs: There are two ways in which BNs can accommodate updated information. The first is *learning* in BNs. This is a feature which makes them particularly attractive in the context of adaptive management. There are procedures for updating the conditional probabilities in the model based on information provided by new cases (evidence) as they become available (Cowell *et al*, 1999). The other approach is to use a *dynamic BN*. In this model, each period of observation is represented by a "static" network model similar to what was described in Section 6.6. Dependencies between time periods are modelled by links between appropriate nodes. The Netica software has capabilities for constructing and analysing dynamic models.

7.6 Phase II – Field Testing

Phase I of this process project has successfully delivered all planned outputs. We therefore recommend that field applications/testing be undertaken under Phase II as described in the project memorandum alongside the previous approaches (excluding RAPFISH) to assess which is best.

Participating projects (and sources of funding) have yet to be identified but potentially include the initiatives running under the ongoing ICLARM/IFM 'Fisheries Co-Management Research Project' in Asia and Africa or the FAO/DFID 'Sustainable Fisheries Livelihoods (SFL) Programme in West Africa. In Bangladesh, they might include the fish sanctuary (harvest reserve) component of the DFID-funded Fourth Fisheries Project involving up to 50 local fishing communities, and Phase III of the CBFM project.

It is recommended that data collection protocols be developed with collaborating project partners and incorporated into monitoring and evaluations programmes to ensure data homogeneity among the units of observation. Collaboration at an early stage of these projects would therefore be required.

The realisation of improved outcomes following the adoption of management recommendations generated from the application of the methodology will depend upon the response time of the institutions involved and biological resources exploited. It is therefore recommended that Phase II be undertaken with stakeholders and institutions who (i) are willing to adopt an adaptive approach to management, (ii) are able to respond to feedback generated from analyses, and (iii) are exploiting short-lived, fast growing resources where the evidence of improved outcomes may be detectable within one or two years, thereby providing the opportunity to demonstrate the utility of the proposed methods during the typical duration of most donor-funded pilot studies.

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Annexes

Annex I Cape Town Workshop Programme

INTERNATIONAL WORKSHOP ON INTERDISCIPLINARY MULTIVARIATE ANALYSIS (IMA) FOR ADAPTIVE CO-MANAGEMENT

University of Western Cape, Cape Town, South Africa,
2nd – 8th March 2001.

Workshop Organisors

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1 Background

Artisanal fisheries are fundamentally important in the developing world but are very complex from resource, technical and institutional perspectives. They are typically characterised by multispecies assemblages exploited with numerous different gear types from diverse habitats under a variety of different institutional and decision-making arrangements by heterogeneous users pursuing multiple livelihoods. Livelihood outcomes based around these fisheries are often further complicated by dynamic spatial and temporal variations in these characteristics and the wider political and natural environments.

Adaptive co-management is increasingly being seen as an effective strategy to redress the failures associated with the 'top-down' stock-assessment-driven management paradigm commonly applied to these fisheries. This approach to management: (i) actively monitors and evaluates management interventions or livelihood strategies; (ii) compares the livelihood outcomes with those in other places or in previous times; and thus (iii) develops appropriate management (livelihood) strategies to improve livelihood outcomes.

Despite the increasingly widespread adoption of adaptive co-management practices by many countries throughout both the developing and developed worlds, few attempts have been made to develop a quantitative statistical approach to help identify and refine activities and institutional arrangements to improve or sustain management performance (see Background Reading below).

In support of their 'Fisheries Co-management Research Project' (FCMRP)', the ICLARM/IFM partnership have developed the 'Institutional Analysis Research Framework' (Figure 1) which shares similar theoretical foundations with the DFID (1999) sustainable livelihoods (SL) framework.

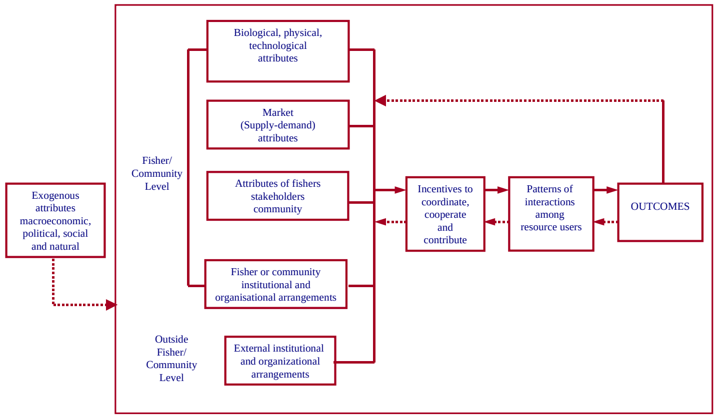

Figure 1 The ICLARM/IFM 'Institutional Analysis Research Framework' (source: ICLARM 2000; adapted from Oakerson, 1992).

By utilising the same sets of contextual variables, the framework is being used to conduct a systematic and comparative analysis of diverse co-management arrangements to identify relationships among variables and outcomes for evaluative, diagnostic and design purposes (ICLARM, 2000).

Using data and information gathered under the FCMRP, and other co-management initiatives, a Department for International Development (DFID) funded collaborative research project entitled **'Interdisciplinary Multivariate Analysis (IMA) for Adaptive Co-Management' (R7834),** aims to develop a statistically robust methodology to support this, and the SL, framework. This includes developing appropriate indicators, scores and measures to quantify co-management project attributes and management performance (outcomes), as well as formulating and testing hypotheses concerning outcomes in relation to subsets of co-management attributes.

By comparing the outcomes of different co-management interventions and arrangements with those in other places and/or in previous times, the project will also seek to identify conditions and arrangements (attributes) that appear to consistently give rise to successful performance and improved livelihood outcomes.

The project collaborators include MRAG Ltd, ICLARM, IFM, the FCMRP National Research Partners, and Reading University.

1.1.1 Workshop Objectives

The objectives of this 7 day workshop are bring together the project collaborators and other workers with considerable co-management experience to:

- Identify and agree upon an appropriate standard set of co-management attributes and management performance criteria, and corresponding quantitative measures/indicators to describe them.
- Formulate 'Outcome Functions'. Hypothesise which sub-sets of attributes are most likely to effect management performance (outcomes).
- Attempt to profile FCMRP initiatives and other co-management projects in Africa and Laos PDR using the agreed set of indicators and measures describing their attributes and management performance. This will allow the project to develop and test the appropriate

statistical methodology and ultimately to help identify generic conditions and arrangements that give rise to successful performance and improved livelihood outcomes. A similar 'profiling' exercise is planned for the FCMRP initiatives in Asia and other co-management projects in Melanesia in the latter half of March and April.

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4 Workshop Programme

	4.1 Planned Activity		
	Morning	**Afternoon**	**Evening**
Fri 2nd	0930 ***Assembly & Introductions*** 1000 ***Presentation*** (AH): Project Background, Collaborators, Project Purpose 1030 *Coffee* 1100 ***Presentation*** (AH): Project Approach/Activities IAD Research Framework Measures and Indicators Previous Methods Potential improvements Workshop Objectives 1200 *Lunch*	1330 ***Discussion Session 1*** Contextual Variables & Measures and Indicators: Resource, Environmental, Technological, Decision Making arrangements, External Factors. 1500 *Coffee* 1530 ***Discussion Session 1 (continued)*** 1645 ***Summary & Conclusions***	
Sat 3rd	0930 ***Discussion Session 2*** Contextual Variables & Measures and Indicators: Resource, Environmental, Technological, Decision Making arrangements, External Factors. 1030 *Coffee* 1100 ***Discussion Session 2 (continued)*** 1200 *Lunch*	1330 ***Discussion Session 3*** Management Performance/ Outcome Criteria & Measures and Indicators: 1500 *Coffee* 1530 ***Discussion Session 3 (continued)*** 1645 ***Summary & Conclusions***	***Trip to Waterfront*** **4.1.1.1 Or Century City**
Sun 4th	**4.1.1.2 Excursion to Cape Point**	**4.1.1.3 Excursion to Cape Point**	
Mon 5th	0930 ***Presentation*** (AH): *Formulating Outcome Functions*	1330 ***Discussion Session 5*** Outcome functions	***Trip to Waterfront Or Century City***

	1030 *Coffee* 1100 ***Discussion Session 4*** Outcome functions 1200 *Lunch*	1500 *Coffee* 1530 ***Discussion Session 5 (continued)*** 1645 ***Summary & Conclusions***	
Tues 6th	0930 ***Discussion Session 6*** Outcome functions 1030 *Coffee* 1100 ***Discussion Session 6 (continued)*** 1200 ***Summary & Conclusions***	***Excursion ?***	
Wed 7th	0930 ***Presentation*** (AH): Profiling Co-management Initiatives 1030 *Coffee* 1100 ***Working Groups*** Profiling Co-management Initiatives 1200 *Lunch*	1330 ***Working Groups*** Profiling Co-management Initiatives 1500 *Coffee* 1530 ***Working Groups*** Profiling Co-management Initiatives 1645 ***Summary & Conclusions***	***Dinner at The Brass Bell, Kalk Bay.***
Thur 8th	0930 ***Working Groups*** Profiling Co-management Initiatives 1030 *Coffee* 1100 ***Working Groups*** Profiling Co-management Initiatives 1200 *Lunch*	1330 ***Workshop Summary and Conclusions*** 1500 *Coffee* 1530 ***Recommended follow-up Activities and Concluding*** **4.1.1.4 Remarks**	

5 Local Travel and Accommodation Arrangements

Please contact Mafaniso Hara mailto:mhara@uwc.ac.za

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NB Important Workshop Preparation (Data Profiling)

The profiling of co-management initiatives/projects or community-managed fisheries using quantitative measures (indicators) of co-management attributes and performance is a major objective of the workshop and key to the success of the project as a whole. It would therefore be extremely useful if participants involved in ongoing or completed studies could ensure that they assemble, and bring with them to the workshop, all relevant data and information for this purpose.

A provisional list of potential co-management attributes and performance criteria (and examples of their measures and indicators) is given in the accompanying Excel file attachment as a guide to the types and range of data and information that may be required for this profiling exercise. Please bear in mind that this is only a guide and that this table is likely to be subject to revision as a primary workshop objective/activity.

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Annex II Explanatory and Dependent Variables

Variable Group	Exaplanatory Variables	Indicators	Units	Notes	VAR_NAME
Key Identifiers	Co-management unit ID number	Co-management unit ID number	Serial Number		ID
	Co-management unit type	Co-management unit type	0;1;3...n	VMA (0); IMA (1); CMA (2); RMA (3); fishery [spp/gear] (4)	TYPE
	Co-management unit name	Co-management unit name	Name		NAME
	Area under co-management	Fishing area of community	km2	or km of coastline (specify)	AREA
	Numbers of fishing villages	Numbers of villages	Number	exploiting fishing area	VILLAGES
	Numbers of fishing households	Numbers of fishing households	Number	exploiting fishing area	HH
	Numbers of fishers	Numbers of fishers (all types)	Number	exploiting fishing area	FISHERS1
	Numbers of fishers	Numbers of fishers (full-time)	Number	exploiting fishing area	FT_FISHM
	Numbers of fishers	Numbers of fishers (part-time)	Number	exploiting fishing area	PT_FISHM
	Numbers of fishers	Numbers of fishers (occasional)	Number	exploiting fishing area	OC_FISHM
	Numbers of fishers	Numbers of fishers (numbers of fishing households x average household size)	Number	exploiting fishing area	FISHERS2
	Numbers of boats	Numbers of boats	Number	exploiting fishing area	BOATS
	Date co-management unit established	Date co-management unit established	Date (mm/yy)	Also see Decision-making arrangements	DATE_EST
	Geographic position	Latitude and Longitude	Degrees, Minutes		LAT_LONG
	Geographic position	Country	Country name		COUNTRY
	District	District/Province	District/Province name		DISTRICT
	Water body or coastal name	Water body or coastal name	Water body or coastal name		WB_NAME
	Water body type	Permenance	0;1;2	Seasonal (0); perrenniel (1); both (2)	PERMEN
	Ecosystem type	Ecosystem type	0;1;2;3....n	River (0); fringing floodplain (1); beel (2); lake (3); coastal inshore (4); coastal offshore (5); coastal lagoon (6); estuary (7); reservoir (8); fringing reef (9); patch reef (10); floodplain-river system (11)	ECO_TYPE
	Position of water body in catchment	Position of water body in catchment	0;1;2	Lower (0); middle (1); upper (2)	POSITION
	Remoteness of co-management unit	Remoteness	0;1;2	Not remote (0); remote (1); very remote (2)	REMOTE
Resource	Production potential	Biolimiting nutrient concentration eg total phosphate	ugl-1 or 0;1;2	Low (0); medium (1); high(2)	BIOLIM
(Group I)	Production potential	Water transparancy (Secchi depth)	m	May not be valid indicator in rivers	SECCHI
	Production potential	Primary production	0;1;2	g/C/m2/year Low <150 (0); medium 150-300 (1); high >300 (2)	PRIM_PRO

	Production potential	Weighted average trophic level of species in catch	Number	weighted by % contribution to catch	TL
	Production potential	Upwelling	0;1;2	None (0); seasonal (1); constant (2)	UPWELL
	Production potential	Allocthonous inputs (eg fruit, seeds, debris etc)	0;1;2	Low (0); medium (1); high (2)	ALLOC
	Abundance/Biomass	(Total annual catch)/(Numbers of fishers)	Tonnes/fisher	All species combined or specify for each target species.	ABUND
	Resiliance of resource	Weighted mean max longevity of species present (or L infinity)	Years	weighted by % contribution to catch	LONGEV
	Resiliance of resource	Weighted mean age of maturity of species present	Years	weighted by % contribution to catch	MAT_AGE
	Resiliance of resource	Weighted mean Lm50/Lmax for species present	0 - 1	weighted by % contribution to catch	LM50LMAX
	Resiliance of resource	Recruitment variability (inter-annual variability in catches)	0;1;2	Low (0); medium (1); high(2)	REC_VAR
	Rule enforcement potential	Clearly defined management boundaries?	0;1	No (0); yes(1)	DEF_BOUN
	Rule enforcement potential	Area under co-management per fisher or community member	km2/fisher	or km of coastline/fisher (specify)	AREA_FSH
	Rule enforcement potential	Boundary perimeter length per fisher or community member	km/fisher		PERIM_LN
	Rule enforcement potential	Distance or time to fishing grounds	km or hours		DISTANCE
	Rule enforcement potential	Landing sites	0;1;2	Dispersed (0); some centralization (1); heavily centralized (2)	LANDSITE
	Rule enforcement potential	Distance of reserve from village/community dwellings	km		DIST_RES
	Rule enforcement potential	Number of marketing outlets	0;1;2	Few (0); Some (1); Lots (2)	OUTLETS
	Rule enforcement potential	Are boundaries defendable?	0;1	No (0); yes (1)	DEFEND
	Rule enforcement potential	Type of boundary	0;1;2;3....n	Physical (0); adminstrative (1); transboundary (2); other (3); political (4); social (5); none (6)	BOUNDTYP
	Divisibility of resource	Migratory behaviour of target species	0;1;2;3	Sedentary (0); locally migratory (1); highly migratory (2); combination (3)	MIGR_BHR
	Target species	Major species harvested/commercially important Species	Species names	Specify	MAJ_SPP
	Discarded by catch	Discarded by-catch	0;1;2	Low 0-10% (0); medium 11-40% (1); high > 40% (2) of total catch	DISCARDS
	Multi- or single species fishery	Multi- or single species fishery	0;1	Multispecies (0); Single species (1)	MULTI_SP
	Connectivity of management area	Stream order association	1-6	see Welcomme (1985) for definition of stream order	STREAM_O
	Connectivity of management area	Biogreographical barriers present?	0;1	No (0); yes (1)	BARRIERS
	Non-use value of resource B100	Non-use value of resource (existence, bequest, option value etc)	0;1;2	Low (0); medium (1); high (2)	USE_VAL
Environment	Environmental health of habitat	Environmental health of habitat - Spawning areas	0;1;2	Low (0); medium (1); high (2)	ENV_SPAW
(Group I)	Environmental health of habitat	Environmental health of habitat - Nursery areas	0;1;2	Low (0); medium (1); high (2)	ENV_NURS

	Environmental health of habitat	Environmental health of habitat - Fishing Grounds	0;1;2	Low (0); medium (1); high (2)	ENV_GROU
	Environmental health of habitat	Environmental health of habitat - Overall	0;1;2	Low (0); medium (1); high (2)	ENV_ALL
	Environmental health of habitat	Health of critical habitat	0;1;2	Low (0); medium (1); high (2)	ENV_CRIT
	Environmental health of habitat	Waste materials	0;1	Absent (0); Present (1)	WAST_MAT
	Environmental health of habitat	Fish kills (% of days/nights)	%		FISH_KIL
	Environmental health of habitat	Degree of siltation	0;1;2	Low (0); medium (1); high (2)	SILT
	Environmental health of habitat	Presence of pollution	0;1	Absent (0); present (1)	POLLUTN
	Other water quality and environmental health parameters	Optimal/thresholds for each species	TBA		THRESH
	Nutrient recycling	Depth of reserve, lake, fishing area ...etc	m		DEPTH
	Habitat descriptors	% Coral cover	%		CORAL
	Habitat descriptors	% Live corals	%		CORAL_LI
	Habitat descriptors	Adjacent/ Local land use	0;1;2;3....n	Agriculture (0); forestry (1); natural forest (2); mining (3); industry (4); residential (5)	LAND_USE
	Habitat descriptors	Predominant substrate	0;1;2;3....n	Sand (0); mud (1); dead/broken corals (2); pebbles (3); tree debris (4); rock (5); live coral (6)	SUBSTRAT
	Habitat descriptors	River discharge rates	m3/sec		DISCHARG
	Habitat descriptors	Mean annual water temperature	oC		TEMP
	Habitat descriptors	River gradient	m/km		GRADIENT
	Habitat descriptors	Riparian vegetation	Species names		RIP_VEG
	Habitat descriptors	Benthic biota	Species names		BEN_BIOT
	Habitat descriptors	Shore gradient	Degrees or ratio		SHORE_GR
	Habitat descriptors	Standing (inundated) trees	0;1	No (0); yes (1)	TREES
	Habitat descriptors	Mangrove cover	% of management/fishing area (unit)		MANGROVE
	Habitat descriptors	Extent of flood corresponding to observations	0;1;2	Below normal (0); normal (1); above normal (2)	FLOOD
	Habitat descriptors	Average duration of flood season	Months		FLD_SEAS
	Habitat descriptors	Average duration of dry season	Months		DRY_SEAS
	Habitat descriptors	Remaining area of water at end of dry season	Average % of management/fishing area (unit)		DRY_AREA
	Habitat descriptors	Lake water levels corresponding to observations	m		LAKE_LEV
Technological	Exploitation intensity	Fisher density	Number of fishers / km2	or km of coastline (specify)	FISH_DEN
(Group I)	Exploitation intensity	Boat density	Number of boats / km2	or km of coastline (specify)	BOAT_DEN
	Exploitation intensity	Gear *i*...n density	Numbers of gear *i* per km2	or km of coastline (specify)	GEAR_DEN

	Exploitation intensity	Mean size of fish caught (EACH main spp) in Month x, with gear x	cm		AVG_LEN
	Exploitation intensity	Number of months fished per year	1-12		MONTHS
	Exploitation intensity	Average number of fishing days per fisher per year	Number		DAYS
	Exploitation intensity	Catch before maturity	0;1;2	None (0); some (1); lots (2) caught before maturity	PRE_MAT
	Exploitation intensity	Exploitation status of fishery (based upon trend in annual catches)	0;1;2;3;4;5;6	Developing (0); mature (1); declining (2); recovering (3); stable but degraded (4); senescent (5); no trend (6)	EXPLOIT
	Exploitation intensity	Predominant vessel type	0;1;2;3....n	None (0); non-motorised (1); sail (2); motorised (3)	VESS_TYP
	Exploitation methods	Types of gears (most important)	0;1;2;3....n	Gillnet (0); small traps (1); barrier traps (2); trawls (3); diving/gleaning (5); seines (6); cast nets (7); hook & line (8); longline (9); baskets (10); fish drives (11); bagnet (12); spear gun (13); liftnets (14); brushpiles (15); Trawls (16)	GEAR_TYP
	Exploitation methods	Numbers of different gear types employed	Number		GEARS
	Exploitation methods	Gear type (Species selective)	0;1;2	Non-selective (0); selective (1); both (2)	SELECTIVE
	Exploitation methods	Gear type	0;1;2;3	Bottom-set (0); pelagic (1); surface-set (2); combinations (3)	GR_POSTN
	Exploitation methods	Destructive fishing practices	0;1	No (0); yes (1)	HARM_GR
	Exploitation methods	Gear type (Active/Passive)	0;1;2	Passive (0); active (1); both (2)	PASS_GR
	Exploitation methods	FADs or artificial reefs	0;1	No (0); yes (1)	FADS
	Exploitation methods	Power gear or electronic aids	0;1	No (0); yes (1)	POWER_GR
	Preservation technology	Predominant preservation technology	0;1;2;3....n	Ice (0); Smoking (1); drying (2); freezing (3); salting (4); canning (5)...etc	PRES_TEC
	Stocking density	Stocking density	kg/ha		STCK_DEN
	Mean stocking size	Mean stocking size	cm	or g of fry (specify)	STCK_SIZ
	Habitat alteration activities	Habitat alteration activities	0 - 5	Destructive (0); none (1)......beneficial (5)	HAB_ALT
	Fishery type	Fishery type	0;1;2	Artisanal (0); industrial (1); recreational (2)	FISHTYPE
Market Attributes	Economic value of resource (at landing Site)	Mean unit value of target species	US$/kg		VALUE
(Group II)	Economic value of resource (International Market)	Mean unit value of taregt species present	US $ / Parity Price		VAL_PAR
	Market facilities/infrastructure	Transport/infrastructure/landing sites...etc	0;1;2	Poor (0); medium (1); good (2)	INFRASTR
	Cost of marketing (market fees)	Cost of marketing (market fees)	0;1;2;3	None (0); low (1); medium (2); high (3)	FEES
	Are there restrictions or rules in fish trading	Are there restrictions or rules in fish trading	0;1	No (0); yes (1)	MRKT_RUL
	Market type	Market type	0;1;2	Monoply (0); oligopoly (1); free market (2)	MRKT_TYP
	Market (demand) stability	Market (demand) stability	COV in price or 0;1	Stable (0); unstable (1)	MRKT_STB
	Price control mechanism	Price control mechanism	0;1	No (0); yes (1)	PRCE_CON
	Market orientation	Market orientation	0;1;2	Local (0); domestic (1); international (2)	MRKT_ORI

Fisher/Community	Homogeneity of users	Ethnicity	0;1	Same (0); mixed (1)	ETHNIC
Characteristics	Homogeneity of users	Religion	0;1	Same (0); mixed (1)	RELIGION
(Group III)	Homogeneity of users	Interests	0;1	Same (0); mixed (1)	INTEREST
	Homogeneity of users	Number of tribes	Number		TRIBES
	Homogeneity of users	Customs	0;1	Same (0); mixed (1)	CUSTOMS
	Homogeneity of users	Migrants	0;1;2;3	None (0); few (1); some (2); lots (3)	MIGRANTS
	Homogeneity of users	Number of different political parties supported	Number		POL_PART
	Homogeneity of users	Gender of fishers	0;1:2	Predominantly male (0); predominantly female (1); mixed (2)	GENDER
	Homogeneity of users	Wealth variation among fishers/households	0;1;2	Low (0); medium (1); high (2)	WLTH_VAR
	Homogeneity of users	Age variation among fishers/households	0;1;2	Low (0); medium (1); high (2)	AGE_VAR
	Social cohesion	Social cohesion	0;1;2	Low (0); medium (1); high (2)	COHESION
	Years resident in village/community	Variation in years resident in village/community	0;1;2	Low (0); medium (1); high (2)	YEAR_VAR
	Dependence on fishery for livelihood	Purpose	0;1;2	Predominantly subsistence (0); predominantly commercial (1); subsistence and commercial (2)	PURPOSE
	Dependence on fishery for livelihood	Alternative sources of income/employment	0;1;2	None (0); some (1); lots (2)	ALT_LIVL
	Dependence on fishery for livelihood	% of household income derived from fishing	%		FISH_INC
	Dependence on fishery for livelihood	Average number of years fishing	Years		FISH_YRS
	Dependence on fishery for livelihood	Willingess of fishers to change occupation	0;1	No (0); yes (1)	DIFF_OCC
	Level of local (ecological) knowledge	Level of local (ecological) knowledge of fishers	0;1;2	Low (0); medium (1); high(2)	KNOWLED
	Level of local education	Average years of education of fishers/community	Years		EDU_YRS
	Level of local education	Literacy rate in community/among fishers	%		LITERATE
Decision-making	Type of management	Type of management	0;1;2	Government (1); co-management (2); self-management / traditional management (3)	MANG_TYP
Arrangements	Local decision-making body	Local decision-making body (accessible to users)	0;1	Absent (0); present (1)	LOC_BODY
(Group IV)	Origin of co-management initiative	Origin of (co-)management initiative	0;1;2;3;4;5	Tradition (0); community (recent) (1); NGO (2); government (3); donor (4); combination (5)	MAN_ORIG
	Legitimacy / widely accepted	Legitimacy of local decision-making body	0;1;2	Low (0); medium (1); high (2)	LEGIT
	Respectability	Respectability for decision-making body	0;1;2	Low (0); medium (1); high (2)	RESPECT
	Traditional decision-making body?	Traditional decision-making body?	0;1	No (0); yes (1)	TRADBODY
	Stability of decision-making body	Stability of decision-making body	0;1	Stable (0); unstable (1)	STABBODY
	Membership to decision-making body	Democratically elected?	0;1	No (0); yes (1)	DEM_ELEC

	Clear access (property) rights	Clear access (property) rights	0;1	No (0); yes (1)	CLR_ACC
	Access (Community)	Open or restricted access	0;1	Open (0); restricted (1)	OA_COMM
	Access allocation mechanism (Community members)	Access (effort) control mechanism	0;1;2;3....n	Lottery (0); auction (1);group decision eg majority consensus (2); licensing system/lease (3);	CTRL_COM
	Access (Non-community members)	Open, restricted or no access	0;1;2	Open (0); restricted (1); no access granted (2)	OA_OUT
	Access allocation mechanism (Non-community members)	Access (effort) control mechanism	0;1;2;3....n	Lottery (0); auction (1);group decision eg majority consensus (2); licensing system/lease (3);	CTRL_OUT
	Resources available to body	Resources available to body (financial, tech, manpower...)	0;1;2	Low (0); medium (1); high (2)	AVLB_RES
	Self-financing mechanism	Self-financing mechanism	0;1	No (0); yes (1)	SELF_FIN
	Management plan	Present/implemented	0;1	No (0); yes (1)	MAN_PLAN
	Management objectives	Clearly-stated management objectives	0;1	No (0); yes (1)	MAN_OBJS
	Management measures (operational rules)	Mesh / gear size restrictions	0;1	No (0); yes (1)	GR_RESTR
	Management measures (operational rules)	Gear ban(s)	0;1	No (0); yes (1)	GR_BAN
	Management measures (operational rules)	Gear ban(s) (specify details including gear type, habitat, months etc)	Specify	eg barrier trap in streams/channels during June and July)	GR_BAN_N
	Management measures (operational rules)	Ban on fish drives (water banging)	0;1	No (0); yes (1)	BAN_DRIV
	Management measures (operational rules)	Ban on using lights to attract fish/other target species	0;1	No (0); yes (1)	BAN_LGHT
	Management measures (operational rules)	Ban on dewatering certain habitats (specify)	0;1	No (0); yes (1) and specify	BAN_DEWT
	Management measures (operational rules)	Closed seasons	0;1	No (0); yes (1) if yes specify month(s) closed	CLS_SEAS
	Management measures (operational rules)	Quota (specify)	0;1	No (0); yes (1)	QUOTAS
	Management measures (operational rules)	Bait ban (specify)	0;1	No (0); yes (1)	BAIT_BAN
	Management measures (operational rules)	Species ban	0;1	No (0); yes (1)	SPP_BAN
	Management measures (operational rules)	Landing size restrictions (specify)	0;1	No (0); yes (1) and specify	SIZE_
	Management measures (operational rules)	Reserve area	km2		RES_AREA
	Management measures (operational rules)	Reserve area as a % of total management/fishing area	%		RES_PROP
	Management measures (operational rules)	Number of months reserved is closed to fishing	Number		RES_MONS
	Reserve type	Reserve type (catchment position)	0;1;2;3....n	Upland (0); floodplain (1); estuary (2)	RES_POS
	Reserve type	Reserve type (Habitat)	0;1;2;3....n	Lake (0); Riverine (1); river pool (2); reef area (3); estuary (4); lagoon bay (5); beel (6); combination (7)	RES_HAB

	Reserve type	Reserve type (Technical)	0;1;2;3....n	Gear ban in reserve (0); closed season in reserve (1); both (2); reserve permenantly closed (3)	RES_TECH
	Reserve depth	Reserve depth (dry season)	m		RES_DEPH
	Reserve location	Reserve location	0;1	In barren, unproductive area (0); in formerly productive area (1).	RES_LOC
	Numbers of reserves	Numbers of reserves	Number		NUMB_RES
	Period of existence of current operational rules	Period of existence of current operational rules	Years		RULE_YRS
	Mechanisms for enforcement	Rules monitored by resource users	0;1	No (0); yes (1)	CS_USER
	Mechanisms for enforcement	Government officers	0;1	No (0); yes (1)	CS_GOV
	Overall support for rules	Overall support for rules	0;1;2	Low (0); medium (1); high (2)	RULE_SUP
	Representation in rule making (Fishers)	Representation in rule making (fishers)	0;1;2	Low (0); medium (1); high (2)	REP_FISH
	Representation in rule making (Fish traders, creditors etc)	Representation in rule making (fish traders, creditors etc)	0;1;2	Low (0); medium (1); high (2)	REP_TRAD
	Representation in rule making (Women)	Representation in rule making (women)	0;1;2	Low (0); medium (1); high (2)	REP_WOM
	Representation in rule making (Other)	Representation in rule making (other)	0;1;2	Low (0); medium (1); high (2)	REP_OTH
	Level of transparency in rule making (General)	Level of transparency	0;1;2	Low (0); medium (1); high (2)	TRANSPAR
	Formal performance monitoring by community?	Formal performance monitoring by community?	0;1	No (0); yes (1)	COMM_MON
	Fora for discussion and dialogue (Communication)	Fora for discussion and dialogue (communication)	0;1	No (0); yes (1)	FORA
	Relevance of rules to local conditions	Relevance of rules to local conditions (fishers perspective)	0;1;2	Low (0); medium (1); high (2)	RULE_REL
	Available scientific information	Available scientific research information on fishery/management	0;1;2	Low (0); medium (1); high (2)	SCIENCE
	Sanctions for non compliance	Sanctions for non-compliance	0;1	No (0); yes (1)	SANCTION
	Graduated sanctions for non-compliance	Graduated sanctions for non-compliance	0;1	No (0); yes (1)	GRADSANC
	Effective conflict resolution mechanisms	Effective conflict resolution mechanisms	0;1	No (0); yes (1)	CONF_RES
	Period of existence of current institutional arrangements	Period of existence of current institutional arrangements	Years		INST_YRS
	Effectiveness of enforcement measures	Effectiveness of enforcement measures	0;1;2	Low (0); medium (1); high (2)	EFFCT_CS
	Effectiveness of enforcement measures	Poaching (% of nights)	%		POACH1
	Effectiveness of enforcement measures	Incidence of poaching/non-compliance	0;1;2	Low (0); medium (1); high (2)	POACH2
	Cost of enforcement	Cost of enforcement	Expenditure or Numbers of Guards	specify	MCS_COST

	Devices installed to prevent illegal fishing B34	Devices installed to prevent illegal fishing or activities to remove illegally set gears?	0;1	No (0); yes (1)	DEVICES
External Decision-	Enabling legislation for co-management	Enabling legislation for co-management	0;1	No (0); yes (1)	LEGISLA
Making Arrangements	Local political/institutional support B67	Local political/institutional support for co-management arrangements	0;1;2;3	Anti (0); Weak (1); indifferent (2); strong (3)	POL_SUPP
(Group V)	Effective coordinating body	Nested structure of co-management arrangements	0;1	Absent (0); Present (1)	NESTED
	Institutional capacity of fisheries department	Frequency of visits to unit by government officers	0;1;2	Never (0); infrequent (1); frequent (2)	VISITS
	Changes in institutional structure of DoF	Changes in institutional structure of DoF to support co-management arranagements	0;1;2	None (0); some (1); signficant (2)	DOF_CHNG
Exogenous Factors	Natural disasters (eg cyclones, extreme floods)	Frequency	0;1;2	Low (0); medium (1); high(2)	DISASTER
(Group VI)	Macroeconomic/political/sociocultural changes	Macroeconomic/political/sociocultural changes	Describe		MACRO
	External financial assistance	Expenditure on community	$/year/fisher		EXPENDIT
	Capacity builiding support from NGO's	Capacity builiding support for community from NGO's	0;1;2;3	none (0); weak (1); medium (2); strong (3)	NGO_SUPP
	Population growth	Population growth	0;1;2	Declining (0); static (1); rising (2) or actual values	POP_GROW
	Economic growth	Economic growth	0;1;2	Declining (0); static (1); rising (2) or actual values	ECONOMY
	Ongoing war or armed conflict	Ongoing war or armed conflict	0;1	No (0); yes (1)	WAR
Outcomes	**Dependent Variables**				
Production/Yield	Annual production per unit area	Catch per unit area (CPUA)	tonnes/km2	or tonnes / km (specify)	CPUA
	Annual production per unit area	CPUA - Trend	0;1;2	Are TOTAL landings: increasing (0); stable (1); declining (2)	CPUA_CHG
	Number of species whose abundance is increasing	Number of species whose abundance is increasing	Number	As perceived by fishers	SPP_CHG
Sustainability/	Sustainability (Resource)	Resource abundance or biomass/ well being	Tonnes/fisher/year	All species combined or specify for each target species.	CPUE
Biodiversity	Sustainability (Resource)	Resource abundance or biomass/ well being - Trend	0;1;2	Declining (0); static (1); rising (2)	CPUE_CHG
	Sustainability (Resource)	Catch variability	COV of total annual catch or 0;1;2	Low (0); medium (1); high (2)	CATCHVAR
	Sustainability (Resource)	Catch variability - Trend	0;1;2	Declining (0); static (1); rising (2)	VARTREND
	Sustainability (Resource)	Stocking financially viable?	0;1	No (0); yes (1)	STCK_VIA
	Sustainability (Resource)	Stewardship	0;1;2	Low (0); medium (1); high(2)	STEWARD
	Sustainability (Resource)	Knowledge of fishers - Trend	0;1;2	Declining (0); static (1); rising (2)	KNWTREND

	Biodiversity	Species richness	Number of species		SPP
	Biodiversity	Species richness - Trend	0;1;2	Declining (0); static (1); rising (2)	SPPTREND
	Biodiversity	Extinct/rare species	Number		EXTINCT
	Biodiversity	Extinct/rare species - Trend	0;1;2	Declining (0); static (1); rising (2)	EXTTREND
	Habitat condition	Trend	0;1;2	Declining (0); static (1); rising (2)	HABTREND
Well-Being	Annual fishing revenue per unit area	CPUA x mean value of species caught	$/km2/year	or km of coastline (specify)	REVENUE
(Fishers/Households)	Annual fishing revenue per unit area	CPUA x mean value of species caught -Trend	0;1;2	Declining (0); static (1); rising (2)	REVTREND
	Annual fishing costs per unit area	Annual costs per unit area	$/km2/year	or km of coastline (specify)	COSTS
	Annual fishing costs per unit area	Annual costs per unit area - Trend	0;1;2	Declining (0); static (1); rising (2)	COSTREND
	Annual fishing profit (income) per unit area	Annual profit (income) per unit area	$/km2/year	or km of coastline (specify)	INCOME
	Annual fishing profit (income) per unit area	Annual profit (income) per unit area - Trend	0;1;2	Declining (0); static (1); rising (2)	INCTREND
	Household income from fishing	Household income from fishing	$/year		HHINCOME
	Household income from fishing	Household income from fishing - Trend	0;1;2	Declining (0); static (1); rising (2)	HHITREND
	Assets eg TV, Bikes, Tin Roofs…etc	Assets eg TV, bikes, tin roofs…etc	0;1;2	Low (0); medium (1); high (2)	ASSETS
	Assets eg TV, Bikes, Tin Roofs…etc	Assets eg TV, bikes, tin roofs…etc - Trend	0;1;2	Declining (0); static (1); rising (2)	ASSTREND
	Savings and investments	Savings and investments	0;1;2	Low (0); medium (1); high(2) or state mean value(s)	SAVINGS
	Savings and investments	Savings and investments - Trend	0;1;2	Declining (0); static (1); rising (2)	SAVTREND
	Well-being of households	Well-being of household/ standard of living	0-10	Poor (0); Excellent (10)	WELBEING
	Well-being of households	Well-being of household/ standard of living - Trend	0;1;2	Declining (0); static (1); rising (2)	WELTREND
	Well-being of households	Access to services (health/water etc)	0;1;2	Low (0); medium (1); high (2)	SERVICES
	Well-being of households	Access to services (health/water etc) - Trend	0;1;2	Declining (0); static (1); rising (2)	SERTREND
	Food security	Number of fish meals/week	0;1;2	Declining (0); static (1); rising (2)	MEALS
	Food security	Days per month without fish meals	0;1;2	Declining (2); static (1); rising (0)	NO_MEALS
	Food security	Food security (General)	0;1;2	Low (0); medium (1); high(2)	SECURITY
	Food security	Food security (General) - Trend	0;1;2	Declining (0); static (1); rising (2)	SECTREND
Institutional	Empowerment	Participation in management	0;1;2	Low (0); medium (1); high (2)	MAN_PART
Performance	Empowerment	Participation in management - Trend	0;1;2	Declining (0); static (1); rising (2)	PARTREND
	Empowerment	Influence of fishers/stakeholders in management	0;1;2	Low (0); medium (1); high (2)	INFLUENC
	Empowerment	Influence of fishers/stakeholders in management -Trend	0;1;2	Declining (0); static (1); rising (2)	INFTREND
	Equity	General	0;1;2	Low (0); medium (1); high (2)	EQUITY

	Equity	General - Trend	0;1;2	Declining (0); static (1); rising (2)	EQYTREND
	Equity	Distributional among community members	0;1;2	Low (0); medium (1); high (2)	DISTRIB
	Equity	Distributional among community members - Trend	0;1;2	Declining (0); static (1); rising (2)	DISTREND
	Equity	Satisfaction with arrangements	0;1;2	Low (0); medium (1); high (2)	SATISFAC
	Equity	Satisfaction with arrangements - Trend	0;1;2	Declining (0); static (1); rising (2)	SATREND
	Equity	Equity of allocation of access rights to resources	0;1;2	Low (0); medium (1); high (2)	ACCES_EQ
	Equity	Equity of allocation of access rights to resources - Trend	0;1;2	Declining (0); static (1); rising (2)	AEQTREND
	Compliance with rules and regulations	Compliance with rules and regulations	0;1;2	Low (0); medium (1); high (2)	COMPLY1
	Compliance with rules and regulations	Compliance with rules and regulations	% not complying		COMPLY2
	Compliance with rules and regulations	Compliance with rules and regulations - Trend	0;1;2	Declining (0); static (1); rising (2)	CMPTREND
	Efficiency	Benefits of management exceed transaction costs? (information, coordination, enforcement)	0;1	No (0); yes (1)	EFFICENT
	Conflicts among fishers within same IMA/VMA	Frequency of conflicts	0;1;2	Low (0); medium (1); high (2)	CONFLCT1
	Conflicts among fishers between different IMAs/VMAs	Frequency of conflicts	0;1;2	Low (0); medium (1); high (2)	CONFLCT2
	Conflicts among fishers in IMA/VMA and other fisheries/sectors	Frequency of conflicts	0;1;2	Low (0); medium (1); high (2)	CONFLCT3
	Conflicts among different gear operators within IMA/VMA	Frequency of conflicts	0;1;2	Low (0); medium (1); high (2)	CONFLCT4
	Conflicts between fishers and others in community eg farmers	Frequency of conflicts	0;1;2	Low (0); medium (1); high (2)	CONFLCT5
	Conflicts(General)	Frequency of conflicts (General) - Trend	0;1;2	Declining (0); static (1); rising (2)	CONTREND
	Conflict resolution capacity	Conflict resolution capacity	0;1;2	Low (0); medium (1); high (2)	CONRESOL
	Conflict resolution capacity	Conflict resolution capacity - Trend	0;1;2	Declining (0); static (1); rising (2)	RESTREND
	Social cohesion	Social cohesion	0;1;2	Low (0); medium (1); high (2)	COHESION
	Social cohesion	Social cohesion - Trend	0;1;2	Declining (0); static (1); rising (2)	COHTREND
Institutional	Sustainability (Institutions)	Self-financing institutional arrangements?	0;1	No (0); yes (1)	SELFIN
Sustainability	Sustainability (Institutions)	Period of existence of local institutional arrangements?	Years		IA_YRS
	Sustainability (Institutions)	Continuing effective transfer of management responsibilities (between fishers/fisheries officers etc)	0;1	No (0); yes (1)	CONTINUE

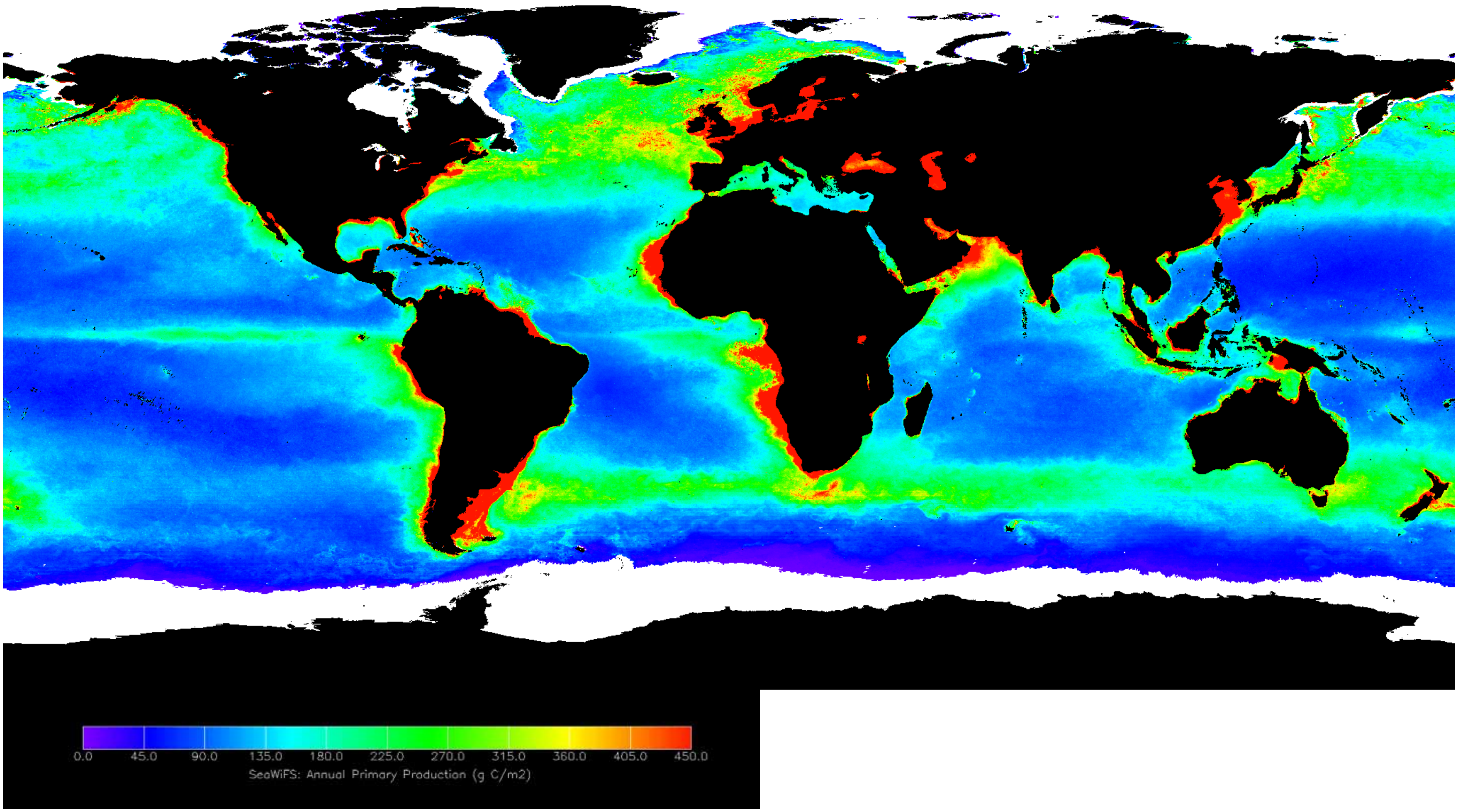
Annex III The management units treated as observations for model development.

Management unit name	Country	Ecosystem	References
Aby Lagoon	Cote Divoire	Coastal lagoon	Kponhassia & Konan (1998); Konan (2001)
Arang Arang	Indonesia	Floodplain-river	MRAG (1998)
Arial-Kha River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Ashurar Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Atchin Island	Vanuatu	Patch reef	Anderson & Mees (1999); Ruddle (1994)
Ban Laem Makham	Thailand	Coastal (inshore)	Masae et al (1999)
Benewa	Indonesia	Floodplain-river	MRAG (1998)
Boyral River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Cautata	Fiji	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Chan	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Chok	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Dano Lamo	Indonesia	Floodplain-river	MRAG (1998)
Det Tavan oke	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Deua Neua	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Deua Tai	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Dhaleswari River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Dikshi Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Don Chom	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Det Oke	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Det Tok	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don En	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Houat	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Khamao Noi	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Nang Khouat	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Peuay	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Sahong	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Som	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Tholathi	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Don Xang	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Dum Nadi Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Emua Village	Vanuatu	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Goakhola-Hatiara Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Halaliu Village	Indonesia	Fringing reef	Novaczek & Harkes (1998)
Hamil Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Hang Khone	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Hang Sadam	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Hang Som	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Hang Xang Phai	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Haruku Village	Indonesia	Fringing reef	Novaczek & Harkes (1998)
Hat Khi Khouay	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Hat Xai Khoun	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Honda Bay	Philippines	Coastal (inshore)	ICLARM (1997)
Houa Lopakdi	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Houa Sadam	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Houa Sen	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Jari Jamuna River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)

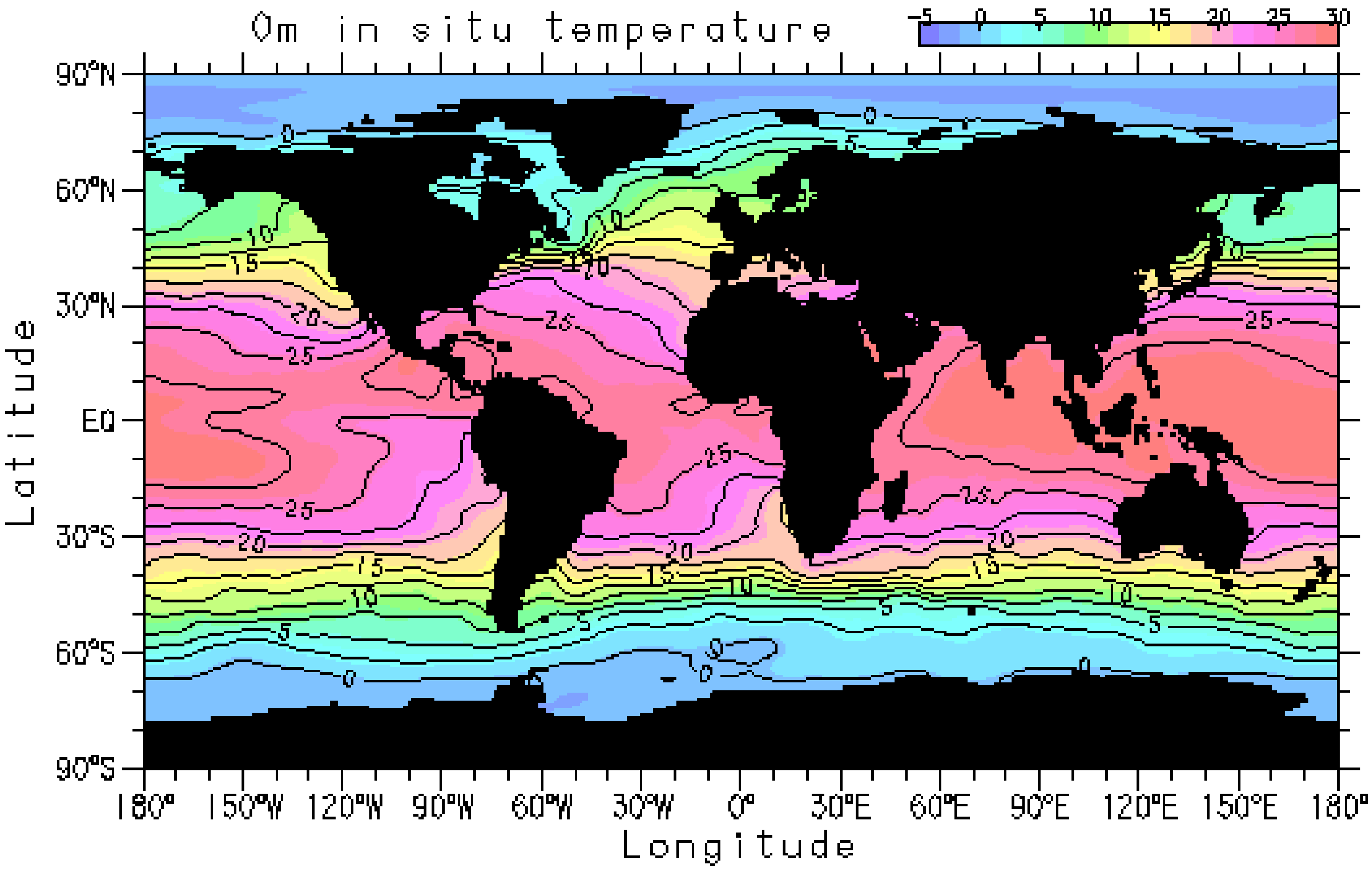
Kadan	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Kali Nodil	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Keng Koum	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Khinak	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Khone Neua	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Khone Noi	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Khone Tai	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Kok Padek	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Kong Keng	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Krishnochandrapur Baor	Bangladesh	Lake	Thompson et al (1999); Middendorp et al (1999)
Kwirkwidge	Mozambique	Coastal (inshore)	Lopes et al (1997)
Lake kariba	Zimbabwe	Lake	Jackson et al (1998); Nyikahadzoi (1995)
Lake Kariba - Northern Shore	Zambia	Lake	Hachongela et al (1997)
Lelepa Island	Vanuatu	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Lopakdi Kang	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Meliau Village	Indonesia	Floodplain-river	MRAG (1998)
Moisherkandi Bornpu River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Mouang	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Nakasang	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Nakhone	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Naweni	Fiji	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Negombo Estuary	Sri Lanka	Estuary	Amarasinghe et al (1997)
Nok Kok	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Nolloth Village	Indonesia	Fringing reef	Novaczek & Harkes (1998)
Olifants River Fishing Community	South Africa	Estuary	Sowman et al (1997)
Oupaxa	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Pedamaran	Indonesia	Floodplain-river	MRAG (1998)
Pellonk Village	Vanuatu	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Phiman Phon	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Phon Pho	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Phon Than	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Phonsavanh	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Photak	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Pulau Majang	Indonesia	Floodplain-river	MRAG (1998)
Rajdhola Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Rusia Baisa Beel	Bangladesh	Beel	Thompson et al (1999); Middendorp et al (1999)
Sala	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
San Miguel Bay	Philippines	Estuary	Pomeroy & Pido (1995); Pido & Pomeroy (1995)
San Salvador Island	Philippines	Fringing reef	Katon et al (1999)
Sekolat Village	Indonesia	Floodplain-river	MRAG (1998)
Sen Hom	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Sen Neua	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Seri Village	Indonesia	Fringing reef	Novaczek & Harkes (1998)
Shemulia Baor	Bangladesh	Lake	Thompson et al (1999); Middendorp et al (1999)
Som Tavan Oke	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Som Tavan Tok	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tacilevu	Fiji	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Tan Tavan Oke	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tan Tavan Tok	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)

Tavua	Fiji	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Tengkidap Village	Indonesia	Floodplain-river	MRAG (1998)
Tetulia River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Tha Kham	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tha Mak Hep	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tha Mouang	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tha Phao	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tha Pho Neua	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Tha Pho Tai	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Than Tavan Oke	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Titas Gokon-Goshaipur River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Titas Ka River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Toisapu and Hutumuri Villages	Indonesia	Fringing reef	Novaczek & Harkes (1998)
Tuhaha Village	Indonesia	Fringing reef	Novaczek & Harkes (1998)
Ubdakhali River	Bangladesh	Floodplain-river	Thompson et al (1999); Middendorp et al (1999)
Uripiv Island	Vanuatu	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Verata	Fiji	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Veun Kham	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Veun Khao	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Veun Som	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Veun Thong	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)
Vitogo	Fiji	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Wala Island	Vanuatu	Fringing reef	Anderson & Mees (1999); Ruddle (1994)
Xiang Vang	Laos PDR	Floodplain-river	Baird (1999a; 1999b; 2000); Baird & Flaherty (1999)

Annex IV Estimated global annual primary production gCm^2y^{-1} for 1997-1998 (Based upon Behrenfeld & Falkowski, 1997).



Annex V Mean Annual Water Temperature Contour Map



Annex VI Variables Omitted from the Analyses Described in Chapter 6

1. Key Attributes:

FT_FISHM	-	Poor quality data
PT_FISHM	-	Poor quality data
OC_FISHM	-	Poor quality data.
FISHERS2	-	Calculated using poor household size estimates and too many zeros.
ID	-	Not relevant
NAME	-	Not relevant

2. Resources (Group I)

LONGEV	-	Only 4 observations.
MAT_AGE	-	Only 4 observations.
MAJ_SPP	-	refers to reports – many alternatives.
DISCARDS	-	All values 0.
MULTI_SP	-	0 except for one value
STREAM_O	-	Missing or takes the value 6.

3. ENVIRONMENTAL (GROUP I)

RIP_VEG	-	Little explanation of the meaning of categories
BEN_BIOT	-	Little explanation of the meaning of different names given
FLOOD	-	Only 1 non-missing observation
SHORE_GR	-	Only 1 non-missing observation
MANGROVE	-	Only 1 non-missing observation
DRY_AREA	-	Only 4 observations
LAKE_LEV	-	Not-applicable to all responding fisheries
DISCHARGE	-	2 observations + value of 17500 for **all** the Laos sites.
GRADIENT	-	No variation
FISH_KIL	-	All zeros except 1 observation.
THRESH	-	Not in data file.

4. TECHNOLOGICAL

GEAR_DEN	-	Only 3 observations
AVG_LEN	-	Only 4 observations
MONTHS	-	Hardly any variation
DAYS	-	Hardly any variation
PRE_MAT	-	All with value 1 except for two observations
VESS_TYP	-	All with value 1 except 1 observation
GR_POSTN	-	All with value 3 except for 3 observations
STCK_DEN	-	All but one case non-applicable
STCK_SIZ	-	All but one case non-applicable
POWER_GR	-	No variation. All with value 0 except 1 observation.
FISH_TYP	-	All with value 0 except for 2 observations.

5. MARKET ATTRIBUTES

MART_TYP	-	All values are 2 except for 1 observation
PRCE_CON	-	All values are 0's except for 1 observation.

6. FISHER/STAKEHOLDER COMMUNITY

YEAR_VAR	-	Only 0 values
KNOWLED	-	No variation
LITERATE	-	All with value 80 except for 4 observations
TRIBES	-	Mostly non-applicable or with value 1 except for 2 obs.

7. DECISION-MAKING ARRANGEMENTS

CTRL_COM	-	Not-applicable to 77% of cases; a further 8% missing.
GR_BAN_N	-	Too many multiple response answers.
BAN_DEWT	-	Mostly 0s except for 3 observations; and many –99's.
QUOTAS	-	All 0s except 1.
BAIT_BAN	-	All 0s except 1.
SPP_BAN	-	All 0s except for some of the Indonesia data.
RES_POS	-	Not-applicable to about 30% of cases.
RES_HAB	-	Not-applicable to about 30% of cases.
RES_TECH	-	Not-applicable to about 30% of cases.
RES_LOC	-	Not-applicable to about 30% of cases.
REP_TRAD	-	Mostly 0s.
SANCTION	-	Except for 6 obs, all others with value 1.
GRADSANC	-	Except for 3 obs, all others with value 1.
POACH1	-	Only 3 available observations.
MCS_COST	-	Only 4 non-zero observations.
DEVICES	-	Only 4 non-zero observations.

8. EXTERNAL DECISION-MAKING ARRANGEMENTS

NONE omitted.

9. EXOGENOUS FACTORS

EXPENDIT	-	Only 3 existing observations.
POP_GROW	-	No variation. All with value=2.
MACRO	-	Does no exist in data file.
WAR	-	All zero values.

Omitted outcome variables

1. Production/Yield variables:

CPUA_CHG – Mostly available only for Laos giving value 0. Non-zeros only for 6 sites in Indonesia (all values=2) and for Lake Kariba in Zimbabwe and at the site in Mozambique.

2. Sustainability/Biodiversity:

VARTREND – Only 3 observations available
STCK_VIA – Applicable only for 1 case.
EXTTREND – All values 1 except for 3 obs.
HABTREND – All values 1 except for 2 obs.
SPP – Mostly influenced by the value 196 for Laos
SPPTREND – Mostly available only for Laos.

3. Well-Being (Fishers/Households)

REVTREND – Takes the value 2 except for 1 obs.
COSTS – Only 7 observations available.
COSTREND – Mostly 0s and many missing.
SAVINGS – All 0s except for 2 observations
MEALS – Hardly any variation
NO_MEALS – Exact oppo. of MEALS & little variation.
SECURITY – Many missing. Only 2 diff from value 2.
SECTREND – Many missing and very little variation.

4. INSTITUTIONAL PERFORMANCE

COMPLY2 – Only 3 non-missing observations.

CMPTREND – I don't like the value 1.5 for all Laos.
EFFICENT – Many missing. Influenced by 1s for Laos.

5. INSTITUTIONAL SUSTAINABILITY

CONTINUE – because no variability.

Annex VII Estimates of CPUA (t km^{-2} y^{-1}) and Fisher Density (Fishers Km^{-2}) for Floodplain-Rivers, Lake and Reef-based fisheries.

Table A1 Estimates of CPUA and fisher density for unmodified floodplain river systems.

Name	Country	Area (Km2)	Catch (t y^{-1})	Fishers	CPUA (t km^{-2} y^{-1})	Fishers Km^{-2}	Reference
Amazon	All	157500	199000	35363	1.263	0.225	MRAG (1994)
Amazon	Peru	9960	13700	3360	1.376	0.337	Welcomme (1985)
Atrato	Colombia	5300	220	170	0.042	0.032	MRAG (1994)
Barotse	Africa	5120	3500	912	0.684	0.178	Bayley (1988)
Benewa	Indonesia				14.400	21.300	MRAG (1999)
Benue	Nigeria	3100	9570	5140	3.087	1.658	Bayley (1988)
Central Delta, Niger	Africa	20000	90000	54112	4.500	2.706	Bayley (1988)
Ganges	India	296	1480	1600	5.000	5.405	Welcomme (1985)
Hail Haor	Bangladesh	136	1671	4313	12.287	31.713	MRAG (1994)
Kafue (1963)	Africa	4340	8554	1112	1.971	0.256	Bayley (1988)
Kafue (1970)	Africa	4340	6747	670	1.555	0.154	Bayley (1988)
Kilombero	Africa	6700	4536	341	0.677	0.051	Welcomme (1985)
Lempuing River	Indonesia	20.32	263	163	12.943	8.022	MRAG (1994)
Logomatia	Africa	600	300	70	0.500	0.117	Welcomme (1985)
Lubuk Lampam	Indonesia	12.15	46.9	31	3.860	2.551	MRAG (1994)
Magdalena	Colombia	20000	65000	30000	3.250	1.500	Bayley (1988)
Mahakam	Indonesia	7178	14500	8000	2.020	1.115	Welcomme (1985)
Negro	Brazil/Colombia	7197	3090	247	0.429	0.034	MRAG (1994)
Niger (1965)	Nigeria	907	4700	1314	5.182	1.449	Bayley (1988)
Niger (1982)	Nigeria	600	3200	3200	5.333	5.333	Bayley (1988)
Nigeria	Nigeria	4800	14350	4600	2.990	0.958	Bayley (1988)
Ogan Komering River	Indonesia	2000	13975	8257	6.988	4.129	MRAG (1994)
Orinoco	Peru	228	1000	200	4.386	0.877	Welcomme (1985)
Oueme (1957)	Africa	1000	6500	29800	4.585	29.800	Welcomme (1985)
Oueme (1969)	Africa	1000	10400	25000	10.400	25.000	Bayley (1988)
Pabna (1995-1996)	Bangladesh				6.600	36.000	MRAG (1997)
Pedamaran	Indonesia				12.381	5.600	MRAG (1999)
Pendjari	Africa	40	140	65	3.500	1.625	Bayley (1988)
Pulau Majang	Indonesia				4.070	1.400	MRAG (1999)
Rufgi	Africa	1450	3589	3000	2.475	2.069	Welcomme (1985)
Sekolat Village	Indonesia				16.000	12.600	MRAG (1999)
Senegal	Africa	5490	30000	10400	5.464	1.894	Welcomme (1985)
Shire River (1970)	Africa	665	9545	2445	14.353	3.677	Bayley (1988)
Shire River (1975)	Africa	665	7890	3324	11.865	4.998	Bayley (1988)
Tengkidap Village	Indonesia				15.650	6.400	MRAG (1999)
Thale Noi	Thailand	282	1475	1187	5.230	4.209	MRAG (1994)

Table A2 **Estimates of CPUA (t km^{-2} y^{-1}) and fisher density (Fishers Km^{-2}) for lakes and reservoirs.**

Name	Country	Area (Km2)	Catch (t y^{-1})	Fishers	CPUA (t km^{-2} y^{-1})	Fishers Km^{-2}	Reference
Abaya	Ethiopia	1162	128	250	0.110	0.215	MRAG (1995)
Alaotra	Madagascar	570	3817.6	2872	6.698	5.039	MRAG (1995)
Albert	International	5600	28230	9600	5.041	1.714	Bayley (1988)
Atitlan	Guatemala	130	30	140	0.231	1.077	MRAG (1995)
Awassa	Ethiopia	90	100	59	1.111	0.656	MRAG (1995)
Ayame	Côte d'Ivoire	197	784.62	829	3.983	4.208	MRAG (1995)
Baao	Philippines	6.7	600	500	89.552	74.627	MRAG (1995)
Babati	Tanzania	21	438.78	198.44	20.894	9.450	MRAG (1995)
Bahi	Tanzania	855	654.6	257	0.766	0.301	MRAG (1995)
Bahut	Philippines	2.06	180	140	87.379	67.961	MRAG (1995)
Bam	Burkina Faso	12	200	400	16.667	33.333	MRAG (1995)
Bang Lang	Thailand	45	70	40	1.556	0.889	MRAG (1995)
Bang Pra	Thailand	17.6	60	40	3.409	2.273	MRAG (1995)
Baringo	Kenya	130	600	330	4.615	2.538	Bayley (1988)
Basuto	Tanzania	2.6	262	64	100.769	24.615	MRAG (1995)
Bato	Philippines	38	2200	1110	57.895	29.211	MRAG (1995)
Bengweulu		7900	14780	13400	1.871	1.696	Bayley (1988)
Bhumipol	Thailand	300	965	5500	3.217	18.333	MRAG (1995)
Birira	Rwanda	5.4	70	6	12.963	1.111	MRAG (1995)
Buhi	Philippines	16.5	1230	550	74.545	33.333	MRAG (1995)
Bulera	Rwanda	54	100	85	1.852	1.574	MRAG (1995)
Buluan	Philippines	61.3	11200	4550	182.708	74.225	MRAG (1995)
Burigi	Tanzania	186	25	20	0.134	0.108	MRAG (1995)
Bustos/angat	Philippines	23	115	55	5.000	2.391	MRAG (1995)
Butig	Philippines	5.14	250	100	48.638	19.455	MRAG (1995)
Catemaco	Mexico	65	1884.2	1965	28.988	30.231	MRAG (1995)
Chad		22000	30000	10000	1.364	0.455	Bayley (1988)
Chala	International	5.2	21	50	4.038	9.615	MRAG (1995)
Chapala	Mexico	1109	8589.8	1118	7.746	1.008	MRAG (1995)
Chilwa	Malawi	1750	9800	1740	5.600	0.994	Bayley (1988)
Chisi	Zambia	135	240.05	34.32	1.778	0.254	MRAG (1995)
Chiuta	International	113	500	193	4.425	1.708	Bayley (1988)
Chulaporn	Thailand	12	45	39	3.750	3.250	MRAG (1995)
Cufada	Guinea Bissau	1.5	5	30	3.333	20.000	MRAG (1995)
Cuitzeo	Mexico	220	673.8	1054	3.063	4.791	MRAG (1995)
Cyohoha	International	76	55	45	0.724	0.592	MRAG (1995)
Danao	Philippines	4.8	500	400	104.167	83.333	MRAG (1995)
Dapao	Philippines	2.6	120	30	46.154	11.538	MRAG (1995)
Dok Krai	Thailand	12.8	76	52	5.938	4.063	MRAG (1995)
Edward	International	2300	16031	5700	6.970	2.478	Bayley (1988)
Gaharwa	Rwanda	2.3	26.33	26	11.448	11.304	MRAG (1995)
Gashanga	Rwanda	2.3	30	13	13.043	5.652	MRAG (1995)
George		270	4242	600	15.711	2.222	Bayley (1988)
Gombo	Tanzania	1.4	77	14	55.000	10.000	MRAG (1995)
Guiers	Senegal	170	2250	370	13.235	2.176	Bayley (1988)
Hago	Rwanda	16.1	90	6	5.590	0.373	MRAG (1995)
Hombolo	Tanzania	15.4	225.92	45.92	14.670	2.982	MRAG (1995)
Ihema	Rwanda	86	240	30.8	2.791	0.358	MRAG (1995)
Ikimba	Tanzania	35.3	5	10	0.142	0.283	MRAG (1995)
Infiernillo	Mexico	600	13579.9	2631	22.633	4.385	MRAG (1995)
Itasy	Madagascar	35	989.64	800	28.275	22.857	MRAG (1995)
Jebel Aulia	Sudan	1050	8108	1547	7.722	1.473	MRAG (1995)

Jipe	International	39	300	514	7.692	13.179	MRAG (1995)
Kainji		1270	7200	6320	5.669	4.976	Bayley (1988)
Kang Kachan	Thailand	49.7	330	721	6.640	14.507	MRAG (1995)
Kariba		5364	4080	1600	0.761	0.298	Bayley (1988)
Kew Lom	Thailand	18	130	70	7.222	3.889	MRAG (1995)
Khashm El Girba	Sudan	125	650	97	5.200	0.776	MRAG (1995)
Kho Laem	Thailand	353.2	346	152	0.980	0.430	MRAG (1995)
Kidogo	Rwanda	2.2	40	8	18.182	3.636	MRAG (1995)
Kindai	Tanzania	2.6	108.88	34.5	41.877	13.269	MRAG (1995)
Kinkony	Madagascar	139	793.38	160	5.708	1.151	MRAG (1995)
Kirimbi	Rwanda	3.4	20	15	5.882	4.412	MRAG (1995)
Kitangiri	Tanzania	1200	4113	317	3.428	0.264	Bayley (1988)
Kivu	International	2699	315	600	0.117	0.222	Bayley (1988)
Koka (galilea)	Ethiopia	200	100	73	0.500	0.365	MRAG (1995)
Kossou	Côte d'Ivoire	1600	8000	3200	5.000	2.000	MRAG (1995)
Krasiew	Thailand	48	530	193	11.042	4.021	MRAG (1995)
Kyoga		2700	48900	6000	18.111	2.222	Bayley (1988)
Lagdo	Camerroon	700	11345	2100	16.207	3.000	MRAG (1995)
Lam Pao	Thailand	230	2875	5010	12.500	21.783	MRAG (1995)
Lam Praplern	Thailand	18.6	190	145	10.215	7.796	MRAG (1995)
Lam Takong	Thailand	44.3	120	107	2.709	2.415	MRAG (1995)
Lanao	Philippines	357	10000	3200	28.011	8.964	MRAG (1995)
Langeno	Ethiopia	241	1000	44	4.149	0.183	MRAG (1995)
Lualaba Lak. Complex	Zaire	9440	12855.5	7668	1.362	0.812	MRAG (1995)
Luhondo	Rwanda	26.1	100	55	3.831	2.107	MRAG (1995)
Lukanga	Zambia	5500	1452.6	1096.33	0.264	0.199	MRAG (1995)
Lusiwashi	Zambia	80	354	163	4.425	2.038	MRAG (1995)
Madarounfa	Niger	2.9	20	90	6.897	31.034	MRAG (1995)
Magat	Philippines	44.6	6729	654	150.874	14.664	MRAG (1995)
Mainit	Philippines	140.6	13000	1560	92.461	11.095	MRAG (1995)
Maji Ndombe	Zaire	2300	1094	1000	0.476	0.435	Bayley (1988)
Malawi		30800	28000	10154	0.909	0.330	Bayley (1988)
Malombe		390	5000	900	12.821	2.308	Bayley (1988)
Malya	Tanzania	0.7	12	5	17.143	7.143	MRAG (1995)
Managua	Nicaragua	1016	488	200	0.480	0.197	MRAG (1995)
Manantali	Mali	600	1590	400	2.650	0.667	MRAG (1995)
Mantasoa	Madagascar	13.75	46.4	10.25	3.375	0.745	MRAG (1995)
Manyara	Tanzania	470	426.25	259.8	0.907	0.553	MRAG (1995)
Massingir	Mozambique	150.8	400	70	2.653	0.464	MRAG (1995)
Mgori	Tanzania	0.8	42.91	15.5	53.638	19.375	MRAG (1995)
Mianji	Tanzania	4.9	37.17	21.82	7.586	4.453	MRAG (1995)
Mirayi	Rwanda	2.3	20	17	8.696	7.391	MRAG (1995)
Mtera	Tanzania	610	10500	1565	17.213	2.566	MRAG (1995)
Mugesera	Rwanda	39	300	325	7.692	8.333	MRAG (1995)
Mujunju	Tanzania	80	421	100	5.263	1.250	MRAG (1995)
Mulehe	Uganda	5	28	33	5.600	6.600	MRAG (1995)
Murago	Rwanda	2.2	10	42	4.545	19.091	MRAG (1995)
Mwadingusha		393	5000	1400	12.723	3.562	Bayley (1988)
Mweru		4580	31000	6000	6.769	1.310	Bayley (1988)
Mweru-Wa-Ntipa		1520	5812	1100	3.824	0.724	Bayley (1988)
Nam Oon	Thailand	86	103	90	1.198	1.047	MRAG (1995)
Nam Pung	Thailand	20	131	60	6.550	3.000	MRAG (1995)
Nasho	Rwanda	13.7	50	25	3.650	1.825	MRAG (1995)
Nasser		3330	7000	3500	2.102	1.051	Bayley (1988)
Naujan	Philippines	79	5000	1250	63.291	15.823	MRAG (1995)
Ngwazi	Tanzania	5.1	25.2	15.4	4.941	3.020	MRAG (1995)

Nicaragua	Nicaragua	8264	1320	500	0.160	0.061	MRAG (1995)
Nzilo		280	2800	450	10.000	1.607	Bayley (1988)
Okavango	Botswana	10000	500	500	0.050	0.050	MRAG (1995)
Oubeira	Algeria	21	80.5	8	3.833	0.381	MRAG (1995)
Pagusi	Philippines	2.53	25	20	9.881	7.905	MRAG (1995)
Pantapangan	Philippines	89	142	71	1.596	0.798	MRAG (1995)
Paoay	Philippines	4	118	170	29.500	42.500	MRAG (1995)
Patzcuaro	Mexico	126.44	1565.9	1465	12.385	11.587	MRAG (1995)
Pool Malebo	International	550	4250	5000	7.727	9.091	MRAG (1995)
Pranburi	Thailand	46.7	105	65	2.248	1.392	MRAG (1995)
Rugwero	International	100	270	230	2.700	2.300	MRAG (1995)
Rukwa	Tanzania	2000	9876	1381	4.938	0.691	Bayley (1988)
Rutamba	Tanzania	2.4	30	30	12.500	12.500	MRAG (1995)
Rwampanga	Rwanda	9.5	30	30	3.158	3.158	MRAG (1995)
Rwehikama	Rwanda	19.2	70	35	3.646	1.823	MRAG (1995)
Sake	Rwanda	14.3	175	100	12.238	6.993	MRAG (1995)
Sebu	Philippines	9.6	525	175	54.688	18.229	MRAG (1995)
Singida	Tanzania	12.3	256.6	45.6	20.862	3.707	MRAG (1995)
Sirikit	Thailand	284	1117	650	3.933	2.289	MRAG (1995)
Sirinthorn	Thailand	292	2190	4802	7.500	16.445	MRAG (1995)
Srinakarinth	Thailand	400	510	146	1.275	0.365	MRAG (1995)
Taal	Philippines	263.5	11800	8400	44.782	31.879	MRAG (1995)
Tana (Africa)	Ethiopia	3500	500	350	0.143	0.100	Bayley (1988)
Tanganyika		32600	73000	15000	2.239	0.460	Bayley (1988)
Titicaca	International	8560	8051	6256	0.941	0.731	MRAG (1995)
Toho	Benin	16	215	97	13.438	6.063	MRAG (1995)
Tsiazompaniry	Madagascar	31	52.75	68	1.702	2.194	MRAG (1995)
Tumba	Zaire	767	443	300	0.578	0.391	Bayley (1988)
Turkana		7570	3144	1208	0.415	0.160	Bayley (1988)
Twali	Tanzania	3.2	6.5	10.17	2.031	3.178	MRAG (1995)
Upemba	Zaire	530	12000	1000	22.642	1.887	Bayley (1988)
Victoria		68800	101082	26000	1.469	0.378	Bayley (1988)
Volta		8482	40000	27700	4.716	3.266	Bayley (1988)
Wood	Philippines	7	80	40	11.429	5.714	MRAG (1995)
Zwai	Ethiopia	442	1571.17	350	3.555	0.792	MRAG (1995)

Table A3 **Estimates of CPUA ($t\ km^{-2}\ y^{-1}$) and fisher density (Fishers Km^{-2}) for reef-based fisheries.**

[1] Fisher density estimated from population of village, community, or island,
[2] Fisher density estimated from canoe density assuming one fisher per canoe.

Name	Country	Area (Km2)	Catch ($t\ y^{-1}$)	CPUA ($t\ km^{-2}\ y^{-1}$)	Fisher Km^{-2}	References
Abemama	Kiribati	67.9	1690	24.900	47.39 [1]	Adams et al 1997
Aitutaki	Cook Island	50	154	3.080	40.00 [1]	Adams et al 1997
Apo Island	Philippines	1.56		10.800	288.46 [1]	Alcala & Luchavez (1981)
Aranuka	Kiribati	22.3	186.7	8.390	44.93 [1]	Adams et al 1997
Atchin Island	Vanuatu			0.710	114.45	MRAG (1998)
Aua Village	American Samoa	0.486		2.810	3026.75 [1]	Wass 1982 & Munro 1984
Butaritari	Kiribati	87.6	1235	14.100	43.22 [1]	Adams et al 1997
BVI	BVI	3130	819	0.262	0.12	John Munro (pers comms)
BVI (North)	BVI	880	110	0.125	0.07	Beets (1997)
BVI (South)	BVI	940	330	0.351	0.20	Beets (1997)
Cautata	Fiji			0.950	24.32	MRAG (1998)
Cokovata	Fiji	29.6	242.7	8.200	28.14 [1]	Adams et al 1997
Discovery Bay	Jamaica	12	60.8	5.067	10.83	John Munro (pers comms)
Emua Village	Vanuatu			1.680	41.28	MRAG (1998)
Fagaitua Village	American Samoa	0.316		3.940	1357.59 [1]	Wass 1982 & Munro 1984
Faganeanea Village	American Samoa	0.294		3.110	649.66 [1]	Wass 1982 & Munro 1984
Fagasa Village	American Samoa	0.16		4.180	4100.00 [1]	Wass 1982 & Munro 1984
Fag'ulu Village	American Samoa	0.368		2.090	2057.07 [1]	Wass 1982 & Munro 1984
Fakaofo	Tokelau	18.5	71.9	3.890	37.84 [1]	Adams et al 1997
Fanafuti	Tuvalu	24.2	120	4.950	164.88 [1]	Adams et al 1997
Fanning Atoll	Kiribati	32.3	60	1.860	40.53 [1]	Adams et al 1997
FSM (Kosrae)		30.8	60	1.950	240.26 [1]	Adams et al 1997
Guam		43.1	38.8	0.790	3089.37 [1]	Adams et al 1997
Ko Ono	Fiji	103.9	270.1	2.600	5.58 [1]	Adams et al 1997
Koro	Fiji	2.5	9.6	3.920	123.60 [1]	Adams et al 1997
Kuria	Kiribati	13	176.4	13.550	75.77 [1]	Adams et al 1997
Lakeba	Fiji	5.9	26.2	4.430	61.86 [1]	Adams et al 1997
Lamotrek	Caroline Island	8.8	18.8	2.140	31.59 [1]	Adams et al 1997
Lauli'l Village	American Samoa	0.4		3.150	1517.50 [1]	Wass 1982 & Munro 1984
Lelepa Island	Vanuatu			1.240	36.84	MRAG (1998)
Leloaloa Village	American Samoa	0.352		1.660	2241.48 [1]	Wass 1982 & Munro 1984
Macuata & Bua	Fiji	957	1521	1.590	30.93 [1]	Adams et al 1997
Maina	Kiribati	84.7	989	11.670	25.79 [1]	Adams et al 1997
Masefau Village	American Samoa	0.449		2.270	701.56 [1]	Wass 1982 & Munro 1984
Matu'u Village	American Samoa	0.44		1.470	715.91 [1]	Wass 1982 & Munro 1984
Moala	Fiji	42.6	434.5	10.200	49.72 [1]	Adams et al 1997
Moorea		50	50	1.000	180.00 [1]	Adams et al 1997
Nanumea	Tuvalu	20.5	25.6	1.250	47.61 [1]	Adams et al 1997
Nauru		7.4	35.2	4.760	1337.84 [1]	Adams et al 1997
Naweni	Fiji			0.460	5.13	MRAG (1998)
New Calendonia	New Calendonia	1600	3000	1.880	102.61 [1]	Adams et al 1997
Niue		6.2	58	9.350	354.84 [1]	Adams et al 1997
Niutao	Tuvalu	3.1	62	20.330	241.94 [1]	Adams et al 1997
Nuktuba	Fiji	16.8	77.3	4.600	13.10 [1]	Adams et al 1997
Ontong Java	Solomon Islands	12.2	7.3	0.600	114.75 [1]	Adams et al 1997
Ouvea	New Caledonia	40	70	1.750	75.00 [1]	Adams et al 1997
Palau		450	1057	2.350	33.33 [1]	Adams et al 1997
Palmerston	Cook Island	16.8	23	1.370	3.93 [1]	Adams et al 1997
Parish A	Jamaica			3.858	1.63 [2]	Munro & Thompson (1983)
Parish B	Jamaica			1.246	0.38 [2]	Munro & Thompson (1983)

Parish C	Jamaica			4.348	3.09 [2]	Munro & Thompson (1983)
Parish D	Jamaica			3.130	5.63 [2]	Munro & Thompson (1983)
Parish E	Jamaica			4.315	4.43 [2]	Munro & Thompson (1983)
Parish G	Jamaica			2.583	4.58 [2]	Munro & Thompson (1983)
Parish H	Jamaica			3.221	4.20 [2]	Munro & Thompson (1983)
Parish I	Jamaica			2.794	1.49 [2]	Munro & Thompson (1983)
Pellonk Village	Vanuatu			0.570	46.29	MRAG (1998)
Port Moresby	Papau New Guinea	116	524	4.520	46.96 [1]	Adams et al 1997
Rodrigues	Mauritius	200	1130	5.650	1.47	Reefbase
Tacilevu	Fiji			0.740	6.65	MRAG (1998)
Tamana	Kiribati	1.7	107	63.690	809.41 [1]	Adams et al 1997
Tarawa	Kiribati	129	3304	25.610	223.26 [1]	Adams et al 1997
Tavua	Fiji			1.940	0.59	MRAG (1998)
Tigak Island	Papau New Guinea	143.7	39	0.270	4.75 [1]	Adams et al 1997
Tikehau	French Polynesia	93	200	2.150	3.01 [1]	Adams et al 1997
Tongatapu	Tonga	100	350	3.500	300.00 [1]	Adams et al 1997
Tutuila	American Samoa	3.6	61.3	17.030	1995.00 [1]	Adams et al 1997
Tutuila	American Samoa	25	176	7.040	2184.00 [1]	Adams et al 1997
Uripiv Island	Vanuatu			0.530	58.22	MRAG (1998)
Utulei Village	American Samoa	0.191		4.400	5188.48 [1]	Wass 1982 & Munro 1984
Uvea (Wallis & Futuna)		70.3	330	4.690	128.02 [1]	Adams et al 1997
Vaitogi Village	American Samoa	0.104		1.650	6355.77 [1]	Wass 1982 & Munro 1984
Vanuatu	Vanuatu	1063	2019	1.900	133.58 [1]	Adams et al 1997
Verata	Fiji			1.400	4.22	MRAG (1998)
Vitogo	Fiji			1.000	0.72	MRAG (1998)
W. Manus	Papau New Guinea	61.1	173.6	2.840	55.30 [1]	Adams et al 1997
W. Samoa	Western Samoa	220	1935	8.800	478.74 [1]	Adams et al 1997
Washington Island		6.4	94.7	14.800	146.25 [1]	Adams et al 1997
Yap	Fed. States of Micronesia	131	226.3	1.730	50.73 [1]	Adams et al 1997