Management Strategy Modelling

Tools to evaluate trawl management strategies
with respect to impacts on benthic biota
within the
Great Barrier Reef Marine Park area

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Executive summary

This document reports on the results of a one-year study to develop and build tools to support the comparison of trawl management options within the Great Barrier Reef Marine Park area, supported by the Great Barrier Reef Marine Park Authority (GBRMPA) and the CSIRO Division for Marine Research (CMR). The main focus of the model is the estimation of the impact of trawling activities on marine benthic flora and fauna in terms of relative biomass removal.

The model implements the spatial and temporal behaviour of the Queensland East Coast Trawl fishing fleet, based on logbook information as collected by the Queensland Fisheries Management Authority (QFMA).

By modelling *ranges* of removal and recovery rates, the model assesses the impacts of trawling on *ranges* of benthic organisms. Estimates of appropriate ranges were obtained from the CSIRO repeated-trawl experiments in the northern section of the Great Barrier Reef (Poiner et al, 1988).

An assessment of the model's performance was obtained by comparing two management options, a spatial closure and an annual fishing effort reduction.

Tests of the sensitivity of the model in respect of the assumptions were conducted and reported.

Main model components

1. Biological model
   The biological model is based on a classical biomass change equation, incorporating logistic (self-limiting) population growth and linear removal rates. The spatial component is implemented as a 6-minute regular grid. Each grid is regarded as containing an independent (from neighbouring grid cells) population of benthic flora and fauna. The model incorporates a range of biomass forcing factors (like sediments and geographic factors) to predict spatial distributions of benthic biota.

2. Trawl activities and impacts
   Each of the benthic populations in the grid cells is thought to receive trawling pressure as estimated from historical commercial logbook data. Logbook data has been recorded as effort (in boat days) in an area. An innovative approach has been developed for this project to express this 'large-scale' effort measure in terms of 'small-scale' impacts in benthic biota. This small-scale effort measure estimates proportions of areas within grid cells that are passed over by trawl gear once, twice etc., according to the aggregation patterns of the trawling itself. Aggregation patterns were estimated from satellite tracking systems and vessel plotting devices. Combining these outcomes with the CSIRO repeated trawl experimental data on depletion of a range of taxonomic units provides a first order estimate for relative biomass removal.

3. Effort allocation
   To enable us to predict the spatial distribution of trawling into the future under various management strategies, an effort allocation model had to be developed. This effort allocation sub-model samples historical fishing effort data to predict future effort allocation. It also allows us to simulate closing areas to

trawling and re-distribute effort from those to other grid cells. Back-prediction to the start of the trawl fisheries in the 1950s has been based on long-term FAO trend catch data for Australia. The user interface software facilitates the definition of different 'historical growth' scenarios of trawl effort in the region.

4. Management option definition
   Two 'families' of management strategies (scenarios or options) are currently supported in the models: spatial and temporal effort management. Spatial management options consist of closing (one or more) areas to trawling for a defined period of time. Temporal effort management includes measures such as annual effort increase/decrease scenarios. Also, combinations of management strategies can be modelled.

5. Management option comparisons
   All management evaluations are compared to a status-quo situation, where the future is seen as a stationary continuation of recent history, based on the most up-to-date effort data available (1997 at the time of writing of this report). A management strategy is reported in terms of relative changes of an indicator (such as 'remaining biomass' or 'number of gridcells with benthic relative biomass less then 20% of initial biomass') after the strategy has been implemented. High-level comparisons among a range of management options expressed in terms of several indicators are summarised in 'decision tables'.

6. User requests and reporting
   To 'streamline' the processing of management strategy evaluation requests, a proforma has been developed enabling potential users to define a range of options and settings they want to see processed. The proforma has two modes of use: a basic scenario definition that requires only the most essential of specification to be supplied by the user. The second mode gives users much more control by allowing detailed specification of model settings and management scenarios.

   The software generates reports in a semi-automated way. Again, the user can request several levels of detail in the reportage.

Findings and restrictions

The model brings together our present knowledge and data in regards to trawl activities and their impacts on benthic biota within the GBR Marine Park. It also highlights the strong and weak points of our understanding of the underlying mechanisms and the availability of data regarding the east coast trawl fisheries and their impacts in benthic biota.

The statistical approach connecting the large-scale effort to the small scale, 'on-the-ground' impacts using the negative binomial distribution allows trawl aggregation patterns to be summarised into a single factor, and this approach has already drawn attention from other (some international) researchers in the field.

Some of the restrictions of the model are based on the absence of appropriate data such as: the spatial distribution of benthic biota; information on population interactions across grid cell boundaries and even interactions between trophic groups within grid cells; spatial distribution of fleet characteristic like gear difference between fisheries; temporal variation of fleet characteristics or 'effort creep'. However, the model implementation is sufficiently flexible to incorporate those mechanisms and data if and when it becomes available.

Management strategy evaluation models tend to produce large amounts of detailed data. The top-down approach in reporting the data allows a good understanding of the results based on the summary outcomes in the decision tables. Guided by the decision tables, examination of the next level of (more detailed) data facilitates the understanding of underlying mechanisms.

The model has been implemented in a way that enables a very flexible management strategy definition and model parameter specification. The software implementation delivers the results in a comprehensive and reproducible form. Reportage is semi-automated and, as such, open to extension and improvements over time. Stochastic model runs enable estimation of uncertainty of outcomes, given observational error and/or process variance.

Future developments

Further development of the model could be achieved by:

- improving the effort (re-)allocation models,
- more flexibility of the underlying biomass distribution forcing mechanisms,
- spatial and intra-grid cell biomass interaction models,
- updating the trawl effort data
- refining the fleet characteristics model to include spatial variation and effort creep, and
- extending the model to other fisheries

This report

This report consists of two parts: a general description with example outputs, and a technical part, explaining the fine detail of the mathematical and statistical reasoning and the methods behind the models.

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Poiner, I, Glaister, J, Pitcher, R, Burridge, C, Wassenberg, T, Gribble, N, Hill, B, Blaber, S, Milton, D, Brewer, D, Ellis, N, (1998), Environmental Effects of Prawn Trawling in the Far Northern Section of the Great Barrier Reef: 1991–1996; Final Report to the Great Barrier Reef Marine Park Authority and Fisheries Research and Development Corporation

Part One

General Report

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1. Introduction

The CSIRO Division of Fisheries and the Queensland Department of Primary Industries began a project in 1992 to provide information on aspects of the environmental effects of prawn trawling in the Far Northern Section of the Great Barrier Reef Marine Park (GBRMP). The project provided a factual basis for GBRMPA and industry to assess the impact of prawn trawling and for GBRMPA and other management agencies to consider zoning and other options.

In 1998 the report *Environmental Effects of Prawn Trawling in the Far Northern Section of the Great Barrier Reef: 1991-1996* was published. This report documented the results from the before-after-control-impact (BACI) experiments and the repeat-trawl depletion study that were performed in a National Park B 'green' zone. This is a 9,400 km^2 area excluded from trawling activities.

A four-year study by CSIRO Marine Research, called *Recovery of the seabed environment from the impact of prawn trawling in the Far Northern Section of the Great Barrier Reef* started in 1996.

Commercial logbook data has been collected by the Queensland Fisheries Management Authority (QFMA) since 1988. This data contains information on effort, catch per species, date and position of the activities for the whole of the Queensland East Coast trawl fishery. The data has been collected in grids of various spatial resolutions. Before 1992 the spatial resolution was 30 minutes (30'), that is grids of dimensions 30' × 30' or 30 nm × 28.5 nm at latitude 18ºS (middle of the GBRMP), after 1992 a voluntary programme of 6' grid reporting was introduced. Methods have already been developed to impute 6' grid effort and catch information from 30' grid effort and catch information.

1.1. Management scenario modelling

Management scenarios aim to estimate the consequences of management actions. For example, management of natural resources can directly or indirectly change impacts on the environment, whilst environmental conservation management can directly or indirectly change impacts on natural resources.

More often than not the results of management actions are very hard to predict due to the complex interrelationships between the impacted areas. Simulation of management scenarios applied to a 'model' of the real world can be a very powerful step in the development of management strategies.

The model obviously has to reflect some essential characteristics of the real world that are important to the processes studied. Incorporating information on trawl impact, recovery, effort distribution and available large-scale distribution of environmental descriptors combined with spatial modelling, statistical expertise, an advanced programming environment and advanced implementation skills enables the development of such models for areas like fisheries resources and conservation management.

1.2. Objectives

The objectives for the project *Management scenario modelling of impacts of trawling in the Great Barrier Reef Marine Park area* are stated as follows:

1. To develop a (spatio-temporal) model estimating the relative impact of trawling on classes/types of benthic organisms within the GBRMP/WHA.
2. To apply this model, combined with information on current trawl effort, in order to estimate the distribution of relative impact on classes of benthic organisms within the GBRMP/WHA.

3. To develop and evaluate a variety of management intervention regimes using this model in order to estimate relative impacts of trawling on classes of benthic organisms, given sets of explicit management objectives. These scenarios should include sub-models for recovery estimation.
4. To test the sensitivity of the model in respect of the model assumptions.

1.3. Methods

1.3.1. Model description

The model is based on a grid with appropriate resolution(s) covering the total of the GBRMP/WHA. The model implements spatial context formed by the topography of the area and existing legal boundaries. It incorporates known and essential environmental parameters, fisheries effort distribution, (proxies for) benthic biota and depletion and recovery sub models. The model also provides for various small-scale trawl distribution patterns. Testing the model for sensitivities based on parameter estimation and assumptions is part of the project.

1.3.2. Management scenarios

Resource and conservation management objectives have been developed in collaboration with participating organizations on the steering committee. Based on these objectives, a range of management scenarios have been developed and evaluated in terms of impact and recovery. A basic effort reallocation model allowing for spatial displacement or adjustment of fishing effort based on historical distributions has also been included to accommodate spatial closures.

2. Approach to modelling

In this section we describe broadly how we go about modelling the impacts of trawling on benthos. All the assumptions of the model are set out in *Appendix 2: List of assumptions employed in the trawl management scenario model*.

Our model consists of several layers. At the lowest level is the *operating model*, which computes impact on the benthos belonging to certain vulnerability classes given a certain degree of trawling effort. Above this layer lies a *management model*, which allocates effort to grids in response to certain interventions. Overseeing these models is a *run management* layer, which keeps track of the inputs to and outputs from the underlying models, thus retaining the context in which the simulations were run. Finally there is a *graphical user interface*, which allows one to interact with all these layers by setting model parameters, running simulations, viewing results and generating reports.

2.1. Operating model

We aim to model the effect of trawling on benthic populations. Our model therefore requires the following components:

- assumptions concerning the spatial distribution of the benthic biomass in its pristine state before trawling and the latest time of pristineness,
- spatial and temporal information on trawling effort,
- a sub-model for the amount of depletion given the level of effort,
- a sub-model for the amount of recovery of the benthos back towards the pristine state
- a description of the vulnerability of each benthic morphic class in terms of its depletion rate and recovery rate.

2.1.1. Spatial distribution of the benthic biomass

We have two approaches to modelling the biomass:

1. Simulate *spatially relative* biomass based on feasible ranges of parameters gleaned from the GBR study (Poiner et al,1988) and other sources. We could allow for the forcing effect of environmental variables such as sediment, depth, distance from shore and latitude. Parameters could be simulated either randomly or deterministically.
2. Do not attempt to model the spatial distribution of biomass; instead use *relative* biomass, which is the biomass relative to the initial pristine state. The initial biomass would then be 1 everywhere.

Because of our current lack of knowledge of the biology, our main focus has been on the second approach. However, we have made provision in the modelling software for the first approach, and we demonstrate some results in *Management scenarios: an example from the Queensland East Coast Trawl fishery* on page 28. For more details on this approach see *Appendix 4: Trawl management scenario modelling request proforma*.

2.1.2. Spatial and temporal information on trawling effort

We use historical fisheries effort data on a spatial and temporal grid. The bulk of this data is recorded on grids of size 30' or 6'. We therefore operate the model at this scale, which we call the *large scale*.

The depletion of the benthos is an effect that occurs on the *small scale*, i.e. at the scale of the width of a net. That is, every pass of the trawl gear removes some of the benthos in the path of the trawl, but leaves the benthos unaffected elsewhere. In order to model depletion on the large scale, we need to scale up this small-scale process by considering the net effect of all the trawling that goes on inside a grid.

To do this scaling up, we need a model for the small-scale pattern of trawling. We used two approaches to this:

1. use real VMS and GPS data from a subset of vessels to represent the pattern of trawling for the whole fleet,
2. simulate trawling patterns using our knowledge of trawling practices.

The apparent area trawled depends on the spatial precision of the effort information: the more precise the information, the less the apparent area trawled. It is therefore important that future data be collected at a scale that is sufficient to give a realistic picture of the pattern of trawling.

2.1.3. Depletion sub-model

The small-scale depletion model is very simple. We assume that each tow removes a fixed proportion of the existing benthic biomass in the path of the trawl. We call this proportion the *depletion rate per tow*. It is a deterministic model.

In scaling this process up to the large scale, we introduce a statistical distribution for the pattern of trawling within each grid. We obtain the parameters of this distribution using the two approaches just described under *Spatial and temporal information on trawling effort*. The process on the large scale—the scale on which the model operates—is then obtained by aggregating over the many small-scale depletion events. This is an averaging procedure with weights given by the statistical distribution that describes the pattern of trawling.

2.1.4. Recovery sub-model

We assume a simple model for recovery on the small scale that is governed by two parameters: the *recovery rate* and the carrying capacity. At low population levels the model describes exponential growth at the recovery rate. At higher population levels competition inhibits growth, and ultimately the population approaches the carrying capacity. We assume that the pristine population is already at this carrying capacity. The recovery model is therefore described simply by the recovery rate.

We have to scale up the small-scale recovery model to the large scale, just as we have done with depletion. How we do this is described in detail in *Part Two: Technical Report*.

2.1.5. Benthos vulnerability

Vulnerability to trawling is a property of the shape of the benthic organism: for instance, flat or flexible organisms are less likely to be dislodged by the trawl gear than tall, rigid organisms. Therefore a particular depletion rate per tow will correspond to a broad morphic class of benthos containing many disparate species, rather than to an individual species.

The other type of vulnerability is the ability (or lack thereof) of the organism to recover. Recovery rates are likely to be determined by life-history characteristics of the biota, which may be available at the level of species, or higher taxonomic group.

The two quantities, depletion and recovery, partition the biota into different groupings. We call the combination of depletion and recovery the *vulnerability*. The question of where actual species lie in this two-dimensional space needs further research.

2.2. Management model

At this project's first steering committee meeting in September 1999, we asked the participants to suggest management options that ought to be in the model. The committee came up with two types of management intervention: effort capping and spatial closures. We have incorporated these into the model. Management intervention is directed at influencing future effort, and so, in order to test such interventions, we also needed to develop methods for predicting the spatio-temporal distribution of effort, based on defined effort scenarios.

2.2.1. Effort capping

In this form of intervention the total effort in a region is capped. The level of the cap is specified relative to a baseline year; so, for example, in 2000 it may be set equal to the total effort in 1996 and thereafter be reduced by 5% each year for 5 years.

2.2.2. Closures

The model allows any grid to be closed to trawling in any future years. Remember that the model operates at the annual time scale and so it does not incorporate seasonal closures. Therefore in a future year, the grid is either fully open to trawling or fully closed.

Note, however, that the annual level of effort in grids where seasonal closures were applied historically does correctly reflect the true reduction in effort due to those closures, through the historical data used to initialise the model. Also the effort displaced from those cells does show up as an increased annual effort in the open cells. The pattern of trawling within a year is assumed uniform. Such inaccuracy in the temporal detail will only be important for species that recover over months.

2.2.3. Effort allocation

Effort allocation is a three-stage process: first, effort is somehow **predicted** for a grid assuming no closures; second, effort in closed grids is **redistributed** to open grids; and third, the total effort is homogenously scaled (or **adjusted**) to meet the effort cap.

Stage 1: Prediction

We have implemented two methods of effort prediction. The simpler method uses sampling; the second method uses catch per unit effort information.

1. Sampling

The simplest way of predicting effort for a future year in the absence of closures is to sample from the effort in the same grid in previous years. Obviously the further in the future we go, the less reliable the prediction will be.

2. Catch per unit effort information

Less direct is the following two-stage approach: first predict the abundance of the target species; then predict the effort from the abundance. We use catch per unit effort as a surrogate for abundance, ignoring improvements in efficiency or increases in engine power of time. The rationale behind this approach is that abundance may be easier to predict than effort. The setting up of the model is rather complicated because it has to take into account all the different fisheries. Details are given in *Appendix 6: Effort allocation based on catch-per-unit-effort data*. This model is still under development and we have not used it in any of our simulations.

Stage 2: Redistribution

If the grid in the future year is closed, then the effort that would have been spent there must be redistributed to the other grids in some way. We have implemented two ways:

1. simple redistribution in proportion to the already allocated effort per grid,
2. constrained redistribution that disallows movement outside a local region.

Method 2 may be appropriate for smaller vessels that only fish locally. Method 1 is more appropriate for larger vessels, which can reach any location in the trawl fishery. For method 2 we have defined four regions: they are aligned along the coast with boundaries roughly at Princess Charlotte Bay, the North-South closure line and the tip of Fraser Island.

Stage 3: Adjustment

This is the simplest stage of effort allocation. The total effort is simply scaled to meet the current effort cap. If the 'local region' redistribution method is used then we use a separate cap in each region (based on the regional effort in the baseline year).

2.3. Running the model

The model is run on all grids independently. The detailed output of the model is the relative biomass in each cell over time. The model can be used to predict relative biomass at future times given a specified effort scenario. Different scenarios can be run with different values for the depletion and recovery rates. Each scenario would correspond to impacts on those species belonging to a particular vulnerability class.

The model is run from a Windows application with a graphical user interface. **Figure 1** is a collage of the major components of the user interface (*windows on dark background*). Also shown is the MS Access database (*bottom middle*) with links to various components. The white box in the centre is the computational heart of the model, which is implemented in C++ in a dynamic link library. This box is reproduced at full size in **Figure 2** and is discussed in depth under *The Depletion-Recovery model*.

The Windows interface allows the user to specify model parameters and management scenarios. Such run specifications are stored in a data base and, as such, define the context in which the results were obtained. The user may also specify outputs to be generated and stored in the data base. Outputs can be detailed information, such as the effort or relative biomass in each grid in each year, or summaries, such as mean relative biomass or quantiles thereof. The application incorporates a run management system which keeps track of all the different runs, their inputs and outputs.

If a run requires projection into the future, the effort is allocated over space and time using a stochastic procedure (see *Management model* on page 5). Alternatively, effort generated from a previous run can be used instead.

Usually, given a generated effort pattern, the program is run deterministically. However, it may be run stochastically with random recovery or depletion between grid cells and time steps. See *Deterministic or stochastic model* in *Appendix 4: Trawl management scenario modelling request proforma*.

A key component of the user interface is the interactive map. This is used to display spatial information, such as effort, relative biomass or the results of general spatial queries on the data base. The map is also used to control the spatial aspects of the model such as closures or areas of interest. The map has a legend allowing flexible control over the colour scale.

The application has a utility for generating reports on a related set of runs. Such reports include a synopsis of the runs, decision tables, graphs of indicators, histograms of biomass and maps. The reports are Word documents. For an example, see *Appendix 5: An example of a Report arising from a Trawl Management Scenario Modelling Request.*

For details of the implementation of the depletion-recovery equation see section 4.2 of *Part Two: Technical Report.*

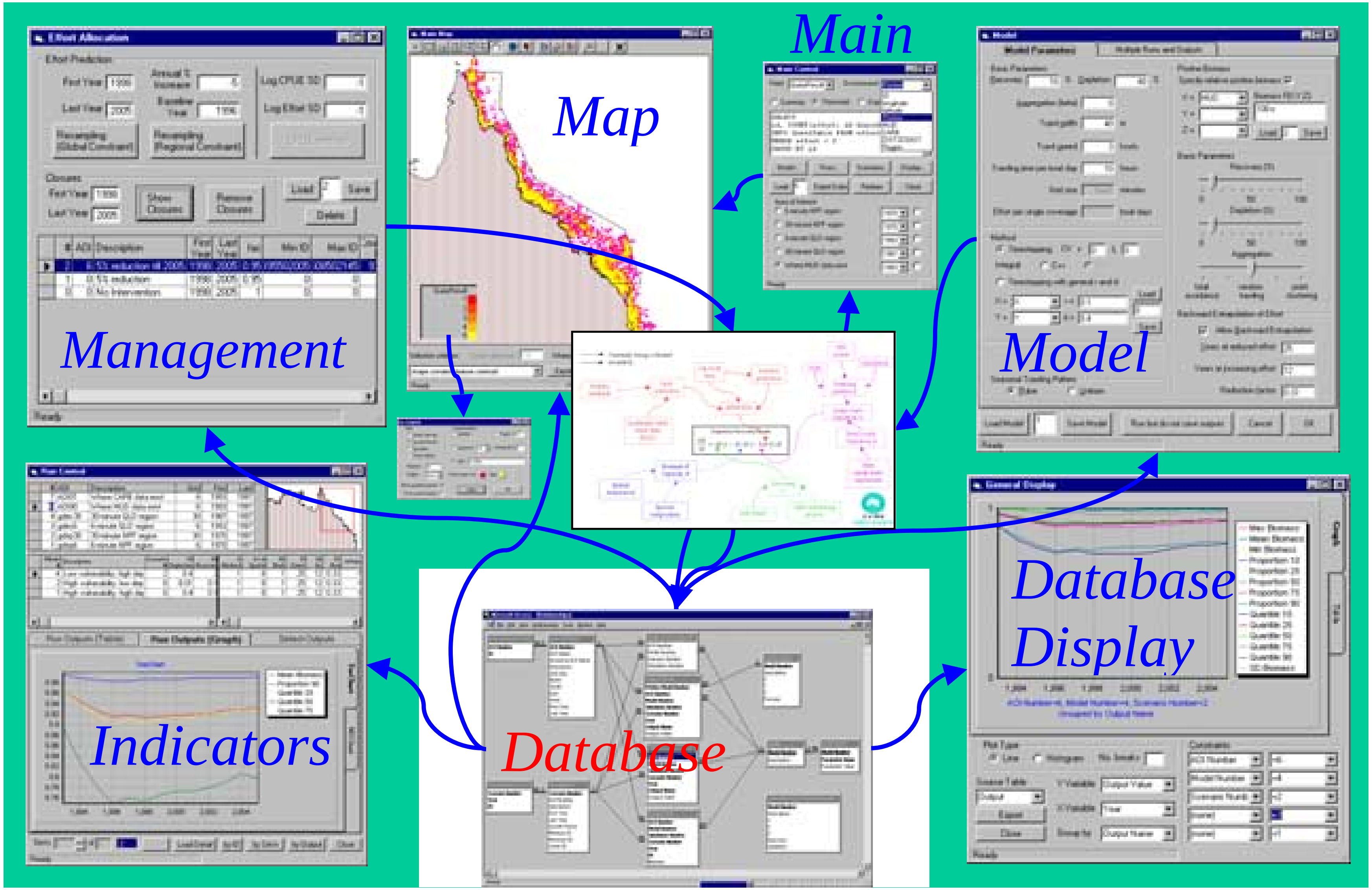
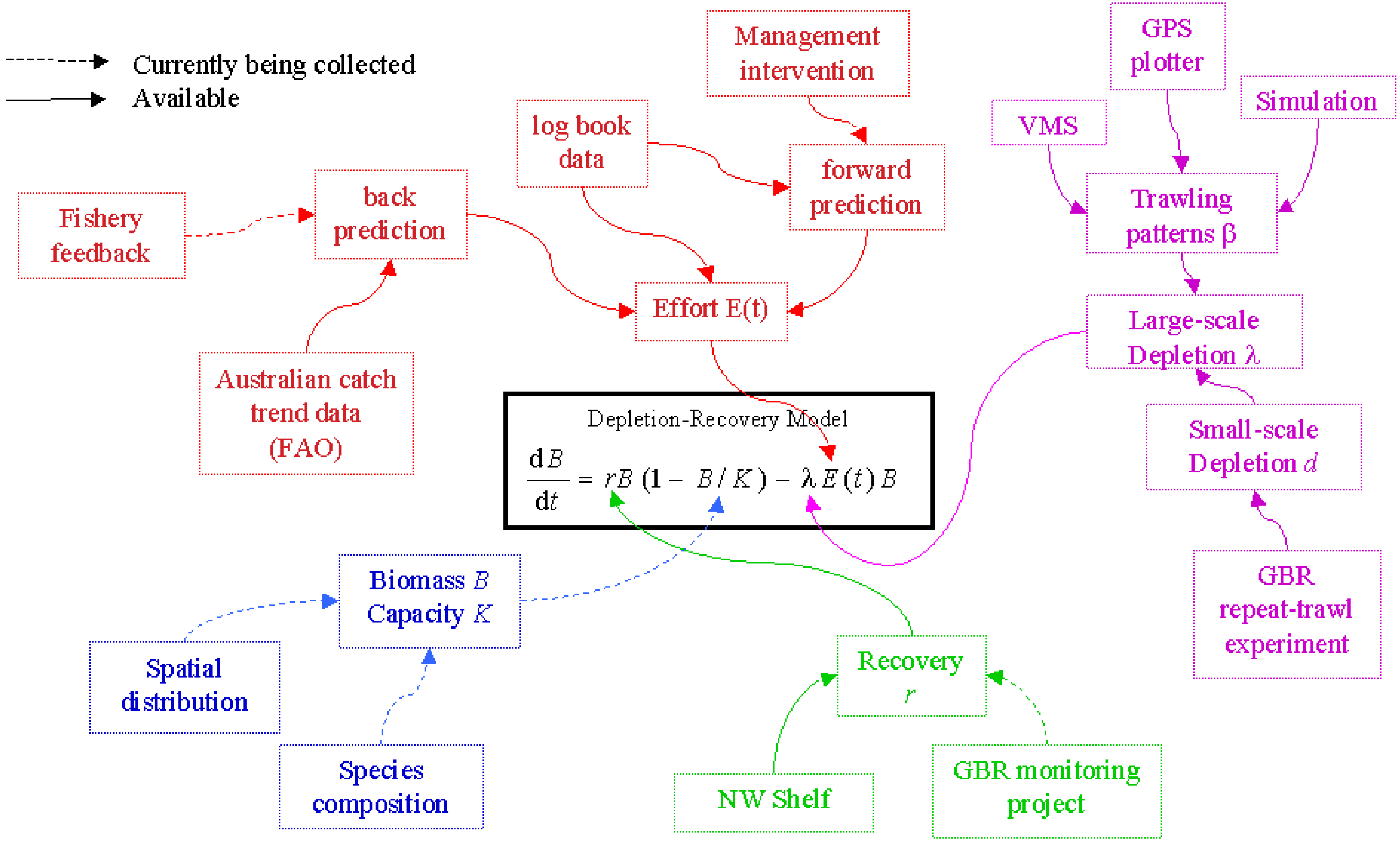


Figure 1. Some of the components of the graphical user interface of the Windows application for running the model.

Figure 2. Outline of the depletion-recovery model. Arrows represent input to the model; dashed arrows denote data that are not yet available



3. The Depletion-Recovery model

The depletion-recovery sub-model lies at the 'business end' of the modelling process, since it describes the actual impact of trawling. We describe the model in detail in this section.

In order to quantify the impact of trawling, we introduce a quantity called *relative biomass*. All assessment of impacts in scenario modelling is carried out in relative terms. We then go on to discuss the scale of the model, and how this is dictated by the available effort data. We also describe how we model historical effort before the advent of logbooks. We next show how we characterise aggregation and how we combine this with depletion on the small scale to arrive at a model of depletion on the large scale. Finally we describe the recovery model and its equivalent scaling up to the large scale.

The finer details of the derivation of the large-scale model are to be found in *Part Two: Technical Report*.

3.1. Formulation of the model

The depletion recovery model is outlined in **Figure 2**. At the heart of the model is the differential equation describing the benthic biomass dynamics:

$$\mathrm{d}B\big/\mathrm{d}t = rB(1-B/K) - \lambda E(t)B \tag{1}$$

where B is the biomass, K is the carrying capacity, r is the large-scale recovery rate, λ is the large-scale depletion rate, and $E(t)$ is the large-scale effort rate (effort per unit time).

The equation (1) states that the rate of change of benthic biomass depends on the rate of depletion and the rate of recovery. The rate of depletion is proportional to both effort and the available biomass, with constant of proportionality λ. The recovery term has the usual form: it is proportional to the biomass for low densities ($B \rightharpoonup K$); and at high densities competition sets in, and recovery is limited by the carrying capacity of the population. The equation applies independently in every grid cell. Our equation is identical to Schaefer's (1954) equation, with λ taking the place of Schaefer's catchability q.

We must specify an initial value for the biomass. We assume that before trawling began (at time $t = 0$, say) the benthos was in a steady state at the carrying capacity K. In other words

$$B(0) = K \tag{2}$$

3.1.1. Biomass, relative biomass and spatially relative biomass

Throughout this report we will mostly be interested in the relative biomass b, which is the ratio of the biomass to its maximum value:

$$b(t) = B(t)/K \tag{3}$$

The differential equation for b is

$$\mathrm{d}b\big/\mathrm{d}t = rb(1-b) - \lambda E(t)b \tag{4}$$

This differential equation is independent of the carrying capacity. It is this equation that is actually solved in our implementation of the model.

The model allows us to specify the carrying capacity K as a function of position. However we do not pretend to know the *absolute* carrying capacity; rather we specify the carrying capacity in one grid relative to the carrying capacity in some reference grid. This means that K can be scaled by an arbitrary value, and so we normalise K to sum to 1 over all grids. Properly speaking, K is the *relative* carrying capacity.

When we desire the biomass, we compute it from the relative biomass thus: $B(t) = Kb(t)$. Because K is specified only up to an arbitrary scaling factor, so is B. We call B the *spatially relative* biomass and we never refer to absolute biomass.

Moreover, from the viewpoint of management scenario evaluation, restriction to relative quantities is not really a limitation at all. This is because, in scenario evaluation, we make *comparisons* between scenarios. Since comparisons involve ratios, absolute quantities are not important; it is only their relative values that are of interest.

Each component of the model (effort, depletion, recovery and carrying capacity) depends on data (denoted by arrows in **Figure 2**), some of which is not yet available. We now explain each component in detail.

3.2. Spatial and Temporal Distribution of Effort

3.2.1. A question of scale

We need to decide on a scale of spatial and temporal aggregation at which to operate the model. With management scenario modelling we are mostly interested in the impacts on moderately vulnerable species over time scales of decades. We believe, therefore, that it is adequate to use effort aggregated within each year. That is, we assume that for each grid the total effort over one year is uniformly distributed within the year. Effort data in fact exist at daily temporal resolution; however, to take advantage of this would require either much greater knowledge of or more complicated assumptions about the biology (e.g. seasonal reproduction rates).

The logbook programme was introduced in the Queensland fishery in 1988. Each day the skipper was required to enter a single 30’ grid as the location of that day’s trawling. Since 1992, skippers were asked to enter their location on a 6’ grid, but there remained the option of using the coarser 30’ grid. The consequence of this is that between 1992 and 1997 the logbook record contains a mixture of data, some at 30’ resolution and some at 6’ resolution.

We therefore have two choices for the scale of spatial aggregation, i.e. the 6' or 30' grid. If we use the 30' grid, then we simply aggregate the data at 6' precision, and add it to the data at 30' precision. Aggregation is accurate, but has low resolution. On the other hand, if we use the 6' grid, then we have to find a way to impute from 30' data down to 6' data. The most obvious way to do this is to assign the 30' data to 6' grids in proportion to the effort available at 6' precision. If there is no effort available at the finer precision for a certain year, we may be able to use instead the pattern in a neighbouring year. Imputation has high resolution, but may be inaccurate.

3.2.2. Extrapolation from historical FAO data

Historical FAO data for all Australian fisheries (see **Figure 12** and **Figure 11** on page 21) show the following patterns: roughly constant catch between 1950 and 1975; about 3-fold growth between 1975 and 1987; and roughly constant, but more variable, catch over the 90's. Suppose we make the following assumptions: (1) total Australian annual catch is proportional to total Australian annual effort, and (2) effort in the fishery is proportional to total Australian annual effort. Then we can extrapolate the Queensland effort data by a four-fold process:

1. linearly extrapolate the 1988–1997 effort for each grid back to 1987,
2. ramp the effort down to one-third its 1987 value in 1975,
3. use the constant 1975 value back to 1950.

4. before 1950, assume that there was no trawling.

The purpose of step 1 is to obtain a starting point for the ramp that is less variable than the 1988 value. Step 4 makes the important assumption that the benthos was in a pristine state before 1950.

Precision	1950–1987	1988–1991	1992–1997
30'	FAO	logbook	logbook
6'	FAO		logbook + 30'

Table 1. Summary of available effort data since 1950 for the Qld East Coast. To get effort at 6' precision from data at 30' precision, we subdivide the coarser data in proportion to the effort available at 6' precision.

Figure 3 shows the results of this backward extrapolation process for three levels of effort (see grids shown in **Figure 10**).

3.2.3. Summary of obtaining gridded effort data

Table 1 summarises the processing involved in obtaining gridded effort data. For years before logbooks were introduced, we have to extrapolate based on the FAO pattern. For recent years, we have fairly accurate data at 6' precision. For intermediate years we have to either aggregate to 30' precision, or impute down to 6', trading accuracy for resolution. The further back in time we go, the less reliable the data become.

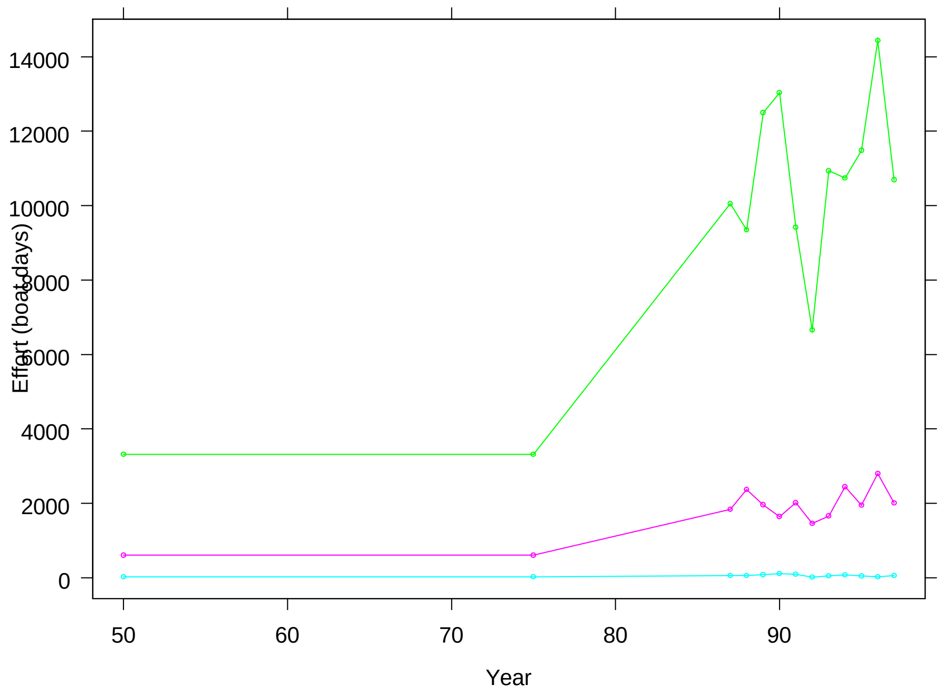


Figure 3. Retrospective extrapolation of effort for three 30-minute grids based on the historical FAO data. Before 1950 the benthos is assumed to be in a pristine state.

3.3. Depletion

We model the impacts of trawling at the scale of an effort grid. Since most of the fisheries effort data is recorded on either the 30' grid or the 6' grid, we may choose either one of these grids as our modelling scale. To describe depletion at such a scale we use a parameter λ, called the large-scale depletion rate. This parameter is actually derived from the small-scale aspects of trawling, namely, the depletion rate per tow and the pattern of trawling within the grid. Knowledge of λ therefore depends on knowledge of these small-scale aspects. Estimates of the depletion rate per tow are available from the repeat-trawl experiment in Poiner et al (1998). Trawling patterns can be obtained from VMS data augmented by simulation (Hall et al, 1999).

3.3.1. A convenient unit for effort

The effect of trawling depends on the product of effort and depletion rate per unit effort. Therefore we are completely at liberty to define convenient units for effort, provided we use related units for depletion. For instance, if we measure effort in boat days, then depletion must have units of 'per boat day'. For our purposes, the most convenient definition of effort is this:

$$\text{effort} = \text{swept area} \div \text{grid area.} \tag{5}$$

Here, swept area is the area swept out by the net irrespective of whether or not it traverses the same ground. This defines effort relative to the area it is exercised in.

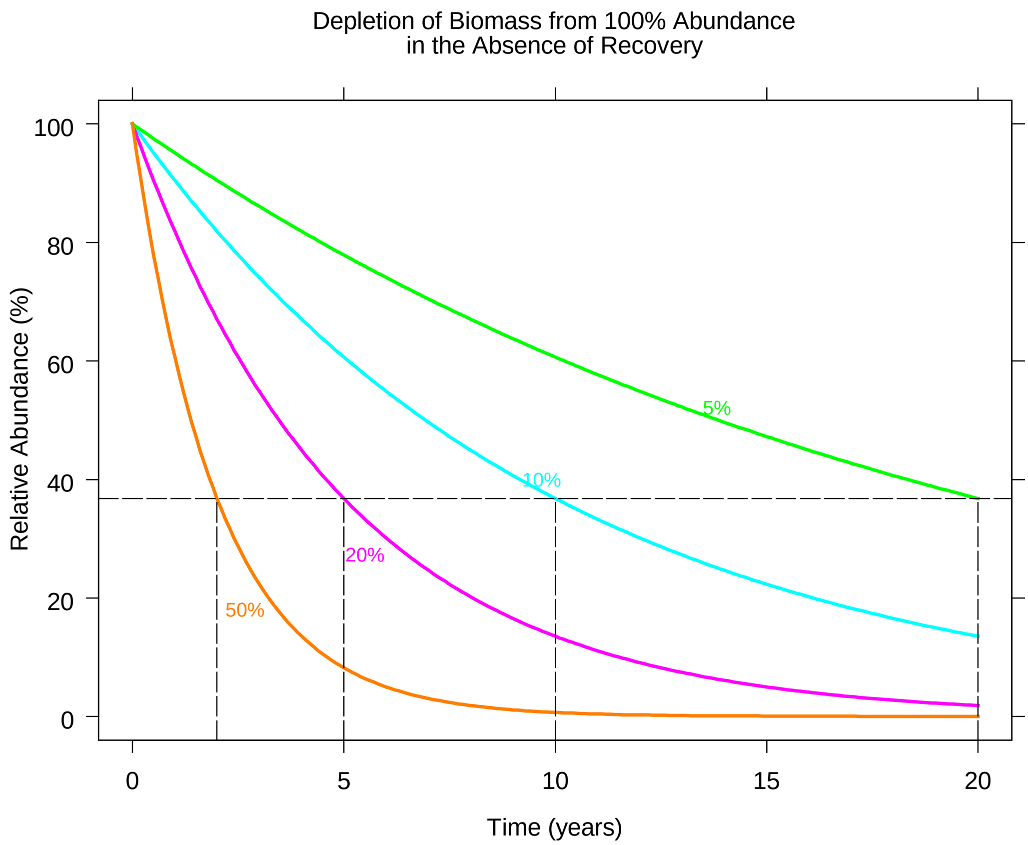


Figure 4. Exponential decay curves for different depletion rates, λ = 5%, 10% 20% and 50% and unit effort (i.e. 100% swept area per year). The depletion time scale (= inverse of the depletion rate) is the time for the biomass to drop to 37% its original value, given unit effort applied continuously over that time.

It is illuminating to translate these units into boat days. For a 6-minute grid and standard trawling practices (see *Appendix* 1: Converting from boat days to effort units), one unit of effort is 66 boat days; for a 30-minute grid, one unit of effort is 1650 boat days.

3.3.2. The large-scale depletion model

In the absence of recovery, the differential equation (1) describes exponential decay with time-varying instantaneous rate $\lambda E(t)$. If effort is constant, then the curves are exponential, as **Figure 4** shows for unit effort. Note that $1/\lambda$ can be regarded as a depletion time scale: it is the time for the biomass to decay to 37% its original value. Another depletion time scale is the half life, $\lambda^{-1}\log 2$, which is the time for the biomass to decay to 50%.

3.3.3. The small-scale depletion model

The large-scale process of depletion, which occurs over the entire grid for an entire year, is actually an average over depletion events that occur on the small scale – i.e. passes of the trawl net over a small area within the grid. The small-scale depletion process is governed by *d*, the depletion rate per tow. If B_n is the biomass in a small patch after *n* tows then:

$$B_{n+1} = (1-d)B_n \qquad (6)$$

This simply states that every tow removes the same proportion *d* of the available biomass, so the remaining biomass is reduced by a factor $(1-d)$. See **Figure 5** for an illustration of this model.

3.3.4. Conversion from small scale to large scale

As stated earlier, the large-scale depletion rate is derived from the small-scale depletion rate and the pattern of trawling. Estimates of the depletion rate per tow are available from the repeat-trawl experiment. However, we somehow have to model the pattern of trawling within a grid.

Trawling patterns fall into three classes: aggregated, uniform and random. Ag-

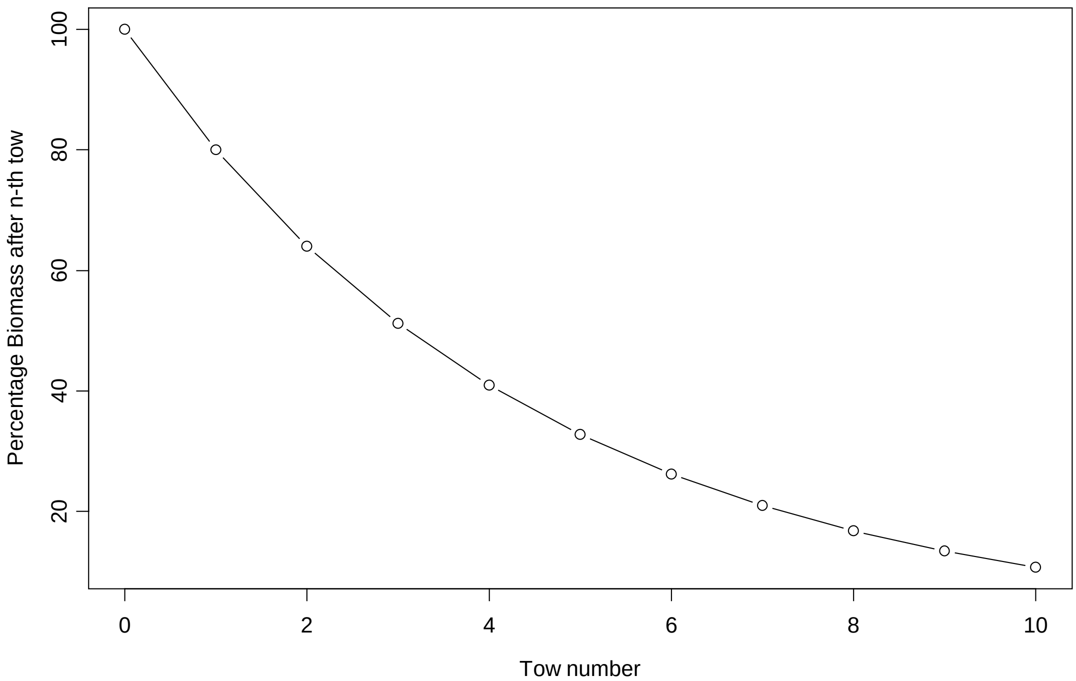


Figure 5. A simple model of depletion. The depletion rate per tow is 0.2.

gregated (or clustered) trawling corresponds to particular patches being targeted by multiple tows from one or more boats. Uniform trawling corresponds to patterns that avoid previously trawled ground; an extreme case is trawling in non-overlapping swathes, like a lawn mower. Random trawling is simply trawling at random without any pattern. Examples of the three classes are shown in **Figure 6**.

We have derived a way to model these classes by a family of distributions characterised by a single aggregation parameter β. If β is positive then we have aggregated trawling; if β is negative then we have uniform or regular trawling. Between these two extremes lies the case $\beta = 0$, which corresponds to random trawling. The three cases are described by the negative binomial ($\beta > 0$), binomial ($\beta < 0$), and Poisson ($\beta = 0$) distributions, respectively.

The nature of these distributions can be seen in **Figure 7**, where we show the histograms of coverage corresponding to the patterns of **Figure 6**. The random trawling histogram (*centre*) is almost exactly Poisson; the uniform case (*left*) is clearly binomial (with $N = 1$ and p slightly greater than ½); the aggregated case (*right*) is like the random case but with a larger variance, and it is reasonably well approximated by a negative binomial with β=1.24. We see that the aggregated case has considerably more zero counts and somewhat more high counts than the random case.

The relationship between the large-scale depletion rate, λ, and the small-scale depletion rate, d, is

$$\lambda = \begin{cases} \log(1+\beta d)/\beta & \beta \neq 0 \\ d & \beta = 0 \end{cases} \tag{7}$$

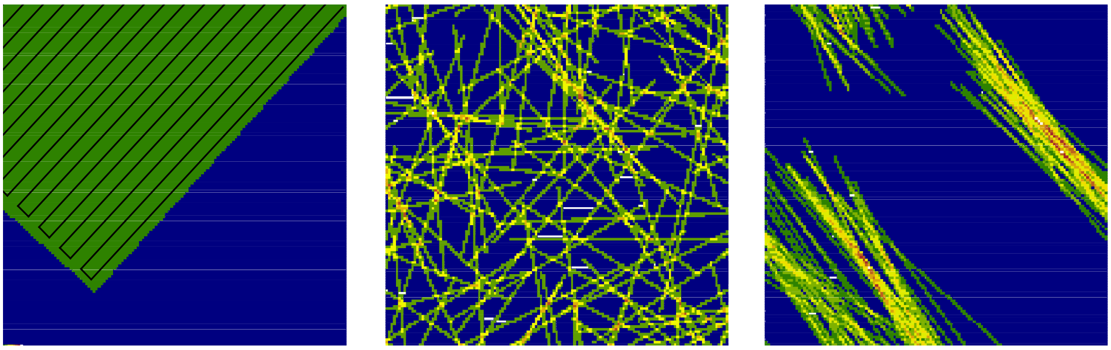


Figure 6. Simulated trawling patterns corresponding to (from left to right) uniform, random and aggregated trawling. Colour indicates number of times trawled (blue 0, green 1, etc). For colour key, see **Figure 7**. The total area swept is roughly half the area of the cell. In the uniform case we have overlaid some trawl tracks to clarify what is going on.

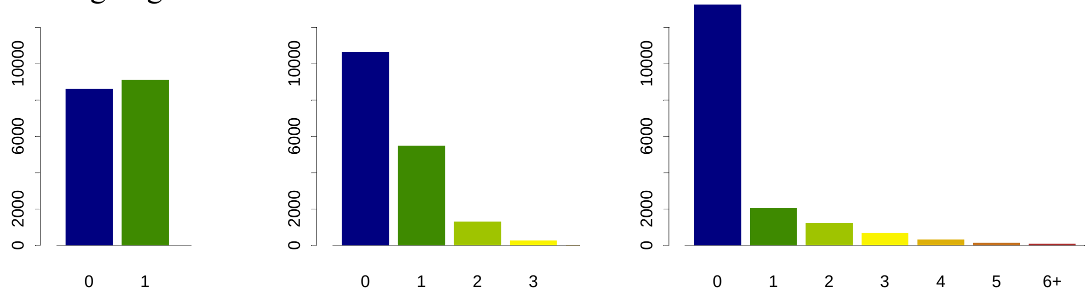


Figure 7. Histograms of trawl coverage for the (from left to right) uniform, random and aggregated trawling patterns of **Figure 6**. The colours in Figure 6 have been used here to paint the bars, and so this figure can be used as the colour key for Figure 6. The vertical axis is the number of pixels, of which there are 17,689 in total.

The parameter β provides the bridge between depletion on the small scale and depletion on the large scale. Remarkably, the two depletion rates, λ and *d*, are identical for random trawling. Aggregated trawling tends to reduce the large-scale depletion rate, whereas uniform trawling tends to increase it, as **Figure 8** shows. This is easy to understand since, in aggregated trawling, subsequent trawls over an area remove less than the first trawl, whereas, in uniform trawling, this effect of 'diminishing returns' is avoided because of the tendency to trawl previously untrawled areas.

It may seem counter-intuitive that λ should not equal *d* for the uniform case; after all, you may ask, is not a proportion *dE* of the benthos being removed per unit time? Yes, if by 'benthos', you mean the *initial* benthos. However, as time proceeds and the total benthos becomes depleted, the proportion of *existing* benthos removed per unit time steadily *increases*, even though the amount removed per unit time remains the same. Therefore λ, which is defined as the rate of change of biomass per unit effort rate *per unit biomass*, should be *greater* than *d*.

To consider the implications of **Figure 8**, suppose we have a sessile epibenthic species that is removed at the rate of 30% per tow. If trawling is aggregated, with β = 1.24, then the species is removed on the large scale at rate 26% per unit effort per year (see figure). For low depletion rates (10% in the figure), aggregation has only a small effect, since λ and *d* are almost the same.

3.3.5. Trawling patterns

The value of the aggregation parameter, β, describes the pattern of trawling. We have two approaches to estimating β: the first uses the vessel positioning data from the NPF; the second uses simulation from a trawling model.

VMS and GPS plotter data

We have two-hourly vessel positions from VMS data and exact vessel tracks from GPS plotter. Hall et al (1999) have coupled these two data sets in order to simulate the

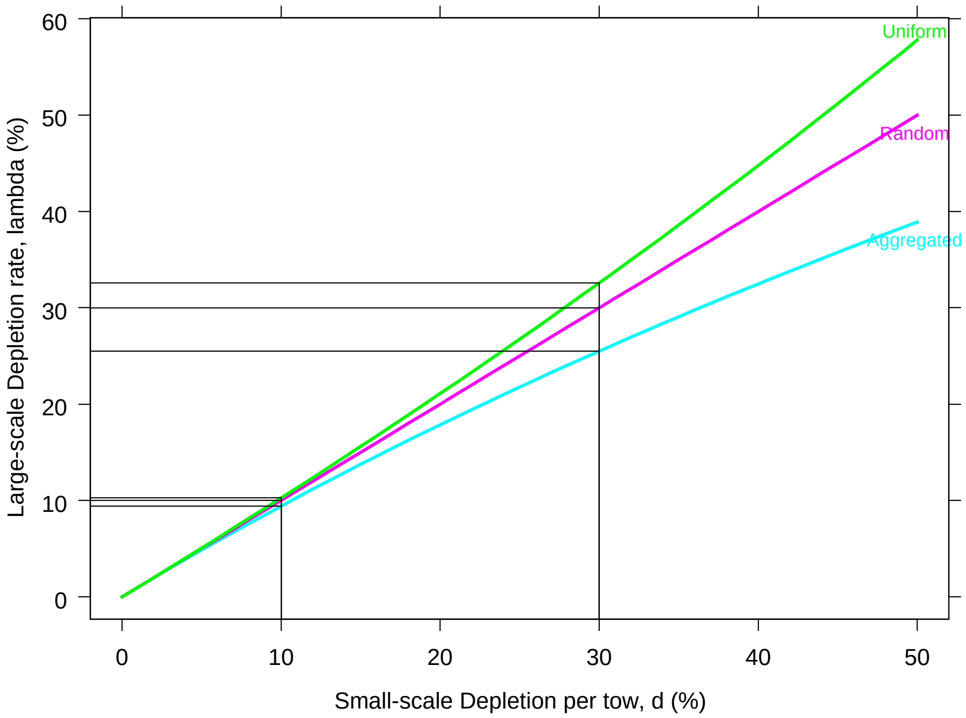


Figure 8. Large-scale vs small-scale depletion for the uniform, random and aggregated fishing patterns shown in Figure 6. The β values are –0.51, 0.00 and 1.24, respectively.

fine-scale pattern of trawling over an entire grid cell. From the resulting distribution of effort we can obtain the most appropriate aggregation model. Hall et al have found values of β roughly in the range 2–5 (see their Table 3 for values of P, which is their notation for β).

Trawl simulation

The second approach is through simulation of the trawling process. We can model a single trawl as a rectangular sweep across the seabed, whose position and orientation can be varied. We can simulate the reported number of boat days of effort by 'trawling' until a chosen level of effort (swept area) is reached. We can introduce aggregation by making multiple sweeps over the same patch, attributable to repeated tows by the same vessel or group of vessels. We can also control the amount of overlap in the multiple sweeps by specifying the size of the turning circle and the relative bearing of the return tow. We generated the trawling patterns in **Figure 6** using this approach.

3.4. Recovery

3.4.1. The small-scale recovery model

At the scale of the tow, i.e. on the order of metres, we assume that recovery follows a sigmoidal growth curve. An example is shown in **Figure 9**: if the biomass is depleted to, say, 5% capacity, then, in the absence of any further depletion, the biomass would take about 30 years to reach 50% capacity and a further 30 years to reach 95% capacity. The shape of the curve is governed by the small-scale recovery rate r_s, which in this case is 0.1 year^{-1}. The curve has maximum slope equal to ¼ r_s at the time when the biomass reaches 50% capacity. We do not distinguish between recovery through population growth (i.e. increase in number of individuals) and recovery through individual growth (i.e. increase in size). We assume that both forms of recovery can be subsumed in a single sigmoidal curve parameterised by r_s.

It may be helpful to interpret the recovery rate in terms of time scales. We can

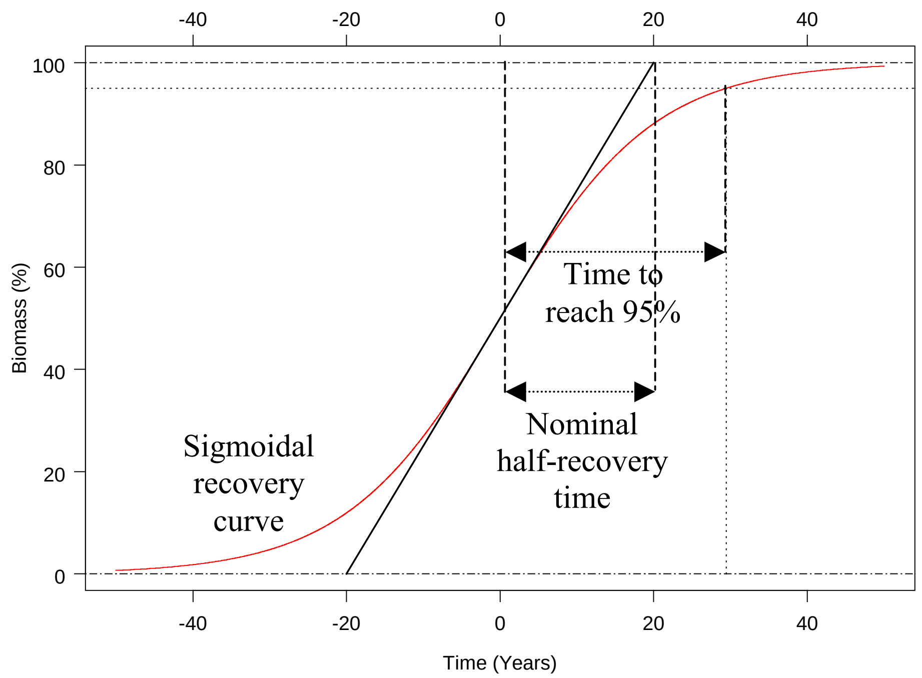


Figure 9. The sigmoidal recovery curve and illustration of the nominal recovery time and actual time to reach 95% recovery from 50% depletion. Here r_s = 0.1 year^{-1}.

regard $2/r_s$ as a *nominal* recovery time: it is the time the biomass would take to recover completely from 50% capacity if it kept on growing linearly at its maximum rate along the straight line in **Figure 9**. Alternatively, $3/r_s$ is the *actual* time taken for the biomass to recover from 50% to 95% capacity.

3.4.2. The large-scale recovery model

Consider now the recovery of the biomass over an entire grid. If the relative biomass in every small-scale patch within the grid were the same, then the total biomass would follow the sigmoidal recovery curve with parameter r_s. That is the large-scale recovery curve would be the same as the small-scale recovery curve. However, the relative biomass will more likely be different from one patch to the next, owing to differing amounts of depletion over each patch. In this case the total biomass will again approximately follow a sigmoidal curve, but now it will have a smaller recovery rate, r.

The fact that r is less than r_s arises from the concavity of biomass as a function of biomass at an earlier time. This fact is most easily understood for the case where the relative total biomass is 50%. The rate of change of relative total biomass is the average of the rates of change of relative biomass over all patches. In patches where the biomass is 50% the rate of change of relative biomass is at the maximum, $\frac{1}{4} r_s$. But, for patches with relative biomass either less than or greater than 50%, the rate of change of relative biomass is *less than* the maximum. Therefore the rate of change of relative total biomass is less than $\frac{1}{4} r_s$, and so r must be less than r_s.

The amount by which r is less than r_s depends on the variance of relative biomass among small-scale patches. Indeed, if b is the mean relative biomass (i.e. the large-scale relative biomass) and the variance is $\phi b(1 - b)$, then $r = r_s(1 - \phi)$. The quantity ϕ, which lies between 0 and 1, depends on the details of the small-scale history of trawling within the grid. In *Part Two: Technical Report* we show how to approximate ϕ with a constant.

The upshot is that the large-scale recovery r is approximately related to the small-scale recovery r_s as follows

$$r = r_s(1 - \tfrac{1}{2} d)\lambda/d \tag{8}$$

It is this recovery rate that is used in the differential equation (1). Note that, in the absence of depletion, $r = r_s$, but when depletion is present the recovery is reduced by a factor $1-\tfrac{1}{2} d$. The effect of aggregation is to further reduce the recovery by a factor λ/d. See *Part Two: Technical Report* for further details on the derivation of this formula.

4. Availability of data

Two forms of data are available: commercial fisheries data and scientific survey data.

The commercial fisheries data consists of catch and effort data per species. These come from two sources: the Queensland East Coast Trawl Fishery (QECTF) and the Fisheries and Agriculture Organisation (FAO).

The scientific data come from publications and research in progress. The main source is the report *Environmental Effects of Prawn Trawling in the Far Northern Section of the Great Barrier Reef: 1991–1996* by Poiner et al (1998). The report contains the best information to date on depletion rates. It also contains environmental and ecological survey data for the Great Barrier Reef area. A second source is the report from the follow-up project *Recovery Monitoring in the Great Barrier Reef* by Pitcher et al (in preparation). This provides information on recovery rates. Sainsbury et al's (1997) paper also gives some information on recovery rates of larger epibenthos.

We describe the data in order of decreasing availability, namely: effort, depletion, recovery and biomass.

4.1. Description of the Fisheries

We describe the effort data in order of decreasing precision, namely: vessel positioning, logbooks, landings and Australia-wide catch data from the FAO.

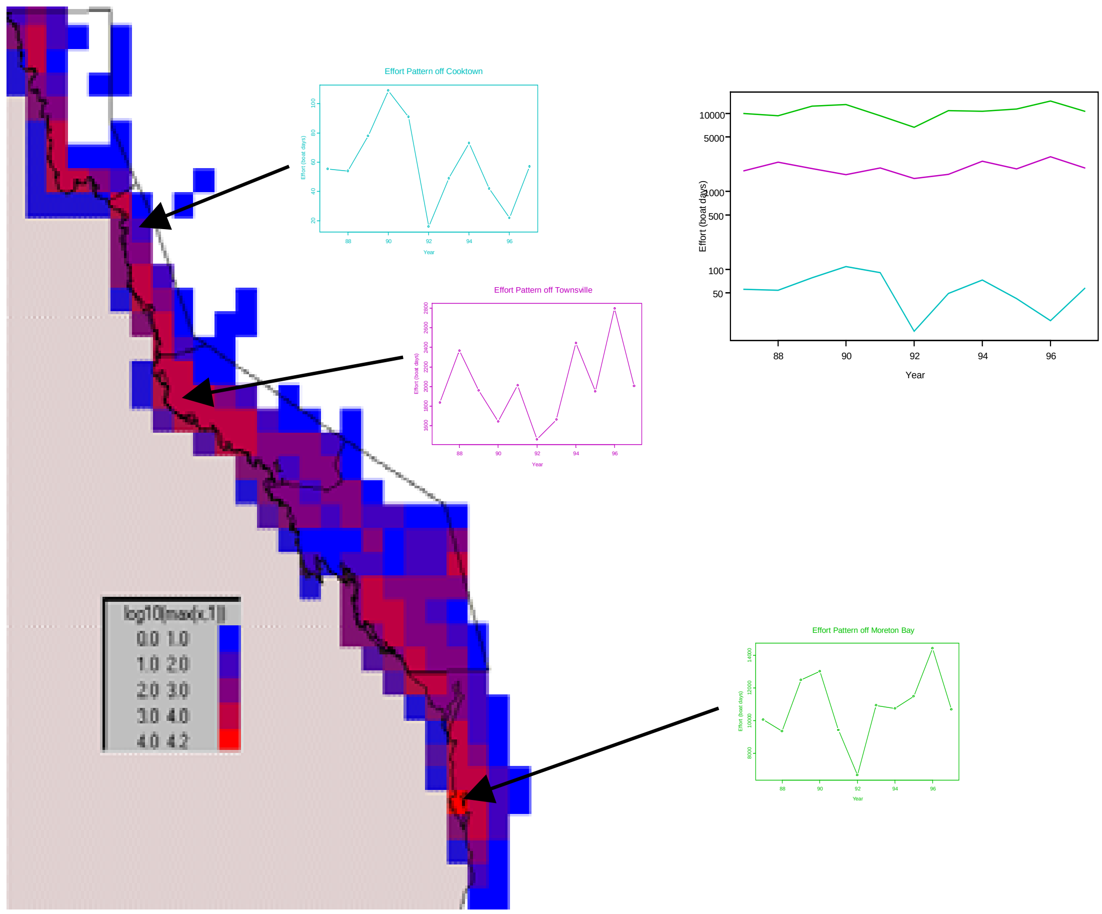


Figure 10. Effort in the Queensland East Coast Fishery for 1996 at 30-minute level. Also shown are patterns of effort for selected grids for period 1988–97.

4.1.1. Vessel positioning data

Vessel monitoring systems (VMS) have been in operation in the QECTF since the end of 1998. There has also been a pilot scheme comprising a subset of about 10 vessels in the north east part of the fishery.

We have access to a small vessel positioning data set in the NPF, which exists at two levels of precision. At the coarse scale we have two hourly *VMS positions* for the entire fleet for two months in the Tiger season in 1998. And at the fine scale we have *Geographic Positioning System (GPS) plotter positions* for about 2% of the boat days. These data are used to find representative patterns of trawling.

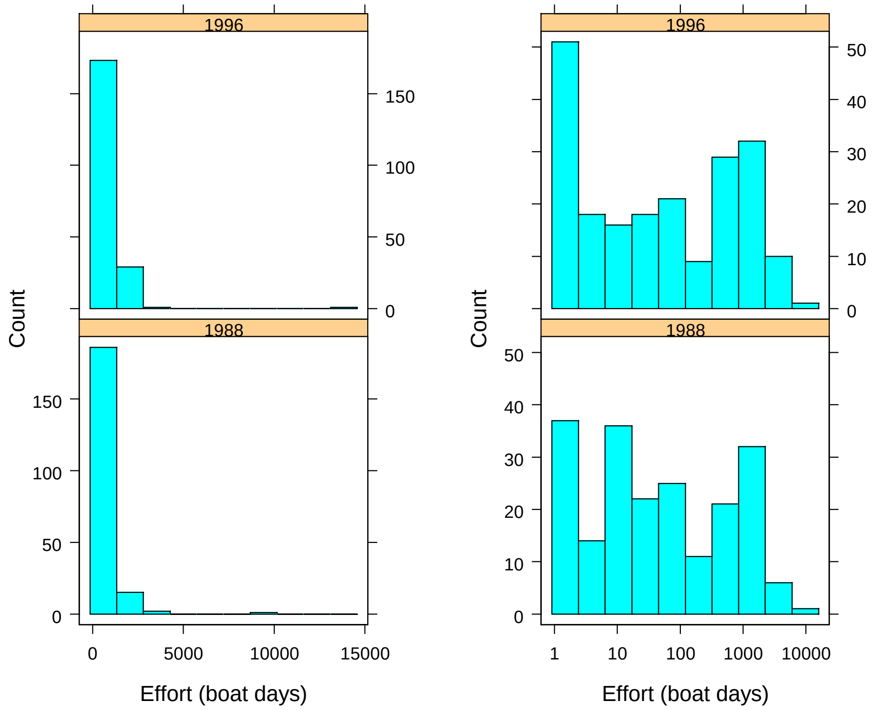


Figure 11. Distribution of effort and log effort for 1988 and 1996 in the Queensland East Coast Fishery.

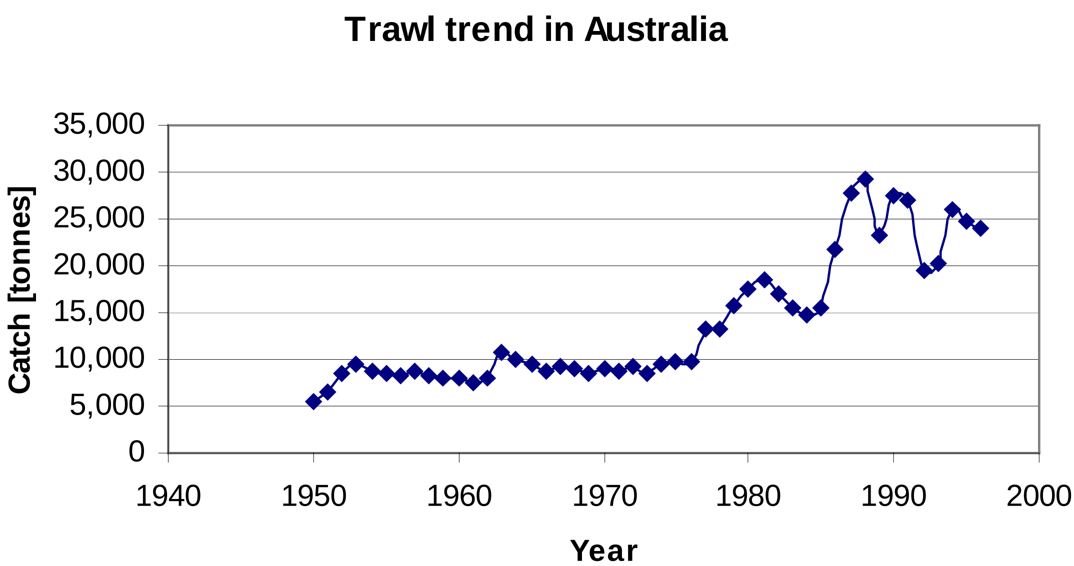


Figure 12. Total catch for all Australian fisheries for 1950–1997 (source: FAO).

4.1.2. Logbook data

We have information on fishing effort from logbooks in the QECTF. Fishers report catch, date and location either on a shot-by-shot basis or aggregated over the fishing days. Effort information obtained from logbooks is generally less accurate than vessel positioning information, especially when the record is an aggregate over a day.

The reliability of logbook data are summarised in two quantities: the *compliance rate*, which is the proportion of effort actually reported; and the *precision rate*, which is the proportion of reported effort recorded at 6' precision or better.

The QECTF logbooks date back to 1988. We do not know the compliance rate. The precision rate was low before 1992; but since 1992 it has risen from 22% to 46%.

Figure 10 shows effort in this fishery for 1996 at 30-minute precision. The spatial distribution of effort is patchy and, in fact, these patches are quite persistent over time. Moreton Bay is very highly trawled with levels around 10,000 boat days per 30-minute grid. (A 30-minute grid is a square region 56 km on the side of area 3,000 km^2.) A large number of grids have about 1000 boat-days of effort and most of the remainder have between 1 and 100 boat days (**Figure 11**). Because the distribution of effort is highly skewed (left-hand figures), we also show the distribution on the log scale (right-hand figures). There is considerable variation across grids.

The logbooks are the main source of information on which the modelling is based.

4.1.3. FAO data

The FAO has recorded catches in all Australian fisheries since 1950 (**Figure 12**). We have used these data to predict effort in both the QECTF and the NPF in the early years of the fisheries. Such prediction is based on these assumptions:

1. total Australian annual catch is proportional to total Australian annual effort, and
2. effort in the fishery is proportional to total Australian annual effort.

4.2. Depletion

4.2.1. The GBR repeat-trawl experiment

CSIRO Marine Research has conducted a repeat-trawl experiment to measure the effects of trawling on the removal of benthic biota in the northern part of the Great Barrier Reef Marine Park (GRBMP). The researchers selected 6 tracks, each 3 km long, from an area of the lagoon closed to commercial trawling. They trawled each track up to 13 times, making sure the same ground was covered each time. For each tow, they recorded the weight of benthic biota brought up in the net. They grouped the biota into broad families. By analysing the change in weights over the sequence of tows, they estimated the depletion rate per tow for a selected set of taxonomic units of benthic organisms. The results from this experiment indicate that depletion rates per tow for sessile benthos (after correction for estimation bias) range from 7±4% for hydrozoans to 32±7% for gorgonians. The experiment and results are reported in Poiner et al (1998). We base the simulation ranges for depletion rates in our modelling on the outcomes from this experiment.

4.3. Recovery

4.3.1. Sainsbury et al's results

Between 1986 and 1990, CSIRO ran an experiment on the North West Shelf, in which a previously trawled area was closed off and monitored annually. The scientists were interested primarily in two commercial fish species, but they also measured the proportion of seabed covered by epibenthos. They grouped the benthos into two classes: small size (< 25 cm) and large size (> 25 cm). They found that the proportion of seabed covered by small benthos rose by about 7% per year; the proportion covered by large benthos stayed about the same within the duration of the study. The research was published by Sainsbury et al (1997).

4.3.2. The GBR recovery monitoring project

CSIRO Marine Research is conducting a follow-up study of the areas that were used in the repeat-trawl experiment. The project sets out to monitor the recovery of the benthic communities in the absence of further trawling. The areas have been visited 1 and 2 years after the repeat-trawl experiment, and a final time point will be sampled at 4 years. The researchers make non-destructive measurements of the benthos by means of a video camera mounted either on a sled or on a remotely operated vehicle (ROV). From the video data they measure the areal density of the benthos and the size of some individual organisms. By comparing measurements at different time points, the researchers plan to estimate growth rates for individual organisms and recruitment rates of benthic organisms to the depleted areas. The project will deliver in July 2001.

4.4. Benthic Biomass

This is the component of the study that we know least about. We have detailed information from the GBR survey (Poiner et al, 1998), but this is based on a relatively small area of the study region in the far north.

4.4.1. Environmental surrogates

In 1991–92 CSIRO conducted a survey in the northern part of the Great Barrier Reef Marine Park (Poiner et al, 1998). The study region was the rectangular area of about 20,000 km^2 between 11°S and 12°S and between the coast and longitude 144.25°E. Running in a band across the region was the cross-shelf closure, an area closed to all trawling. The scientists chose 150 representative sites within the study region, from areas both within and outside the closure and at different cross-shelf positions. At these sites, they sampled the benthos with a benthic dredge and the sediment with a sediment grab.

5. Results from the model

We divide the results into two sections: sensitivity analysis, with emphasis on sensitivity to the vulnerability parameters *r* and *d*, and management scenario evaluation, where we concentrate on the practicalities of scenario evaluation for the Queensland trawl fishery.

In the sensitivity analysis, we run simulations on the historical and logbook data only, without specifying scenarios or projecting effort into the future. The simulations are run for grid of values for *r* and *d*. We show the sensitivity of various indicators to *r* and *d* by evaluating them on this grid. A very important case is that of constant effort. This case helps greatly in understanding how the differential equations behave, and so we discuss it first.

In the scenario evaluation example, we introduce some realistic management scenarios. We then describe how to evaluate and compare them using a top-down approach based on decision tables and comparative indicators. We also address the issue of choice of indicator, and how drilling down to the details can help.

5.1. Sensitivity analysis

5.1.1. Steady state for constant effort

If effort, depletion rate and recovery rate remain constant, then the benthic relative biomass tends to a steady state. Some examples are shown in **Figure 13**. Initially the relative biomass declines at a rate given by the depletion rate (5% or 20%). Eventually the relative biomass settles down to a constant (denoted by dashed lines) that is smaller the slower the recovery, and may even be zero. The steady-state relative biomass b_{ss} is given by a very simple equation:

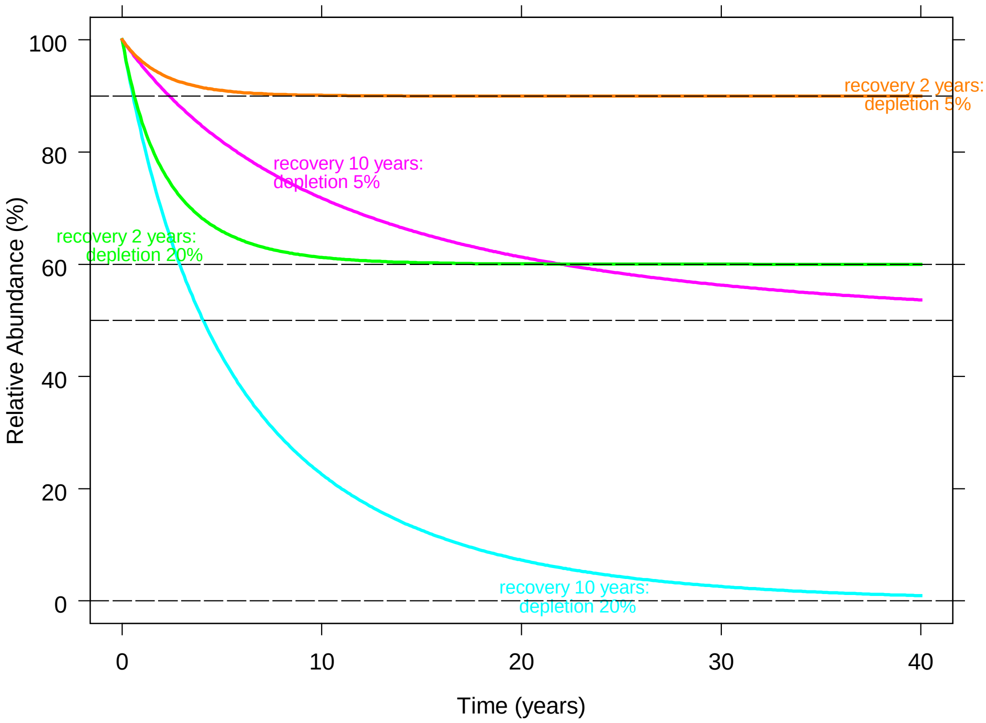


Figure 13. Relative biomass vs time for unit effort per year under constant depletion (λ = 0.05 and 0.2) and recovery (r = 0.1 and 0.5). Corresponding recovery time scales ($1/r$) are 10 and 2 years, respectively.

$$b_{ss} = \begin{cases} 1-\lambda E/r & r > \lambda E \\ 0 & r \le \lambda E \end{cases} \tag{9}$$

If the recovery rate exceeds the long-term depletion rate then the population survives at a reduced level. However if the long-term depletion rate exceeds the recovery rate, the population dies out, as in the slow-recovery, high-depletion case in **Figure 13**.

The steady-state relation is illustrated in **Figure 14**. We see that increasing any of depletion, effort or recovery time scale reduces the steady-state biomass. Also, for given recovery rate and effort, there is a critical depletion rate beyond which the population dies out.

5.1.2. Extreme aggregation: two-stage models

The result that biomass can be completely removed by sufficiently heavy trawling seems reasonable; but what if the trawling is so highly aggregated that it is confined to a single track? The biomass surely cannot be affected outside the track, so the conclusion that biomass goes to zero, even for heavy trawling, must be false. What has gone wrong?

The problem is that this extreme pattern of aggregation is not adequately described by the negative binomial distribution. Such patterns, where trawling is restricted to particular areas within the grid, are better described by a two-stage model. In the first stage the areas are selected for trawling, and in the second stage trawling is carried out within those areas with aggregation parameter β. See *More complicated patterns: the two-stage model* under section 2.2 of *Part Two: Technical Report*. In the case of a grid where only a proportion p is subject to trawling, the steady state relative biomass is given instead by

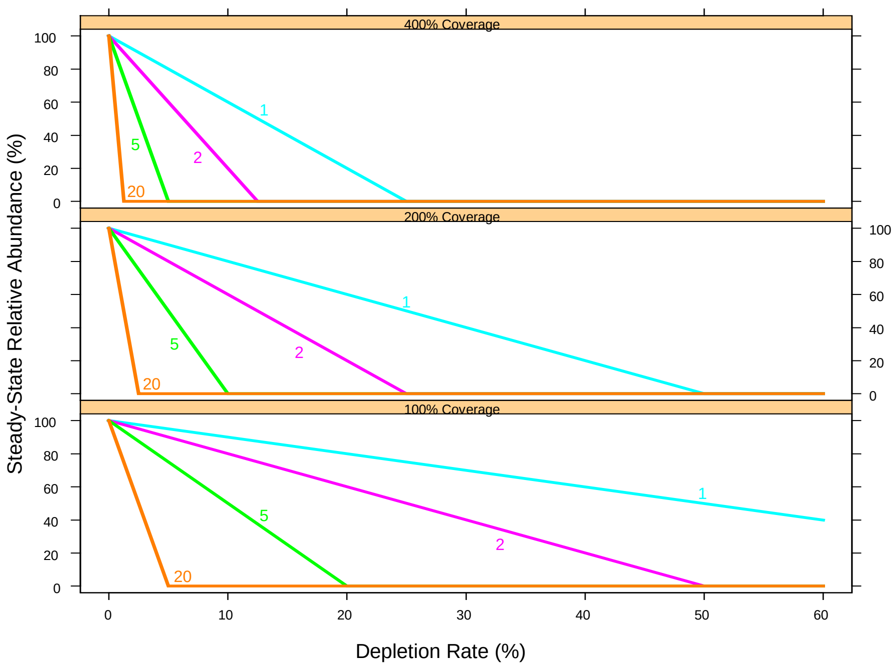


Figure 14. Steady-state relative biomass vs depletion rate for various recovery rates (labelled as recovery time=$1/r$) and different levels of effort (100%, 200% and 400% coverage). The depletion rate at which extinction will occur is $1/rE$.

$$b_{ss} = \begin{cases} 1-\lambda E/r & \lambda E/r < p \\ 1-p & \lambda E/r \geq p \end{cases} \tag{10}$$

In this case, only a proportion p of the biomass can be completely removed.

We have not run any simulations using this two-stage model. There are two sources of information whose availability would justify using the two-stage model: sub-grid management boundaries and VMS data.

Given locations of management boundaries that subdivide a grid, it would be straightforward to compute the proportion p of grid available to trawling. Such information is indeed available; however, the adjustment would have a small effect on the results of simulations, mainly because boundaries tend to be on lightly trawled grids.

The more important source of information would be VMS data. It is conceivable that trawling in some grids is so aggregated that a two-stage model is required. In that case, VMS data would be needed to drive the model. Such information, though not available historically may become available in the future. In fact the QFS began

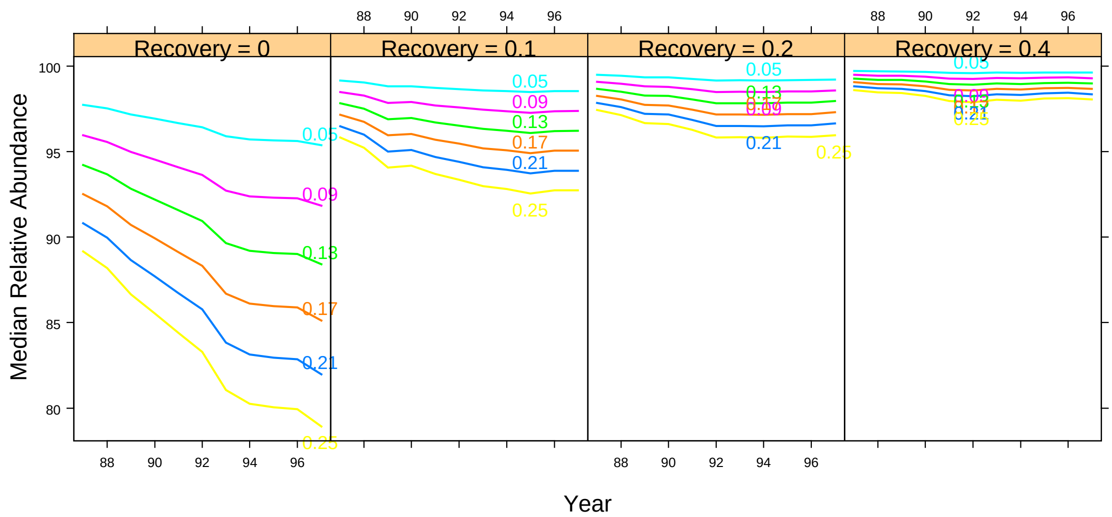


Figure 15. Median relative biomass vs year over 30' grids of the QECTF for various values of depletion and recovery. Lines are labelled by large-scale depletion, λ, and each panel denotes a different value of large-scale recovery, *r*.

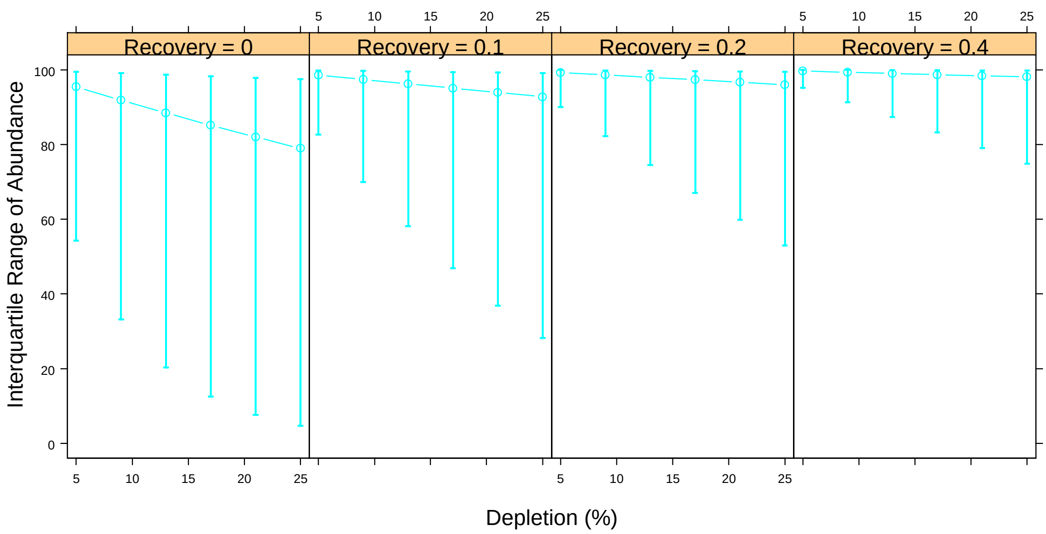


Figure 16. Median and interquartile range of relative biomass over 30' grids of the QECTF in 1997 for various values of depletion and recovery.

hourly polling of the fleet from January 2001. In the longer term, onboard gear monitors, if introduced, may complement the information collected with VMS. In any case, it usually happens that, the finer the scale of information on which a model is based, the smaller the overall impact the model predicts.

5.1.3. Sensitivity to *r* and *d* for Queensland East Coast Trawl Fishery data

We have run the depletion-recovery model on the 30' effort data for the QECTF. We used the backward extrapolated effort back to 1950 as described in *Extrapolation from historical FAO data*. We also simulated a range of large-scale depletion and recovery values.

Figure 15 shows how the median relative biomass changes over the recorded years. (We prefer the median rather than the mean because the distribution of relative biomass is highly skewed; recall from **Figure 11** that effort is highly skewed.) All the

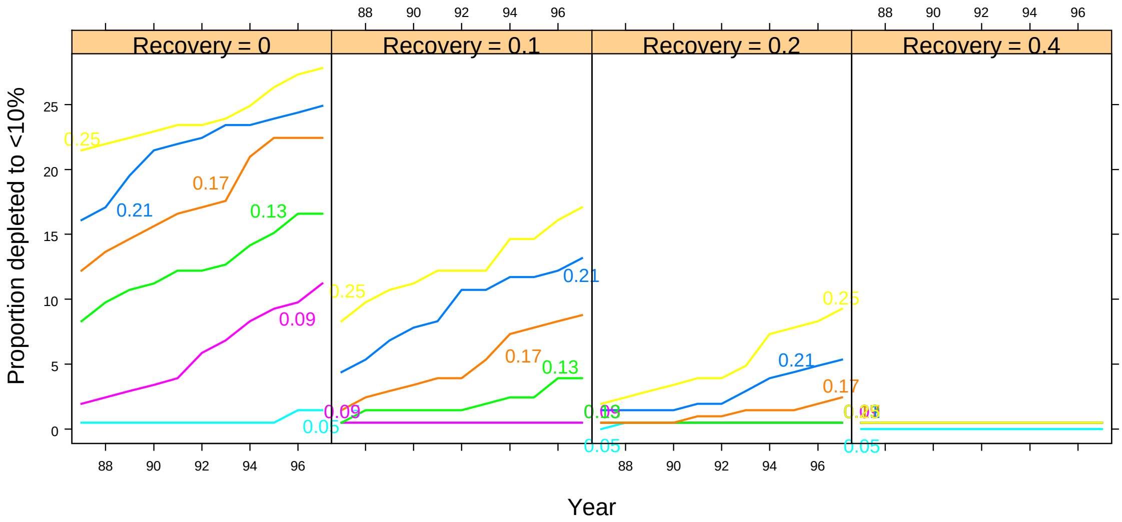


Figure 17. Proportion of 30' grids of the QECTF that have been depleted to 10% or less of their initial pristine state for various values of depletion and recovery. Lines are labelled by large-scale depletion, λ, and each panel denotes a different value of recovery.

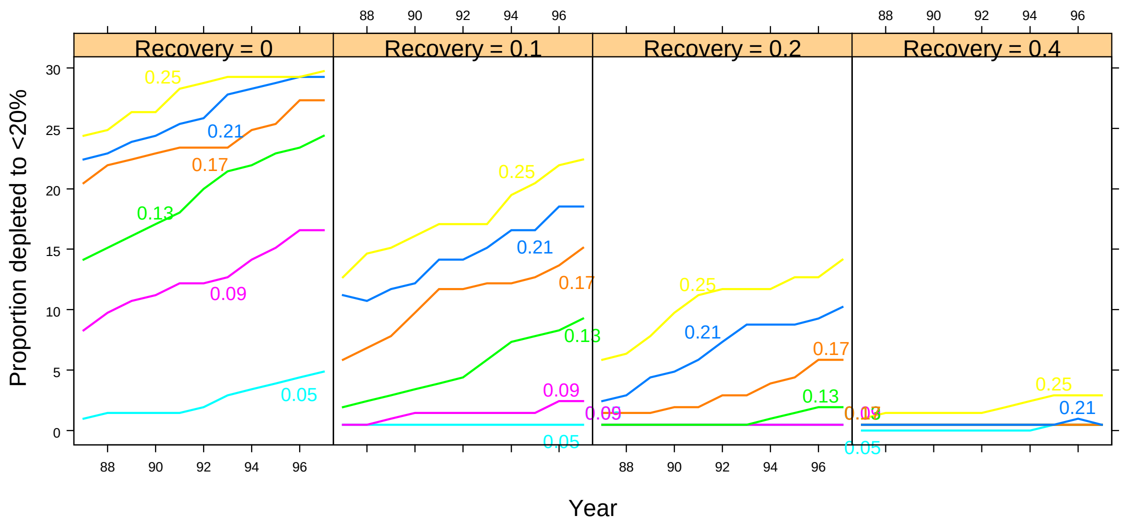


Figure 18. Proportion of 30' grids of the QECTF that have been depleted to 20% or less of their initial pristine state for various values of depletion and recovery. Lines are labelled by large-scale depletion, λ, and each panel denotes a different value of recovery.

curves show a decline that is steeper for higher depletion rate, as expected. The rate of decline slows down, and some curves for higher recovery even appear to level out, suggesting approach to a steady state (corresponding roughly to the mean effort over years for the median grid—see equation (9)). The fluctuations are due to variation in overall effort from year to year. The median effort is about 40 boat days or 2.5% coverage. The median biomass corresponds *approximately* to simulation with effort fixed at the median value.

5.1.4. The long-term effect of trawling

The long-term effect of trawling on the relative biomass is shown in **Figure 16**. Here we see the median biomass for the final year only (1997), for a range of depletion and recovery rates. Also shown are 'whiskers' denoting the 25th and 75th percentiles of biomass. The skewness of the biomass distribution is evident.

The effect of *median* level trawling is to reduce the biomass to 80% in the worst case we consider ($r = 0$, $\lambda = 25\%$). This mild effect is because the median effort is rather low (2.5%). However, there are grids where the effect is much more severe. For instance, for 25% depletion rate and 10-year recovery time scale ($r = 0.1$), 25% of grids have biomass less than 30%.

Figure 16 is closely related to the sensitivity analysis plot (**Figure 14**). The bottom panel of Figure 14 is for unit effort or 1650 boat days. We can see from the distribution of effort (**Figure 11**) that 1650 boat days lies roughly around the 80th percentile of the distribution. So the severity of impacts (including extinction) in Figure 14 applies to about 20% of grid cells. In Moreton Bay, the most heavily trawled grid, effort is around 800%, twice the level of the worst case in Figure 14.

Figure 17 and **Figure 18** show the proportion of 30' grids that have been depleted to less than 10% and 20% respectively of their pristine state. This proportion is plotted against year for various levels of depletion and recovery. For low depletion (5%) there is at most one grid depleted to 20% or less, except for the case of zero recovery, when more grids are depleted. However for higher levels of depletion the proportion of depleted grids increases almost linearly with time.

5.2. Management scenarios: an example from the Queensland East Coast Trawl fishery

In this section we show how scenario modelling can be used in practice in the evaluation of management scenarios. We explain how management scenarios can be compared by using a top-down approach. This approach allows us to make broad comparisons at the top level, but also allows us to ‘drill down’ into the data in order to further understand the results. We show the process in action on real data using real scenarios provided to us by GBRMPA. The results, first presented at the second steering committee meeting, are repeated here.

5.2.1. Management scenario evaluation

Management scenario evaluation in general uses models of the real world, based on best knowledge and data to compare the outcomes of different management strategies based on indicators that describe the status of the system under consideration. The evaluation of management scenarios will typically involve a large number of model outputs that have to be condensed into comprehensive descriptions of the available options.

One of the problems associated with understanding the outputs of management scenario evaluation is the number explosion. Suppose we have a spatio-temporal model with: 1500 six-minute grid cells, 25 years of simulation, 3 scenarios with 1 management level each, 9 vulnerability classes and 2 indicators (mean relative biomass and pristine area). Such a model would result in an output of around 2,025,000 numbers. Add 20 stochastic simulations and we have 40 million numbers. Add 5 management levels and we have 200 million numbers.

5.2.2. Decision tables and the top-down approach

To keep 200 million numbers organised, a *top-down* approach is advisable. This approach runs along the following lines. First, find 'efficient' indicators that describe what you are interested in. This is challenging; stakeholder involvement is central in this process. Second, arrange these indicators and the management strategies to form a matrix or *decision table*. Third, fill that decision table with the outcomes of your scenario runs and make pair-wise comparisons. At all costs avoid looking at all 200 million numbers!

Our example from the Queensland fishery has the following dimensions:

- About 1500 six-minute grid cells
- 6 vulnerability classes formed by combinations of r (0.1, 2) and d (0.01, 0.2, 0.4)
- 2 scenarios with only one level of management in each
- 3 indicators: median remaining relative biomass, number of grids with < 20% initial biomass and median pristine area, all at end of simulation in 2005
- 2 biomass models to contrast: a spatially homogeneous initial relative biomass and forced spatial distributions of relative biomass.
- No stochastic runs

The 2 scenarios, effort reduction and marine protected areas, and the status quo scenario were specified as follows

Status quo

We assume here that the total effort remains at the level in 1996. There are no closures except the green and blue zones currently in place. The logbook data does actually include a small amount of effort in these zones. Therefore we impose these closed zones explicitly to prevent the model from putting any effort into them (otherwise it may sample from one of the years when they were trawled).

Because we do not have data for the years 1998–2000, which are (mostly) already in the past, we use the 'status quo' scenario to predict for these years, even for the two management scenarios below.

Premier's working group

Effort in 2000 is capped at the 1996 level; thereafter it is reduced by 5% each year until 2005. The same green and blue zones are used as in the 'status quo' scenario.

Marine protected areas

This is the same as the 'status quo' scenario, except that certain marine protected areas (MPAs) are also closed. Because the model works on a 6 minute grid, this actually means that only grids whose *centroid* lies within the MPA are closed; grids that intersect but whose centroid lies outside the MPA remain open. This compromise is a consequence of the resolution of the grid, which arises from the resolution of the log book data. The closed areas are shown at right in **Figure 19**.

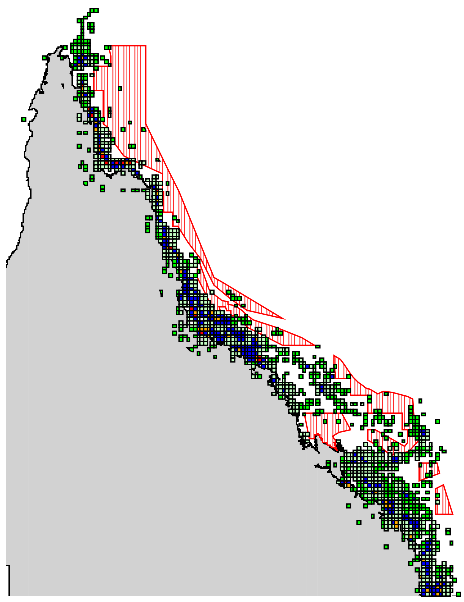


Figure 19. Closures (*in red*) for the marine protected area scenario.

5.2.3. Choice of indicator

Management scenarios are compared relative to a ‘status quo’ scenario by expressing indicators in terms of a percentage change between the management action to be evaluated and the status quo. For instance, suppose the two scenarios result in the raw indicator given in the following table:

Management action	% of grids fished to less than 20% initial biomass B_0
status quo	10%
Premier’s working group	8%

Then the indicator for this management scenario would be –0.2, which is the change in the underlying raw indicator relative to the status quo, i.e. (8–10)/10.
The benefit of using such a relative indicator two-fold: first, it avoids difficulty in trying to interpret the underlying indicator; and second, it reduces the sensitivity of the outputs to assumptions made in the modelling.

5.2.4. Model output

The decision table is shown in **Table 2**. We see it contains the 3 indicators and 2 management scenarios. Inside each cell of the table is a 2-by-3 array of the relative indicator for each of the 6 vulnerability classes. If the indicator is positive, then the management action has a conservative effect (except for the second indicator, where a *negative* value indicates a conservative effect). It is clear therefore that the effort reduction scenario is more effective than the MPA scenario with respect to conservation.

Notice that the indicator for pristine area does not depend on the vulnerability class; it depends only on the overall level of effort and the pattern of trawling. Since the overall level of effort is less for the first scenario, the amount of pristine area is conquently greater.

It is often of interest to ‘drill down’ into more detailed data in order to see why a particular indicator has the value it does. We illustrate this in **Figure 20** for the 3 highlighted cells in **Table 2**. The underlying indicator is the median relative biomass. Looking inside the data base, we see the values are 0.964, 0.446 and 0.173 for depletion values 0.01, 0.2 and 0.4. We can see how these values arise by looking at the hist-

Indic \ Scenario	5% annual effort decrease over 5 yrs				MPA			
		depl				depl		
	recover	0.01	0.2	0.4	recover	0.01	0.2	0.4
Change median remaining biomass	0.1	0.28	6.25	8.47	0.1	0.03	0.86	-0.16
	2.	0.05	0.96	1.94	2	0.01	0.12	0.24
		depl				depl		
	recover	0.01	0.2	0.4	recover	0.01	0.2	0.4
Change of # of grids with B0 <20%	0.1	N/A	-2.77	-1.31	0.1	N/A	0	-0.52
	2.	N/A	-50.	-45.45	2	N/A	0	9.09
		depl				depl		
	recover	0.01	0.2	0.4	recover	0.01	0.2	0.4
Change Median Pristine Area	0.1	20.44	20.44	20.44	0.1	2.8	2.8	2.8
	2.	20.44	20.44	20.44	2	2.8	2.8	2.8

Table 2. Decision table for indicators at end of 2005. The indicator is the percentage change of the underlying indicator (median relative biomass, etc) relative to the status quo scenario. N/A implies the indicator was 0 for the status quo.

ograms of relative biomass. For two of the cases the distribution is distinctly bimodal, that is most of the grids are either severely depleted or hardly depleted at all. This observation might lead us to reappraise the usefulness of the indicator and look around for alternatives. One alternative is the proportion of grids depleted to less than 20% initial biomass, which we have already included.

A further way of seeing the detail is to draw a map, as we show in **Figure 21**. Here we have plotted the relative biomass for each of the 3 highlighted cases. The biomass pattern is strongly negatively correlated with the effort pattern. Each grid has its own history, and we show this in the time plots underneath the maps. This shows how rapidly the biomass is decreasing in time and how the introduction of a manage-

recover	depletion	med. Biomass Status Quo	med. Biomass	% change med biomass	# grd< 0.2 B0 Status quo	# grd< 0.2 B0	% change # grd<20% B0	med % prist area Status quo	med % prist area
0.1	0.01	0.964	0.967	0.280	0.0000	0.0000	N/A	0.0042	0.005
0.1	0.2	0.446	0.474	6.250	0.3658	0.3556	-2.77	0.0042	0.005
0.1	0.4	0.173	0.187	8.470	0.5159	0.5091	-1.31	0.0042	0.005
2	0.01	0.998	0.998	0.050	0.0000	0.0000	N/A	0.0042	0.005
2	0.2	0.959	0.968	0.960	0.0014	0.0007	-50.00	0.0042	0.005
2	0.4	0.918	0.936	1.940	0.0074	0.0041	-45.45	0.0042	0.005

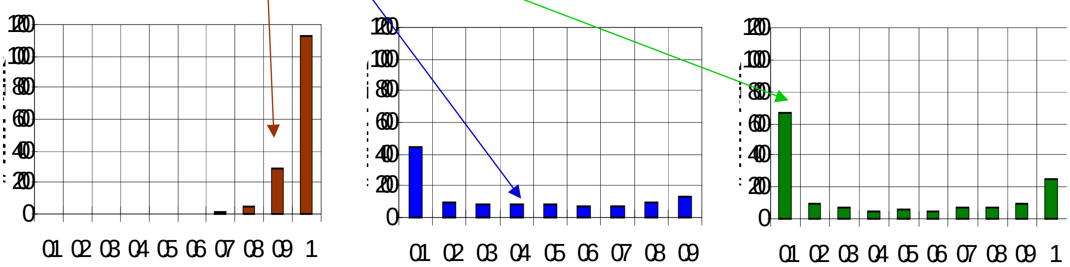


Figure 20. A look at the some of the underlying detail on which the decision table is based. The highlighted entries are the same as those in the decision table. The actual indicator value (median relative biomass) for each scenario is shown, as well as the histograms of relative biomass for the status quo, from which the median has been extracted.

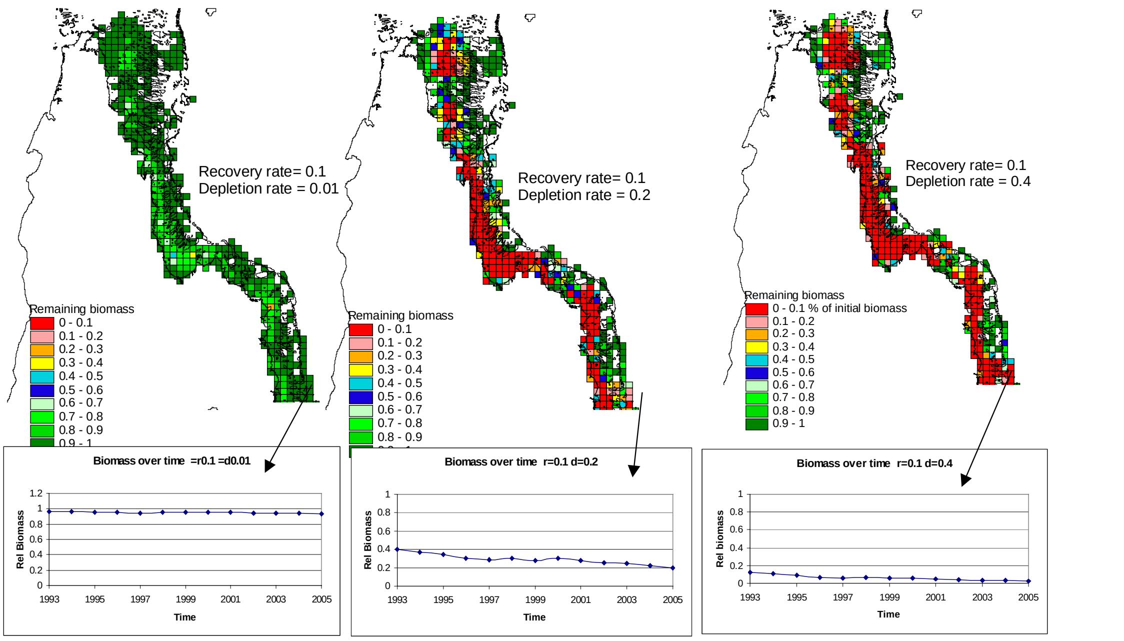


Figure 21. Maps of relative biomass for the three highlighted cases in the decision table ($r = 0.1$, $d = 0.01, 0.2, 0.4$). The results are for status quo scenario in 2005. Also shown are time histories of the relative biomass in a particular grid cell between 1993 and 2005.

ment action checks this trend.

We show some more examples of the kinds of output that can be obtained from scenario modelling in Appendix 5.

5.2.5. Carrying capacity models

A further dimension in the modelling is the choice of carrying capacity *K*. The results we have looked at so far are for homogeneous carrying capacity. We can look at results for which the carrying capacity varies spatially. **Table 3** shows the decision table for two models: (1) *K* is proportional to percentage mud in the sediment (mud+); and (2) *K* is proportional to percentage *not* mud in the sediment (mud–). See also *Carrying capacity models* in Appendix 4. In this case the indicator is the relative change in the median *spatially* relative biomass.

We do not show entries for the other two indicators because they are the same as before. The proportion of grids depleted to <20% initial biomass depends only the relative biomass, not the spatially relative biomass, and the pristine area is independent of the biomass.

Once again the effort reduction scenario is more effective in conservation than the MPA scenario. This trend is also seen for other carrying capacity models.

5.2.6. Summary

All three indicators show the same trend for all vulnerability groups in comparing effort capping scenario with the MPA scenario:

- median relative biomass *increases*
- proportion of grid cells < 20% B_0 *decreases*
- median pristine area *increases*

These trends are consistent with outcomes from other carrying capacity models.

Some conclusions regarding indicators:

- median relative biomass *will change* with change of carrying capacity model, recovery and depletion and management strategy,
- number of grids < 20% B_0 is sensitive to changes in recovery and depletion rates; it is *not affected* by different carrying capacity models,
- change in median pristine area (without recovery) is *not affected* by carrying capacity models but can be affected by management strategies.

Decision tables

<table>
<tr><th>Scenario / Indic</th><th>5% annual effort decrease over 5 yrs</th><th>MPA</th></tr>
<tr><td>Change Median Remaining Biomass mud+</td>
<td><table>
<tr><td></td><td>depl</td><td></td><td></td></tr>
<tr><td>recover</td><td>0.01</td><td>0.2</td><td>0.4</td></tr>
<tr><td>0.1</td><td>0</td><td>1.39</td><td>10.6</td></tr>
<tr><td>2</td><td>1.42</td><td>0</td><td>0</td></tr>
</table></td>
<td><table>
<tr><td></td><td>depl</td><td></td><td></td></tr>
<tr><td>recover</td><td>0.01</td><td>0.2</td><td>0.4</td></tr>
<tr><td>0.1</td><td>0.02</td><td>1.25</td><td>3.06</td></tr>
<tr><td>2</td><td>-0.08</td><td>0</td><td>0</td></tr>
</table></td></tr>
<tr><td>Change Median Remaining Biomass mud-</td>
<td><table>
<tr><td></td><td>depl</td><td></td><td></td></tr>
<tr><td>recover</td><td>0.01</td><td>0.2</td><td>0.4</td></tr>
<tr><td>0.1</td><td>0</td><td>4.46</td><td>7.88</td></tr>
<tr><td>2</td><td>0</td><td>0</td><td>3.08</td></tr>
</table></td>
<td><table>
<tr><td></td><td>depl</td><td></td><td></td></tr>
<tr><td>recover</td><td>0.01</td><td>0.2</td><td>0.4</td></tr>
<tr><td>0.1</td><td>0</td><td>0.93</td><td>2.61</td></tr>
<tr><td>2</td><td>0</td><td>0</td><td>-0.23</td></tr>
</table></td></tr>
</table>

Table 3. Decision table for two carrying capacity models (mud+ and mud–) at end of 2005. The indicator is the percentage change of the median spatially relative biomass relative to the status quo scenario.

- can be an efficient way to summarise large amounts of information,
- create an overview of the outcomes and focus attention to comparing strategies,
- facilitate the interaction between stakeholders and science providers,
- can contain economical, social and other indicators.

There needs to be a way down from the decision table to more detailed information. This is the first step towards a decision support system.

6. Discussion

6.1. What have we achieved?

The starting point for this project has been the measurement of depletion rates (Poiner et al, 1998) and the prospect of measuring recovery rates (Pitcher et al, 2000) for benthic species in the Great Barrier Reef Marine Park. Based on these measurable quantities, we have developed simple models for the dynamics of depletion and recovery of benthos at the small scale. By assuming a statistical model for the pattern of trawling, we have been able to scale the dynamic process up to the scale on which trawling effort information is available. We have called this scaled up model the *operating model*.

Motivated by the manager's need to evaluate different management options, we have developed a *management model*, which allocates effort to grids in response to management interventions. The types of management options, arrived at through consultation with industry and conservation representatives, are closures and effort capping.

The models have been combined into a software tool. The tool has a crucial *run management* component that keeps track of the results of the simulations and the context in which they were run and allows retrieval of the results for analysis and display. The tool itself comprises a graphical user interface that allows one to interact with the models and the run management system.

At a higher level we have provided an interface between the manager and the CSIRO operator of the software. This is in the form of the scenario modelling request proforma (*Appendix 4*). This document allows the manager to set parameters for the operating and management models and to specify different kinds of output. The end result of a scenario modelling request is a report document (*Appendix 5*), in which are presented the input settings of the simulations and their consequent outputs.

We have also shown how a top-down approach based on decision tables can be used for evaluating scenarios (*section 5.2.2*). The advantage of this approach is that it allows the manager to quickly assess the broad consequences of a scenario without getting bogged down in the details. The manager is therefore freed up to pursue complex management actions.

Nevertheless, it is important to have access to the details, and this is indeed provided in our framework. One is able to 'drill down' and view the data in various graphical formats and at different degrees of summarization. It is also possible ask complex questions through general queries of the data base.

6.2. The modelling framework

The modelling tool provides a framework for running complex scenarios in order to assess the implications of management interventions. The framework is *integrated*, *flexible*, *portable* and *adaptable*.

By 'integrated' we mean two things. First, we have brought together a range of data and activities from scientific surveys, commercial logbooks, VMS and national trends into a coherent model operating at a carefully chosen scale. Second, we have implemented the model into a software environment in which all the desired aspects of scenario modelling (specification, simulation, evaluation) are at hand.

- The framework is 'flexible' because it caters for a range of scenarios. These can be simple (constant vulnerability, uniform biomass) or complex (spatially varying vulnerability and biomass, stochastic vulnerability, time-varying closures and

effort capping). The degree of knowledge about the ecology would dictate the complexity of the scenarios.
- The framework can be 'ported' across to other trawl fisheries around Australia or elsewhere in the world, where effort is measured on a rectangular grid.
- The framework is 'adaptable' because it has the potential to be modified as improved methods become available. For instance, should a more reliable means of effort allocation be developed, perhaps based on time series approaches or incorporating spatial correlation, the new method could be plugged into the existing framework. This would be especially simple if the method were already encapsulated in a dynamic link library.

6.3. The merits of scenario modelling

It is sometimes said that scenario modelling answers 'what if?' questions. It may at first seem that scenario modelling can only be useful when the inputs to modelling are well understood, the so-called *data-rich* case. Certainly in this case the outputs of scenario modelling (the *what*s) are most accurately determined, and conclusions can be drawn with confidence. But scenario modelling also has an important role to play in *data-poor* circumstances. In such cases, scenario modelling can be used to probe the consequences of our ignorance through sensitivity analysis. This helps to identify which gaps in our knowledge (the *if*s) need stopping up.

Managers usually have to decide, amongst several feasible *alternatives*, which one gives the most desirable outcome. In this context, it is more accurate to say that scenario modelling answers questions of the form 'what if A *compared to* B'. The process of comparison mitigates against the uncertainty arising from ignorance of the inputs to the operating model. In other words, though we may be uncertain as to the absolute impacts of scenarios A and B, we may nevertheless be confident that A produces a more desirable outcome than B.

6.4. Further development

There are two areas where management scenario modelling can be improved: the quality of the data and the accuracy of the models. The former dictates the latter: as data quality improves, the models should be improved in step. Examples of improvement in data quality could be an increase in spatial resolution or the simple measurement of a quantity (like recovery) where none existed before.

6.4.1. Ignorance of the ecology

The biggest deficiency at the moment is our ignorance of the ecology. We have poor knowledge of the spatial distribution and composition of benthic assemblages. From the GBR survey we know that the distribution of benthos is highly variable. At first examination, the environmental descriptors, such as sediment, depth and cross-shelf position, have rather low predictive power. Also, owing to the large latitudinal extent of the GBR, the survey data may have limited application to other areas, especially outside tropical latitudes. We also know very little about between-species and within-species interaction, which may either limit or enhance the degree to which a population recovers after impact.

The model is one step ahead of the data here, since it can accommodate a spatial distribution for biomass of a particular vulnerability class. However, in such data-poor circumstances, it is preferable to assess impacts on relative biomass, or, equivalently, using a spatially homogeneous biomass model.

6.4.2. Spatial correlation

As stated, the model treats every grid as independent of every other grid. The changes in biomass depend only on the past effort in that grid and the depletion, recovery and trawl-pattern parameters. Spatial correlation would be introduced if we include recruitment from neighbouring grids. For instance, we could simulate a range of gamete exchange rates across cell boundaries. However, such a complication would only be justified if we knew more about the spatial processes on which to base simulation. It would also require knowledge of the spatial distribution of biomass. There are as yet no data to stimulate efforts in this area of modelling.

6.4.3. Vessel monitoring system data

An important improvement in data quality is the introduction of VMS to the Queensland fishery. This was introduced in 1998 throughout the fleet. Positions are taken every 2 hours. VMS is obviously an improvement on logbook data, since it records many positions per day to an accuracy of tens of meters, whereas only a single 6-minute grid needs to be entered in the logbook. From VMS data it is possible to obtain either more accurate effort at the 6-minute grid scale or effort at a finer resolution, on a 1-minute grid, for instance.

A further benefit of VMS is that it may be possible to resolve individual trawl tracks. This could be achieved either by collecting vessel position at a fast polling rate, or by collecting position, course and speed at a moderate polling rate. From the speed information one could determine whether the vessel was trawling or steaming. (Alternatively, onboard gear monitors, if introduced, could provide data on actual trawl time.) Being able to resolve tracks would remove the need for a statistical model describing the pattern of trawling, since we would have the pattern itself. Finally, VMS data could be used to calibrate the aggregation parameter. This would be an important advance because currently our only knowledge of β comes from the NPF.

6.4.4. Intermediate-scale aggregation

The current model assumes that the entire grid is subject to aggregated trawling. However, it may be more realistic to confine trawling to certain regions within the grid. For instance, parts of the grid may be untrawlable owing to the presence of reefs, or there may be management boundaries inside of which trawling is prohibited. This is a form of aggregation on an intermediate scale. It could be modelled using the two-stage approach described in section 2.2 of *Part Two: Technical Report*. Calibration of the model at the intermediate scale could be provided by VMS data. This method provides a way to overcome the current restriction that management closures be applied at the resolution of the grid.

6.4.5. Historical data

A large gap in our knowledge is the absence of logbook data before 1988. Our backward extrapolation model based on FAO data is necessarily simplistic. In particular, the model is spatially homogeneous, whereas it is believed that growth in different areas of the fishery occurred at different times. Consequently simulated impacts will tend to be overestimated in recently developed areas relative to more established areas. Biases such as this would affect the evaluation of management scenarios that differentiated between new and establish areas.

The project steering committee has proposed to canvas industry experts for information on the history of development of the fishery. A sketch proposal is given in *Appendix 3: Spatially varying back-projected effort*.

6.4.6. Sub-year temporal scale

Although effort data are available at daily temporal resolution, it is not necessary to model at such a fine resolution. This is because impacts, though strongly dependent on the cumulative effort, are fairly insensitive to the seasonal variation within that accumulation. The exception is for rapidly recovering species, but such species may be of less interest for conservation. The model does in fact solve the differential equation on a fine temporal grid (0.1 year) but the effort is assumed uniform within the year.

6.4.7. Vessel characteristics

The model assumes that vessel characteristics (trawl speed, gear width, duration of trawling) can be represented by an average over the fleet. However, these characteristics vary across the fishery. Remote areas such as Princess Charlotte Bay will attract larger vessels capable of sweeping more area per day. The vessel characteristics also depend on location through the target species: for instance, scallop trawlers tow wider gear at a slower speed than prawn trawlers. Vessel characteristics also vary in time through so-called ‘effort creep’.

An important issue is the effect of management plans that have a potential to change the structure of the fleet. For instance, a scheme designed to reduce effort through the trading in or surrender of effort units may also lead to a redistribution of vessel size across the fleet. This would affect the average vessel characteristics.

The model is capable of accounting for spatio-temporal variation in vessel characteristics in an approximate way through the depletion rate d. That is, if trawl speed increases by 1%, say, then we take this into account by increasing d by 1%.

Type of data	Availability	Provision in model
Depletion rates	For selected set of taxonomic units from GBR study area	Yes, either constant or spatio-temporally varying
Recovery rates	From GBR study area on completion of recovery dynamics project	Yes, either constant or spatio-temporally varying
Logbook effort	At 30’ from 1988 and a mixture of 30’ and 6’ since 1992	Yes
Spatial distribution of benthos	Weak relationships from GBR study area	Yes
Spatial correlation of benthos	Not available.	No
VMS	Measured since 1998	Can be accommodated if data binned in finer grid. If individual tracks resolvable, requires redesign of model.
Vessel characteristics	Recorded by QFMA	Approximately modelled by spatio-temporal depletion rates
Historical effort	Not available. Requires a survey of industry groups.	Simplistic model based on scaling down from recent effort levels
Sources of randomness	Some measurement of between-tow depletion rates	Large-scale depletion and recovery only

Table 4. Summary of the availability of various types of data and provision within the current model. The GBR study area is the green zone and the zone immediately to the north and south, as described in Poiner et al (1998).

This is a reasonably good approximation because the large-scale depletion rate λ is almost proportional to d (see **Figure 8**).

We did not have access to individual vessel data for this project. Nevertheless, if such data become available in the future, they could be analysed to provide a more accurate vessel characteristic for our model.

6.4.8. Stochastic simulations

Deterministic simulations assume that the input parameters are fixed or known without error. But we may wish to model natural variability in recovery or measurement error in effort, to give two examples. The modelling tool already allows for random variation in large-scale recovery and depletion, and this stochastic element could indeed be extended to other parameters of the model. However, once again we are in a data-poor environment, especially for the recovery parameters.

Burridge et al (2000) have estimated the variance of d between tows. In section 5.2 of *Part Two: Technical Report* we show how this translates into variation in large-scale depletion.

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Acknowledgments

We would like to thank the following people for their contributions to this project: Roland Pitcher, for the original concept of scenario modelling in the GBRMP; Ian Poiner for chairing the steering committee and providing guidance; Phil Cadwallader, Jon Day, Mike Dredge, Mark Flanigan, Neil Gribble, Allan Hansen, Eddie Hegerl, Burke Hill, Rosemary Lea, Katrina Maguire, Conall O'Connell, Mark Gough, Duncan Souter and Ilona Stobutzki for providing input on the steering committee; Michael O'Neill and Neil Trainor for advice on trawl gear and VMS issues respectively; Janet Bishop, Geoff Laslett, Ian McLeod, Tom Taranto and Bill Venables for technical and statistical advice; and the QFMA for supplying the trawl logbook data.

Appendix 1: Converting from boat days to effort units

Assume that, on average, a vessel trawls at 3 knots for 10 hours a day with effective gear width of 25m (bottom rope length × spread ratio). Taking a 6-minute grid in the middle of the GBRMP at latitude 18ºS as an average for the entire region, we find the number of boat days equivalent to a unit of effort. Note that 1 minute of latitude is 1 nautical mile which is 1.85 km.

6 minutes latitude = 6×1.85 km;
6 minutes longitude = $6 \times 1.85 \times \cos(18^{\circ}) = 10.6$ km

Effort = swept area ÷ grid area = 1. Therefore swept area = grid area = 11.1×10.6 km^2.

$$\begin{aligned} \text{swept area} &= \text{effective gear width} \times \text{length of trawl} \\ &= \text{effective gear width} \times \text{speed} \times \text{trawling time/day} \times \text{no. of days trawling} \end{aligned}$$

$$\begin{aligned} \therefore \text{ number of days trawling} &= \text{grid area} \div (\text{effective gear width} \times \text{speed} \times \text{duration}) \\ &= 11.1 \times 10.6\ \text{km}^2 \div (25\ \text{m} \times (1.85 \times 3)\ \text{km h}^{-1} \times 10\ \text{h}) \\ &= 84.8\ \text{days} \end{aligned}$$

Therefore, a 6’ grid will take 85 days to trawl, and a 30’ grid will take 2120 days to trawl. Alternatively 1 day of effort will result in 0.012 of a 6’ grid trawled.

Appendix 2: List of assumptions employed in the trawl management scenario model

Scale and extent of the model

Spatial

The model covers the East Coast Trawl Fishery from Northern NSW to Cape York, and the Northern Prawn Fishery from Cape York to Joseph Bonaparte Gulf, excluding the Torres Strait Fishery. The model can be operated at two levels of precision: 30-minute grids and 6-minute grids.
Remark: results of the model for a particular 6-minute grid (say) are averages of processes occuring within that grid. We do not attempt to report outcomes at a finer resolution than this.

Temporal

The logbook effort data are aggregated to yearly totals. Actual logbook data exist since 1988 in the QECTF (since 1993 at 6-minute precision) and since 1970 in the NPF. Events both before and after these dates are extrapolated from the available data (see below).

Biological model

The biological model has two components: depletion and recovery. Depletion is characterised by a depletion rate per tow d and recovery is characterised by a recovery rate r. We call the combination of these components the vulnerability. Different species may belong to different vulnerability classes. We therefore model each vulnerability class separately.

Assumption:

- the benthic population begins in a pristine state at some specified time (see *Historical effort model* later),
- in the absence of depletion and at low densities, the biomass increases exponentially at rate r.
- the population is bounded by a maximum capacity equal to the original pristine biomass.
- each tow removes a fixed fraction $1–d$ of the available biomass.

The 'available biomass' is the biomass remaining after prior depletion and recovery are taken into account.
The model can be run in either *fixed parameter* or *variable parameter* mode.

- In fixed parameter mode r and d are fixed in time and space. The outcome of the model is the relative biomass of those benthic species with recovery rate r and depletion rate d.
- In variable parameter mode r and d may be arbitrary functions of covariates that exist in the database (e.g. latitude, carbonate concentration or year). This mode could be used either to model the spatio-temporal variation of a particular vulnerability class of organisms or to try to account for the spatio-temporal variation of the average vulnerability over all organisms.

<u>Mathematical Assumptions and Approximations:</u>

- The *effective recovery rate* in the presence of depletion is $r(1-\frac{1}{2}d)\log(1+\beta d)/\beta d$. That is, depletion has an adverse effect on recovery over and above the normal effect of depletion in the absence of recovery. This result is justified on theoretical grounds and borne out by numerical simulation.
- We solve the recovery-depletion equations by simple time-stepping. We use a fixed time step of 0.1 years.

Impact model

The fishing fleet is represented by an average vessel with fixed trawling speed, gear width and time spent trawling per day. These three parameters are adjustable, but do not vary within a particular model.

<u>Assumption:</u>

- the pattern of trawling within a grid (that is, the area swept by gear zero times, once, twice, etc), accumulated since trawling began in the grid, is described at any time by a negative binomial distribution.

<u>Remark</u>: the negative binomial distribution is governed by a parameter β which determines the degree of aggregation. Random, lawnmowing and clustered patterns are all accommodated by different values of β.

Historical effort model

<u>Assumptions:</u>

- trawling began simultaneously in all grids in year y_1.
- the level of effort in each grid was f % of the level of effort in the grid in the earliest year $y_{logbook}$ for which we have log book information.
- the level remained constant until year y_2.
- between y_2 and $y_{logbook}$ the effort increased linearly.

The three parameters y_1, y_2 and f are adjustable, but do not vary among grids.
<u>Remark</u>: the biomass before y_1 was pristine, and the resulting biomass is relative to this supposed pristine state.

Logbook effort model

The effort data is obtained directly from the log books. Before 1992 all data were reported with 30-minute precision. After 1992 the data base contains a mixture of 30-minute and 6-minute precision.

<u>Assumption:</u>

- the effort reported at 30-minute precision was spent proportionally within each of the 25 6-minute grids inside the 30-minute grid.

Projected effort model

Effort is predicted for any future year by the following procedure:

1. generate effort in each grid by randomly sampling the effort in that grid uniformly over the most recent R years,
2. set the effort to zero in any grids with a closure for the year in question,
3. scale the effort in the remaining grids so that total effort equals the effort cap for the year in question.

Appendix 3: Spatially varying back-projected effort

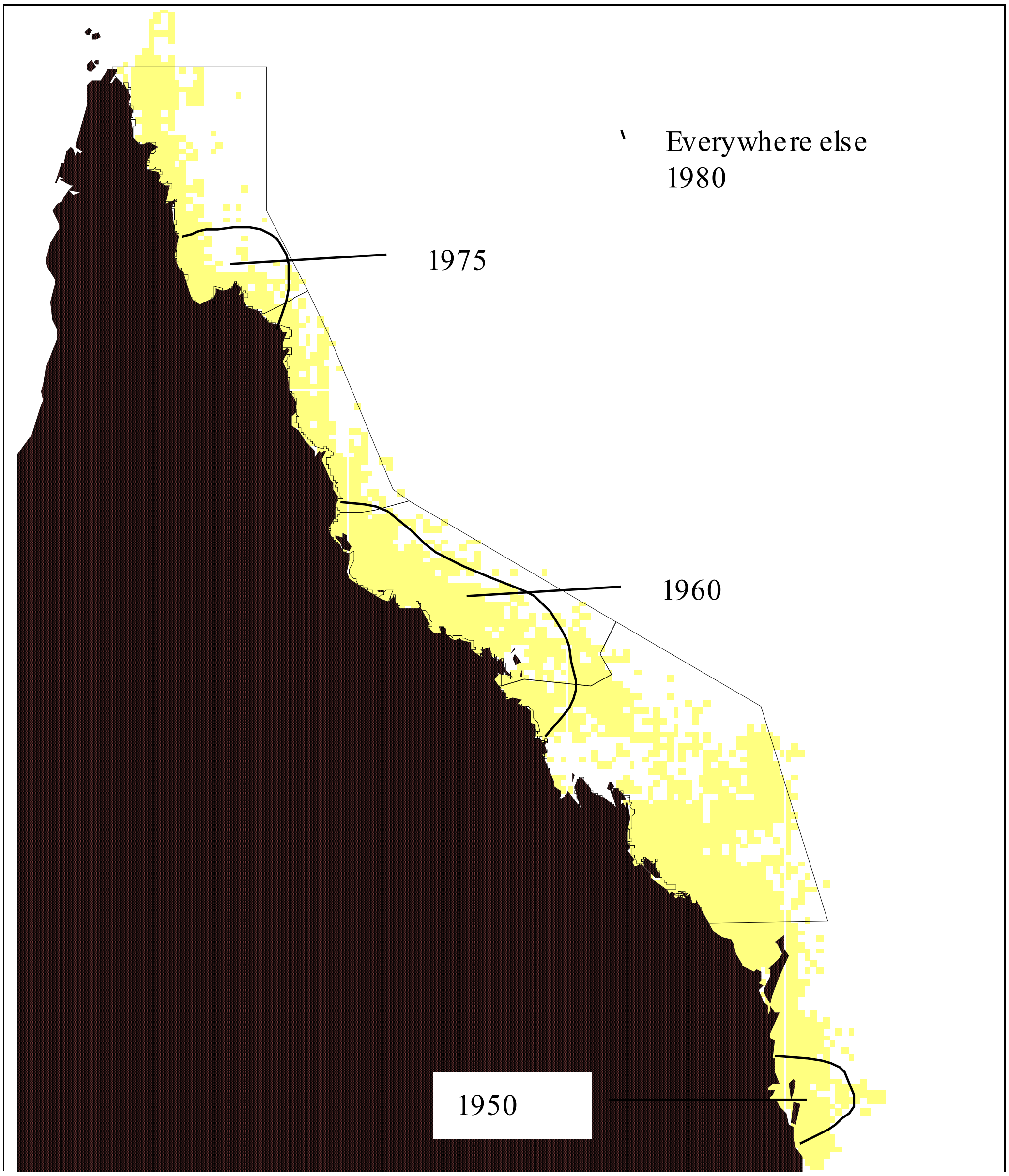
This is a proposal for obtaining back-projected effort from historical spatial and temporal information provided by experienced fishers.

Information provided by the fishers

Spatial information on the extent of the fishery

The fishers could provide a sketch of the first year fishing for each region. For example:

We would need to have information for all the yellow grids.



Temporal information on the extent of the fishery

The fishers could provide a rough sketch of the total effort over the whole East Coast Trawl Fishery. They could sketch over a template like this:

How to incorporate the information provided by the fishers

At the end of the day we would have tables looking like this:

grid cell	**year it entered fishery**
1422501025	1965
1422501075	1957

and this

year	**total effort over fishery**
1950	1000
1951	1100

If we made the assumption that once a grid enters the fishery it stays, then we can say for each grid g and each year y whether the grid was in the fishery. *I.e.* we have an indicator function I_{gy}, which = 0 if grid is not in the fishery and = 1 if it is in the fishery. We also have T_y which is the total effort for year y. We can get the spatial pattern over grids by scaling proportional to current effort levels $E_{g,\text{current}}$. 'Current' could mean 1993 (for 6-minute grids) or the average over recent years. Then an estimate of the effort E_{gy} in grid g and year y is

$$E_{gy} = \frac{T_y E_{g,\text{current}} I_{gy}}{\sum_{\text{all } g} E_{g,\text{current}} I_{gy}} .$$

A complication that is not catered for here is if there exist grids, trawled historically, but lying outside of the recently fished areas. i.e. grids that never had a logbook record. A possible solution is to partition off a small amount of 'trial' effort, and extend the fishery each year over some predefined number of potential grids, if suitable (non-reef) grids exist.

Appendix 4: Trawl management scenario modelling request proforma

Introduction

The purpose of this proforma is to specify models, management interventions and outputs for the trawl management scenario modelling tool. The tool will be run by CSIRO staff (in particular Nick Ellis) and outputs will be returned to the requester as a report.

The proforma can be used in two modes: the *novice* mode or *advanced* mode. We recommend novice mode for initial requests. As the requester becomes familiar with the types of output and gains experience with the capabilities of the proforma, he or she can later move on to advanced mode.

Novice mode
In novice mode, the requester specifies only the management options and leaves the remaining specification of the model at default values. Default values are either explicitly stated or denoted by an `[X]`.

Advanced mode
In advanced mode, the requester sets options other than the default values, in particular options describing the recovery-depletion model, the biomass distribution or vessel characteristics. Such requests will usually be in response to output received from an earlier request. It is likely that, as the dialogue between requester and modeller proceeds, the structure of the proforma will change as some options prove of little worth and other options, perhaps not currently included, show their usefulness.

The document is split into two parts: *Inputs* and *Outputs*. The novice user need only fill in the *Management scenarios* section under *Inputs*. The default outputs will be generated and returned to the user in a report entitled *Management scenario modelling report.*

NB: the default range for recovery is 0.1–2 per year and for small-scale depletion is 0.01–0.4. These ranges are limits on the simulations, not on the real world. There may be organisms that have recovery and depletion rates outside these ranges. Similar remarks apply to all the other default settings.

Inputs

Area of interest

The area of interest is the region within which the model will be run, management interventions will be applied and over which indicators will be calculated. You can define this region in several ways:

- by name (e.g. entire QECTF, GBRMP, section(s) within marine park)
- using geometrical coordinates,
- with a shapefile you supply,
- in terms of known spatial variables (e.g. everywhere within 50km of the coast). See *Available Data* for a list of known spatial variables.

tick one box [ ]

- Great Barrier Reef Marine Park .... [X]
- East Coast Trawl Fishery .... [ ]
- Other named region (specify)... [ ]
  ....
  ....
  ....
  ....
- General polygonal region (specify polygon vertices in decimal degrees) .... [ ]
  ....
  ....
  ....
  ....
- Name of shapefile containing polygon shape(s) .... [ ]
  ....
- Definition in terms of known spatial variables (see *Available Data*) .... [ ]
  ....
  ....
  ....
  ....
- Other definition of area of interest (if none of above apply) .... [ ]
  ....
  ....
  ....
  ....
  ....

Management scenarios

Management scenarios involve interventions that change the spatial distribution and level of trawling in future years. There are two types of management intervention:

1. *Effort capping.* Total effort in a projected year is fixed at some proportion of the total effort in a baseline year. You need to provide the baseline year, the year in which the management intervention begins, the reduction in effort per year and the final year up to which the projection runs.
2. *Closures.* You may close any grids in any future years. We do not incorporate seasonal closures. However, the level of effort in grids with seasonal closures currently in place will correctly reflect the true reduction in effort due to those closures.

Effort that would have been spent in closed areas gets displaced to other grids, in proportion to the effort already in those grids.

Management Intervention

Provide a name for this management intervention. If you have more than one, simply duplicate this page. If you do not provide a status quo, the defaults will be used.

Name (*default:* Status Quo)..

Effort capping

Fill in all the blanks (defaults in parentheses)

Run projections from (1998) .... to (2005) ....

Baseline year for effort cap (1996) ....

% reduction in effort per year (status quo = 0%) ....starting in (2000).................

Closures

Closures can be specified in the same way as areas of interest (polygonal region, shape file, in terms of spatial variables) or simply as a list of grid centres. You also have to provide the years over which the closure applies.

Tick at least one box [ ]

- No closures.. [X]
- General polygonal region (specify polygon vertices in decimal degrees) .... [ ]
  ....
  ....
  for years (*example* 2000–2005)......... ....
- Name of shape file containing polygon shape .... [ ]
  for years (*example* 2000–2005)......... ....
  ....
- Definition in terms of known spatial variables (*example* where *dcross* > 0.9).. [ ]
  ....
  ....
  ....
  for years (*example* 2000–2005)......... ....
- Name of text file containing grid centres* .... [ ]
  ....

*Format of text file should be: year, longitude, latitude. Example:

```
2000, 153.35, -25.45
2000, 153.25, -25.55
2000, 153.95, -25.05
```

Note that grid centres lie at 0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85 or 0.95 of a decimal degree.

Recovery and depletion model

There are two ways provided for selecting a recovery and depletion model:

1. Choose a matrix of constant *r* and *d* values.
2. Choose one or more spatially and/or temporally varying forms for *r* and/or *d* in terms of known covariates (see *Available Data*).

The first choice is simpler and we recommend it for routine use. In this case *r* and *d* are constant in space and time. The second choice may be justified if there are known surrogates for recovery or depletion. For instance, cross-shelf changes in productivity may affect *r*, and gear differences between fisheries may affect *d*. We provide a template below for specifying the spatial form of *r* and *d* in terms of the range of the parameter and its correlation with a single covariate. If you prefer you can supply your own formula of one or more variables; however you should then ensure that the formula provides sensible values.

For guidance in choosing reasonable *r* and *d* values, see *Choosing r and d* below.

Choose either the matrix-of-constants model or the spatio-temporal model

- Matrix-of-constants model .... [X]

Parameter	Values
r (year^{-1})	*provide one or more values* (default: 0.1, 2.0)
d (%)	*provide one or more values* (default: 1%, 20%, 40%)

- Spatio-temporal model .... [ ]

Parameter	Formula #	Min	Max	Correlated with	+ve/–ve correlation
r (year^{-1})	example	0.1	2	*dcross*	+ve
r (year^{-1})	1				
r (year^{-1})	2				
r (year^{-1})	3				
r (year^{-1})	4				
d (%)	example	10%	12%	*fisheryX**	+ve
d (%)	1				
d (%)	2				
d (%)	3				
d (%)	4				

* *fisheryX* is an indicator for ‘fishery X’ (=1 for grids within fishery X; =0 for grids outside fishery X). The grids would have to be supplied by the requester in the same way as an area of interest or closure is defined (see *Area of Interest*). In this example *d* is 12% inside fishery X and 10% outside.

The actual formula used for the recovery example would be

$$r = \text{Min} + \frac{(\text{Max} - \text{Min})(dcross - \min(dcross))}{(\max(dcross) - \min(dcross))}$$

Choosing *r* and *d*

For guidance in choosing the recovery rate *r*, consult **Table 5** in conjunction with **Figure 22**. For guidance in choosing the depletion rate per tow *d*, consult **Table 11** on page 63. This lists observed depletion rates for various species groups along the 6 tracks of the repeat-trawl experiment (reproduced from Table 5.04 in Poiner et al, 1998).

Recovery rate *r* ($year^{-1}$)	Nominal recovery time (years)	Time to reach 95% (years)
0.1 (slow)	20	30
0.4 (medium)	5	7.5
2 (fast)	1	1.5

Table 5. Nominal recovery time (2/*r*) and actual time (3/*r*) to reach 95% recovery after removing 50% of biomass in terms of recovery rate *r*.

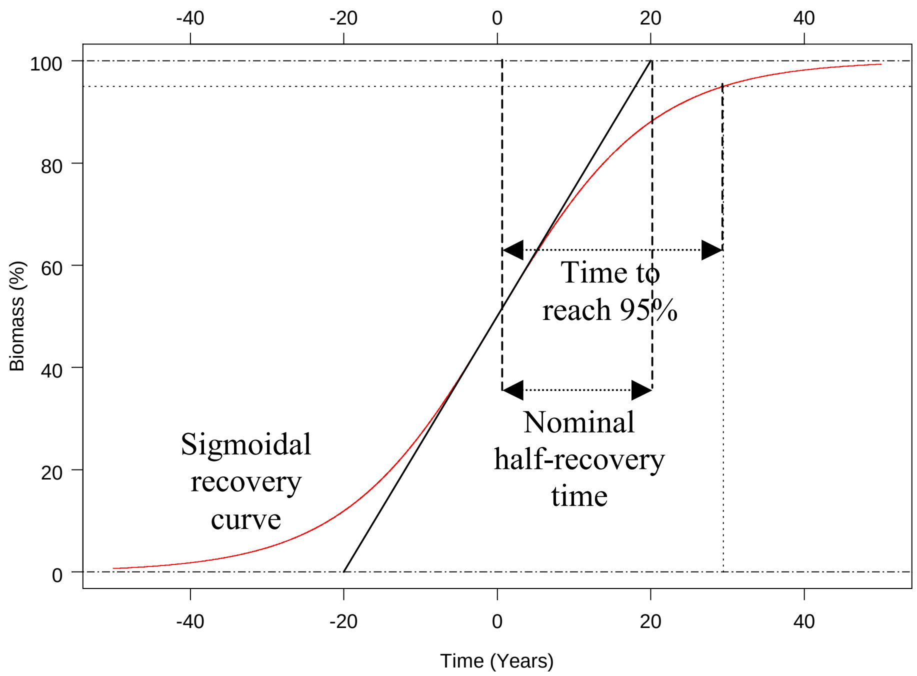


Figure 22. The sigmoidal recovery curve and illustration of the nominal recovery time and actual time to reach 95% recovery from 50% depletion. Here $r = 0.1$ $year^{-1}$.

Deterministic or stochastic model

The above models are **deterministic**, and so do not allow for random variation. You can investigate variation or sensitivity in the outcomes by specifying a matrix of constant parameters. This is a **response surface** approach where the parameters are varied systematically.

An alternative is to use a **stochastic** model in which *r* and λ vary randomly from one grid to the next and from one time step to the next. With a stochastic approach, we run many simulations and look at the mean and variance of the outcomes of those simulations. For sensitivity analysis this approach is rather inefficient. However, the approach can be justified as a way to account for natural variation in recovery or depletion between tows.

To use the stochastic model, you must specify the coefficient of variation (variance divided by squared mean) below. The distributions are log-normal and their means are equal to the respective values *r* and λ would have in the deterministic case. The variation must be expressed at the grid scale, not the fine scale of the organism (*r*) and the tow (*d*). However, the experimental data from the repeat-trawl and recovery dynamics projects will yield variation at the fine scale. The analysis of these data for variation has not been carried out, so we cannot as yet provide guidelines for variation at the fine scale. However, the technical report contains some results (*Part Two: Technical Report*, Figure 11) which help link variation in *d* to variation in λ.

NB: if the stochastic model is chosen then the *matrix-of-constants* model must be chosen above under *Recovery and depletion model*. The current implementation does not support a *spatio-temporal* stochastic model.

Choose either the deterministic *model or the* stochastic *model*

- Deterministic recovery and depletion .... [X]
- Stochastic recovery and/or depletion .... [ ]

Parameter	Values
coefficient of variation of *r*	*provide one or more values* (example: 0*, 1, 2)
coefficient of variation of λ	*provide one or more values* (example: 0*, 1, 2)
number of simulations	*specify one number* (example: 10)

*A coefficient of variation of 0 is the same as no variation. If both coefficients of variation are zero the model is deterministic.

Carrying capacity model

Just as you can specify a spatially varying recovery and depletion term, so you can make the carrying capacity spatially varying too. The model could then capture variation in the relative biomass of a particular species, which also belongs to a particular vulnerability class. For instance, if a species prefers muddy sediments, then you can specify the carrying capacity to be proportional to the variable *mud*.
Specifying the carrying capacity means that instead of looking at the biomass relative to the initial biomass in a grid (which we assume to be the carrying capacity) you can look at the biomass relative to the biomass in other grids. This *spatially relative biomass* is the relative biomass times the carrying capacity.
The carrying capacity is normalised to sum to 1 over all grids. You may opt not to specify a spatially varying carrying capacity, in which case only the relative biomass is used in output.

tick one box [ ]

- Do not specify carrying capacity.. [X]
- Use spatially varying carrying capacity .... [ ]

Model #	Correlated with	+ve/–ve correlation
example	*mud*	+ve
example	*mud*	–ve
1		
2		
3		
4		

The actual formula used in the first example would be

$$\text{Carrying Capacity} = \frac{mud}{\sum mud}$$

and in the second example would be

$$\text{Carrying Capacity} = \frac{(100 - mud)}{\sum (100 - mud)}$$

because the range of *mud* is 0 to 100.

Trawl pattern model

The level of aggregation in the trawling patterns is determined by a single parameter β, which specifies which negative binomial distribution best describes the level of coverage on the ground. The higher β the more aggregated the trawling. The least aggregated trawling can be is when the entire grid is covered uniformly, corresponding to β = –1. Simulation results based on combining VMS and GPS plotter data suggest β = 2–4, at least for the NPF. Use the pictures in **Table 6** to decide on a suitable value for β.

Parameter	Values
Aggregation β	*provide one or more values* (default: 2)

Examples: 'Lawn-mower' trawling (β = –1) , random trawling (β = 0) , mildly aggregated trawling (β = 1) , NPF results (β = 2–4) , highly aggregated trawling (β = 10).

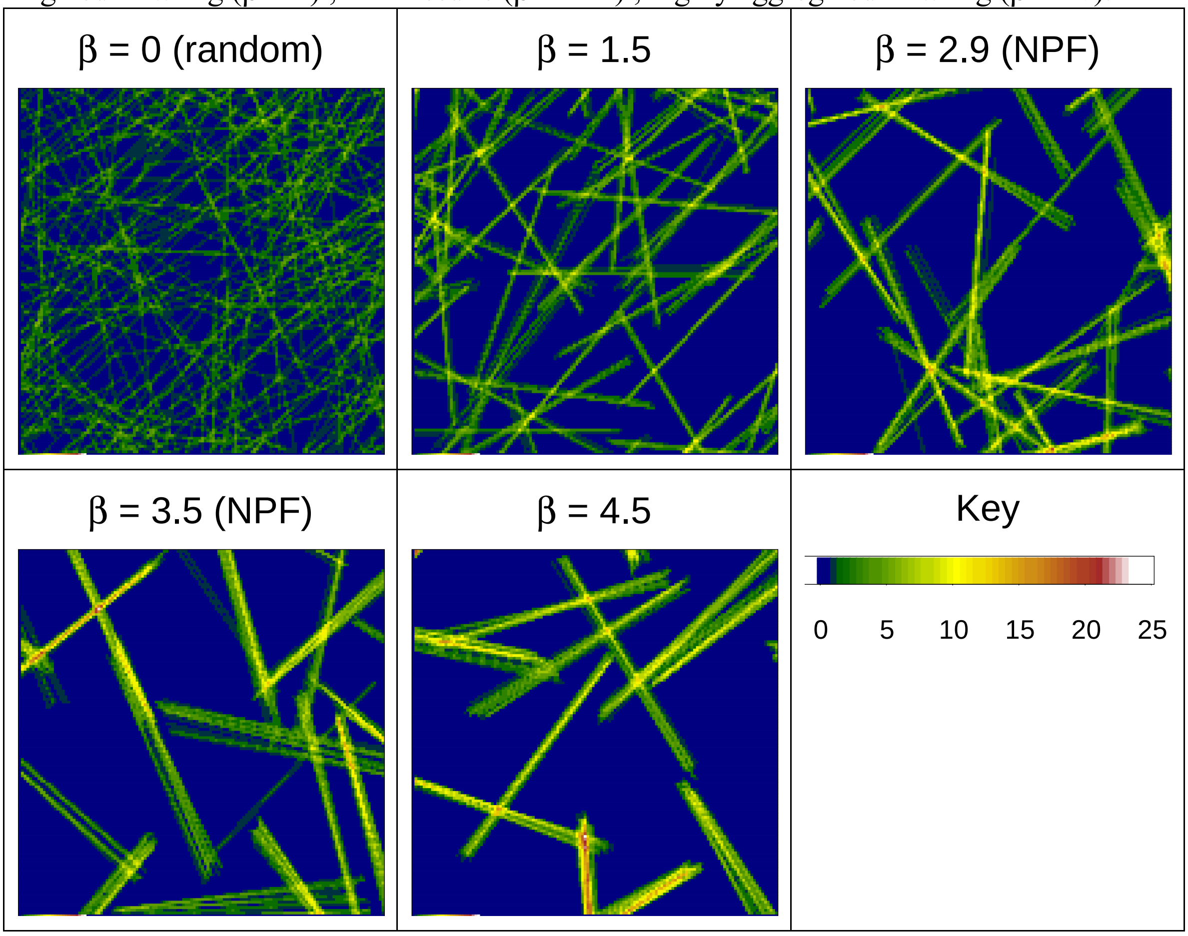


Table 6. Simulated trawling patterns for different levels of aggregation. Each picture represents a typical trawling pattern for the given value of the aggregation parameter β. Colour represents the number of times the ground is trawled (blue 0 times, yellow 10 times, red 20 times). Tows are straight and 2.7km long, corresponding to a half-hour at 3 knots. The square has area 16km^2 (4km on the side) and the swept area is 17.6km^2.

Historical effort model

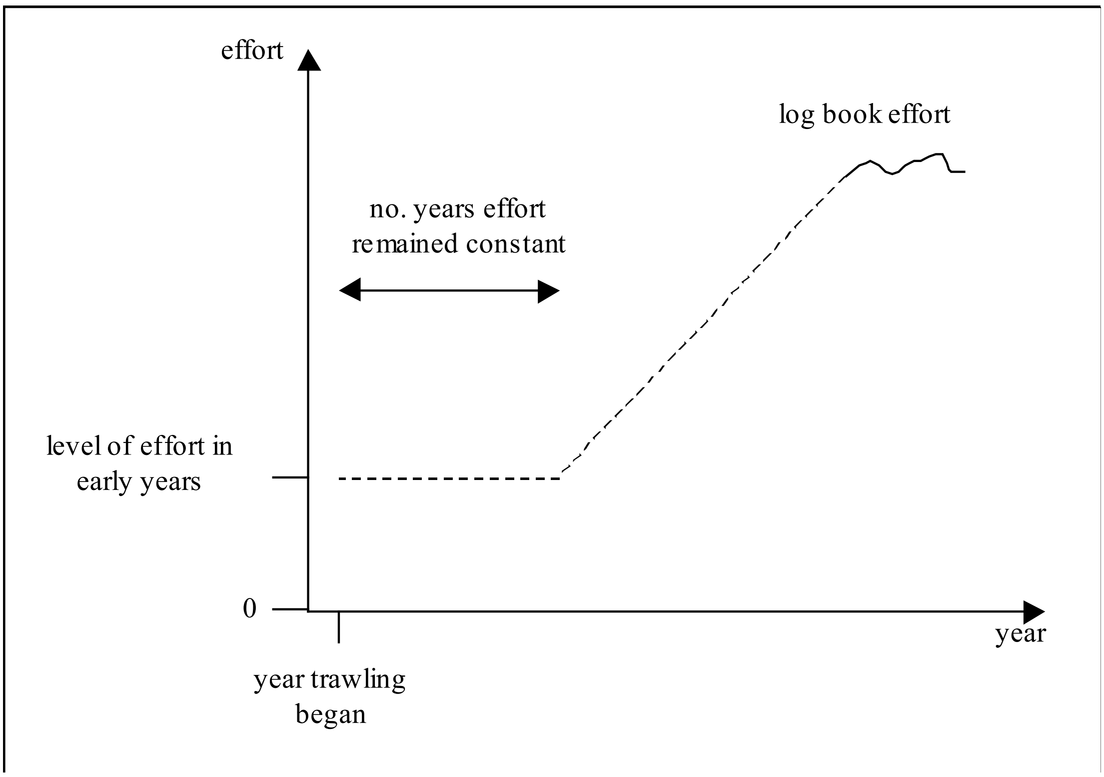
Because the 6-minute log book data only go back to 1993, whereas trawling actually began much earlier, we have to model the effort prior to 1993. In the future we envisage incorporating information obtained from fishery experts on the history of effort and its spatial extent. In the meantime we have a simplistic model that obeys the following assumptions:

- trawling began simultaneously in all grids in year y_1,
- the level of effort in each grid was f % of the level of effort in the grid in the earliest year 1993 for which we have log book information,
- the level remained constant until year y_2,
- between y_2 and 1993 the effort increased linearly.

See the sketch below for clarification.

Provide values for the three parameters (or use defaults, given in parentheses)

Parameter	Description	Value
y_1	Year trawling began	*provide one value* (default: 1956)
f (%)	Level of effort in early years as % of current level	*provide one value* (default: 33%)
$y_2 - y_1$	Number of years over which effort remained constant	*provide one value* (default: 25 yrs)



Available data

All spatial data are stored at 6-minute resolution; temporal data are stored at yearly resolution. The currently available datasets are given in the following table. If you have data at the above resolution that you wish to use for a scenario run, it may be possible to add the data to the database. Contact Nick Ellis (nick.ellis@marine.-csiro.au) to discuss this.

Variable name	Description
effort	effort for 1993–1997
y	year
lat	latitude
lon	longitude
d2coast	shortest distance to the coast in degrees
d2reef	shortest distance to the reef edge in degrees
dcross	relative cross-shelf distance (coast=0, reef edge=1)
mud	percentage mud in sediment (GBRMP only)
carb	percentage carbonate in sediment (GBRMP only)

The maps in **Figure 23** show the availability of mud and carbonate sediment data (*light green*). These data sets are mostly restricted to the GBRMP/WHA. There are some small pockets (*light blue*) where data are missing.

The maps in **Figure 24** show the definition of *dcross*. The red line defines the edge of the reef where *dcross* is 1. At the coast *dcross* is zero. Beyond the reef *dcross* is greater than 1. On the right hand map the reef is also shown for comparison. We define *dcross* as follows: *dcross* = *d2coast*/(*d2coast* ± *d2reef*), where the '+' applies between the line and the coast and the '–' applies to the east of the line. South of the GBRMPWHA the line has been artificially extended so that we can use *dcross* over the entire fishery.

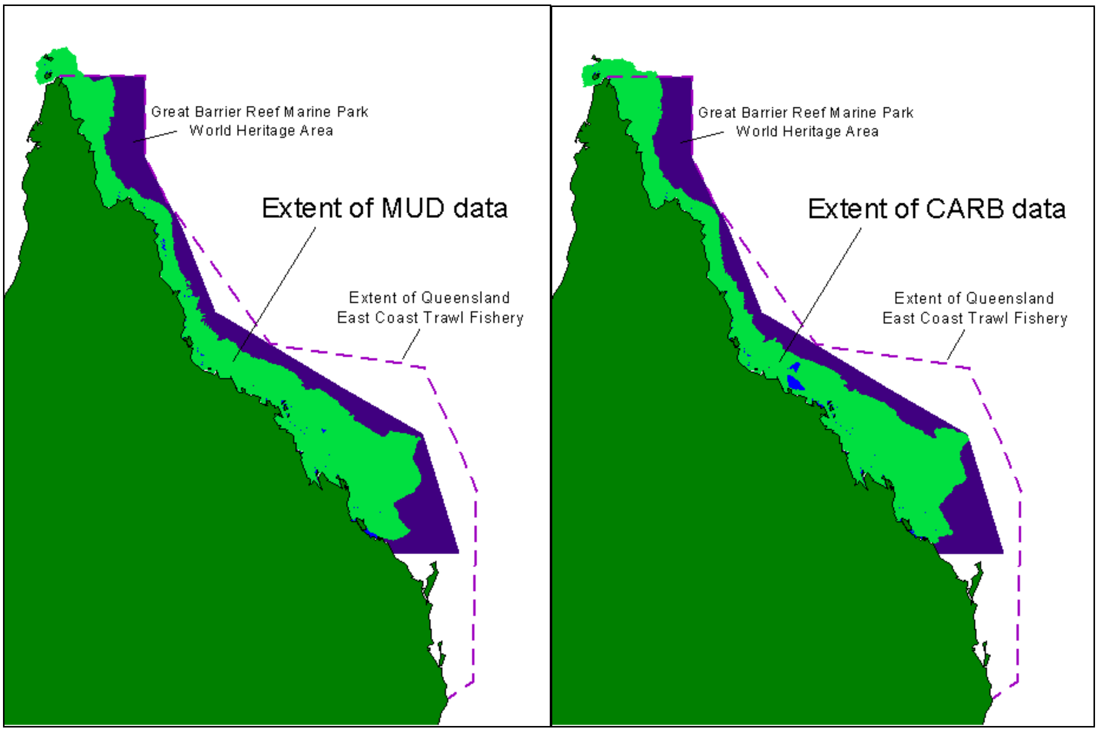


Figure 23. Extent of sediment data.

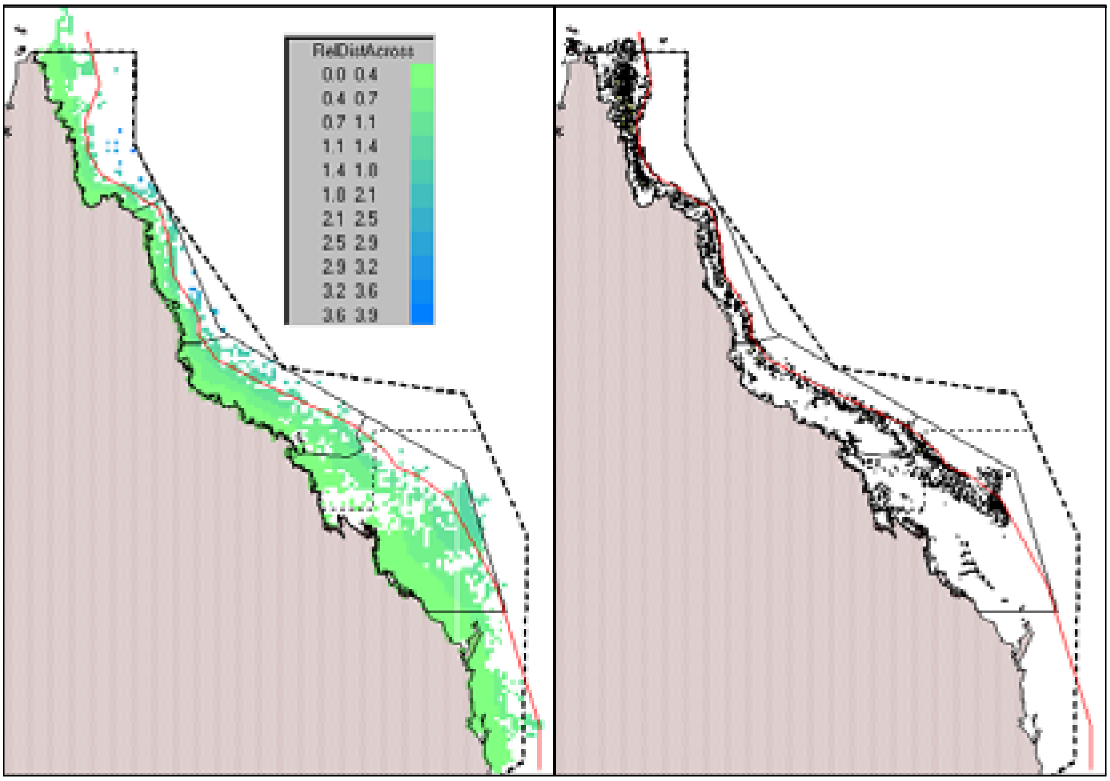


Figure 24. Definition of relative distance across reef.

Outputs

Introduction

The number of outputs from a set of scenario modelling runs is potentially very large. It is helpful to think of outputs in a top-down manner, from broad-scale information to fine detail.

Decision tables

At the top-most level we have **decision tables**, where management scenarios are compared on a few indicators, possibly for a range of vulnerability classes. This is the broadest level of information. The decision table reports the percentage change of an indicator relative to the status quo scenario.

Two fictitious examples are given in **Table 7** and **Table 8**. These decision tables would indicate that the first management intervention was more effective in ensuring benthic recovery.

Indicator plots

Having seen the decision tables you might want to 'drill down' to see some more detail. In particular you might want to see what the actual indicator values are, as opposed to change in indicator relative to the status quo. There are many ways to look at indicators. One possibility is to look at the change in a particular indicator over time for the different management interventions and a particular vulnerability class. See **Figure 25** for an example.A second possibility is to assess the sensitivity of the indicator to changes in vulnerability class. **Figure 26** shows an example.

In the case of stochastic models there are multiple simulations for each model. These can be plotted on a single graph, or summarised by error bars or 'confidence bands'.

Histograms

Histograms of the relative biomass are very useful for assessing the representativeness of an indicator. For instance, the biomass distribution is typically highly skewed and

Percentage change relative to status quo	Management Intervention	
Indicator	5% annual reduction	Marine Protected Areas
Median biomass	+5	–1
Proportion grids > 20% biomass	+3	+2
Pristine area	+2	+2

Table 7. An example of a decision table. This would be for a particular combination of *r* and *d* (vulnerability class). Numbers are fictitious.

Percentage change relative to status quo		Management Intervention			
		5% annual reduction		Marine Protected Areas	
Indicator	*d* / *r*	high	low	high	low
Median biomass	slow	+5	+1	–1	+1
	fast	+3	+0	+0	+0
Proportion grids > 20% biomass	slow	+3	+1	+2	–2
	fast	+3	+0	+1	+0
Pristine area	slow	+2	+2	+2	+2
	fast	+2	+2	+2	+2

Table 8. An example of a decision table with more detail. Here the cells of Table D1 are expanded to include 4 vulnerability classes. Numbers are fictitious.

often bimodal. Consequently the mean may be very misleading as an indicator of the overall relative biomass. For highly skewed unimodal distributions the median is usually a better indicator than the mean, and, for bimodal distributions, quantities like the 10th percentile can be more representative if the interest is in large impacts. An example histogram is shown in **Figure 27**. If you desire a histogram of the spatially relative biomass, then it is advisable also to request a histogram of the relative carrying capacity, since all impacts are relative to this carrying capacity.

Maps

The finest level of detail is the relative biomass in individual grids. We can display this either as a map or as a time series for selected grids. Time series plots tend to look rather 'busy' if there are too many grids. A map (like a histogram) can only display a single quantity. The quantity could be relative biomass for a particular model and management scenario in a particular year. It could also be a more complicated quantity such as average relative biomass over several years or the difference in rela-

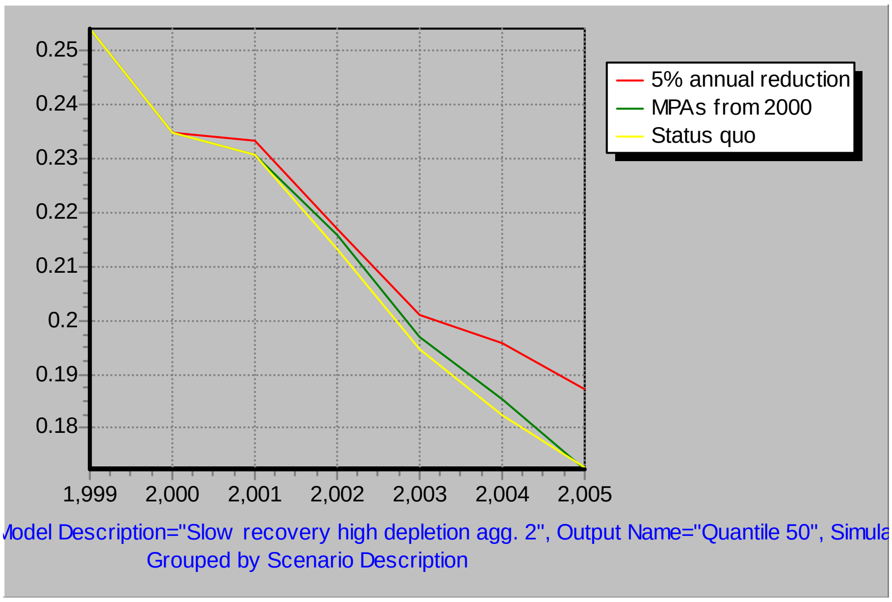


Figure 25. Median relative biomass against time for the 'slow recovery, high depletion' vulnerability class.

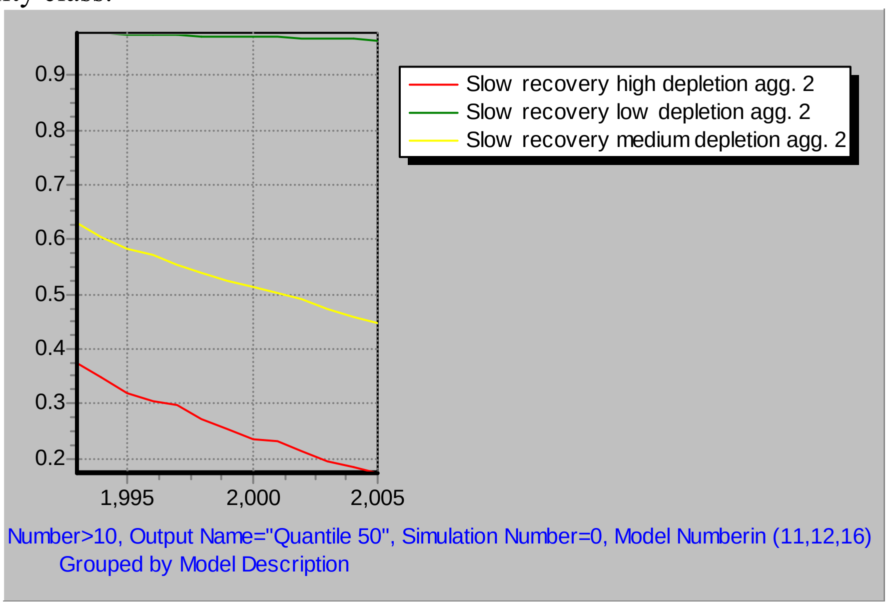


Figure 26. Median relative biomass against time for the 'status quo' management intervention and each of the 'slow recovery' vulnerability classes.

tive biomass between two scenarios (see **Figure 28**).
The choice of outputs is likely to be an iterative process: results from the decision table may suggest you need to look at a particular indicator plot, or check the indicator with a histogram. Or you might want to check the spatial distribution with a map; this might prompt a further analysis on a particular area of interest. An important practical use of maps, especially for black and white output, is to show regions above a certain threshold or within certain bands; for instance, regions depleted to 10% original biomass or within certain depth ranges.

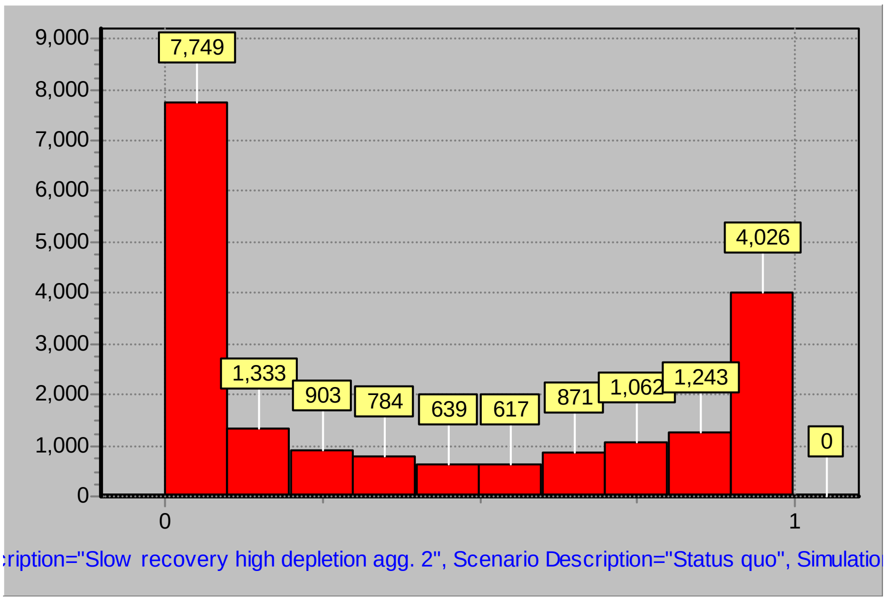


Figure 27. Histogram of relative biomass in 2005 for the ‘status quo’ management intervention and the ‘slow recovery, high depletion’ vulnerability class. The distribution is strongly bimodal.

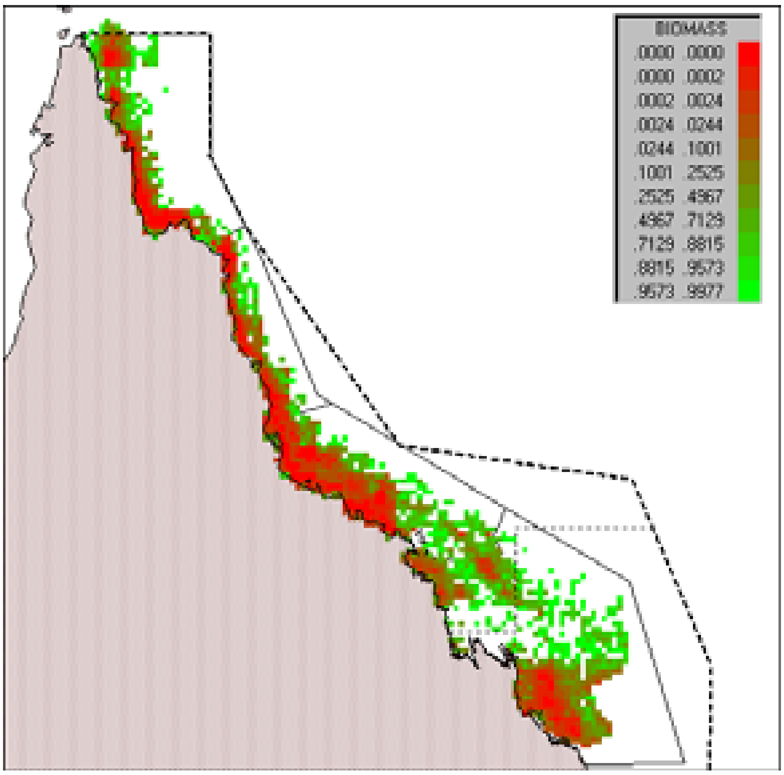


Figure 28. Map of relative biomass in 2005 for the ‘status quo’ management intervention and the ‘slow recovery, high depletion’ vulnerability class. Colour scale is chosen so that there are equal numbers of grids in each colour class.

Decision Tables

tick at least one box [ ]

No decision tables .... [ ]

Expanded decision table.. [X]

which indicators (see **Table 9**)? (default: Mean, P_{20}, Q_{50}) ....
....
which management interventions? (default: all)..
....
which year? (default: final year) ....
which models? (default: all r, d, β combinations)...
....
....
which carrying capacity models, if any? (default: none) ....
....

Simple decision table .... [ ]

which indicators (see **Table 9**)?...
....
which management interventions? (default: all)..
....
which year? (default: final year) ....
which single model?..
....
which carrying capacity models, if any?..
....

Name	**Description**
Pre-defined indicators	
Mean	Mean relative biomass
Max	Maximum relative biomass
Min	Minimum relative biomass
Q_n (n = 5, 10, 15, 20, 25, 30, 40, 50, 60, 70, 75, 80, 85, 90, 95)	nth percentile of relative biomass (Q_{50} is the median)
P_n (n = 5, 10, 15, 20, 25, 30, 40, 50, 60, 70, 75, 80, 85, 90, 95)	Proportion of grids whose relative biomass exceeds n%
Pristine Area	Proportion of area of trawled grids that has never been trawled
SMean	Mean spatially relative biomass
SMax	Maximum spatially relative biomass
SMin	Minimum spatially relative biomass
SQ_n (n = 5, 10, 15, 20, 25, 30, 40, 50, 60, 70, 75, 80, 85, 90, 95)	nth percentile of spatially relative biomass (SQ_{50} is the median)
Your own indicators	
fill in name	*fill in description or formula*

Table 9. Pre-defined and user-defined indicators.

Indicator plots

Tick at least one box [ ]. *For multiple plots, duplicate the relevant sections.*

No indicator plots .... [ ]

Comparison of management interventions.. [X]
which indicator (see **Table 9**)? (default: Mean, P_{20}, Q_{50})..
which model? (default: all r, d, β combinations) ....
....
....
which management interventions? (default: all) ....
....

Comparison of models (sensitivity) .... [ ]
which indicator (see **Table 9**)?...
which management intervention? ....
which models? (default: all r, d, β combinations)..
which carrying capacity model, if any? ....

Other plot (please describe)... [ ]
(example: Q_{50} in final year vs model grouped by management intervention) ....
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....
....

Histograms

Tick at least one box [ ]. *For multiple histograms, duplicate the relevant sections.*

No histograms .... [ ]

Simple quantity, single year.. [X]
which quantity? (see **Table 10**) (default: relative biomass)..
....
which year? (default: final year) ....

Derived quantity.. [ ]
which quantity? (describe fully)
(examples: average relative biomass 2000–5, [relative biomass for scenario X – relative biomass for scenario Y] in 2005 for model A)..
....
....
....

Name	Description
Effort	Logbook, back-extrapolated or future predicted
Relative biomass	Biomass in grid relative to carrying capacity in grid
Relative carrying capacity	Carrying capacity in grid relative to carrying capacities in all grids (normalised to sum to 1)
Spatially relative biomass	Biomass in grid relative to biomass in all grids (normalised to sum to 1 in initial year of trawling)
Pristine Area	Proportion of grid that has never been trawled
Environmental or other spatial quantities	See *Available data*

Table 10. Quantities defined at the grid level.

Maps

Tick at least one box [ ]. *For multiple maps, duplicate the relevant sections.*
No maps.. [ ]

Spatially and temporally varying quantity, single year.. [ ]
which quantity? (see **Table 10**)...
....
which year? (example: final year)..

Spatially varying quantity .... [ ]
....
which quantity? (examples: recovery or depletion (if spatio-temporal model used), carrying capacity (if specified), closures, mud, dcross, etc) ....
....
....

Derived quantity.. [X]
which quantity? (*describe fully*) (default: [relative biomass for first scenario – relative biomass for status quo scenario] in last year for all *r*, *d*, β combinations)
(*examples:* average relative biomass 2000–5, [relative biomass for scenario X – relative biomass for scenario Y] in 2005 for model A)...
....
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Other kinds of output

The above list is not exhaustive. Please describe fully any other kind of output you require. However, please note that we cannot guarantee to provide it..................... [ ]
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Table 11. Estimated percent depletion rate *d* for sessile benthic classes on each track, with average for all classes. (From I. Poiner, J. Glaister, R. Pitcher, C. Burridge, T. Wassenberg, N. Gribble, B. Hill, S.Blaber, D. Milton, D. Brewer and N. Ellis (1998). Final report on effects of trawling in the Far Northern Section of the Great Barrier Reef: 1991–1996. CSIRO Division of Marine Research, Cleveland.) These are **underestimates** of the actual depletion rate and the report recommends they **should be inflated by at least 25%**.

	Shallow Tracks						**Deep Tracks**						**Average for all tracks**	
Track no.	**4**		**18**		**21**		**12**		**15**		**19**			
Class	***d***	**SE**	***d***	**SE**	***d***	**SE**	***d***	**SE**	***d***	**SE**	***d***	**SE**	***d***	**SE**
All sessile	10.6	*3.3*	3.1	*4.8*	1.6	*5.0*	3.3	*3.4*	12.3	*4.2*	9.7	*3.4*	6.8	*1.7*
Algae	2.9	*7.3*	5.4	*4.5*	–10.8	*5.2*	–2.9	*3.8*	24.8	*10.8*	9.5	*21.6*	4.8	*4.4*
Porifera	7.4	*5.9*	8.8	*6.8*	4.4	*7.2*	3.4	*3.8*	12.5	*4.9*	9.9	*3.5*	7.7	*2.2*
Hydrozoa	7.9	*5.8*	7.1	*5.0*	–15.4	*4.1*	7.3	*4.6*	22.6	*10.2*	–0.4	*5.3*	4.9	*2.5*
Gorgoniacea	69.4	*5.2*	9.9	*5.3*	9.5	*6.8*	24.8	*10.7*	18.4	*6.7*	12.1	*4.3*	24.0	*2.8*
Alcyonacea	15.6	*6.3*	21.1	*7.4*	–5.6	*5.9*	7.6	*4.4*	14.4	*4.4*	10.2	*4.9*	10.6	*2.3*
Zoantharia	26.5	*2.7*	–23.3	*8.4*	7.5	*6.1*	–2.3	*7.5*	17.8	*4.7*	5.7	*5.3*	5.3	*2.5*
Bryozoa	8.6	*5.1*	7.0	*6.9*	–12.9	*5.6*	7.0	*4.4*	10.4	*3.0*	16.2	*3.6*	6.1	*2.0*
Ascidiacea	13.1	*3.1*	13.9	*6.1*	11.4	*5.6*	3.5	*5.9*	9.2	*4.2*	5.3	*6.2*	9.4	*2.2*

Appendix 5: An example of a Report arising from a Trawl Management Scenario Modelling Request

In this appendix we present the results of certain scenario runs requested by a management body, in this case GBRMPA, whom we refer to as *the manager*. We used the request proforma of Appendix 4 to guide the manager in the choice of scenario options. The manager decided to use ‘novice mode’, leaving most of the options at the default values, and instead concentrating on management options. The management area chosen was the entire Queensland fishery, and the projected period was up to 2010.

The first management option was closures, which were used in Scenarios 0 and 1. The manager provided us with an ESRI shape file of the closed areas. Any 6-minute grid whose centroid lay inside the closed areas was deemed to be closed, otherwise it was deemed open.

The second management option was effort capping. The manager provided a detailed capping schedule for Scenario 1, and an outline of Scenario 2 as ‘unlimited growth continuing the trend for 1988–1998’.

The manager also provided annual effort totals for 1988–1998. As these totals were more up-to-date than our own, we decided to scale up our effort data proportionately in each 6-minute grid to make our totals agree with the manager’s totals. From these totals we estimated the trend over 1988–1998 by fitting a simple exponential model. We used the extrapolation of this trend beyond 1998 as the basis for Scenario 2, the unlimited growth case.

All three scenarios were straightforward to implement with our software. We ran each scenario for the default 9 vulnerability classes. We then generated the tables, graphs and maps, using an interface to the database that allows these standard outputs to be generated and inserted automatically into the report.

Management interventions

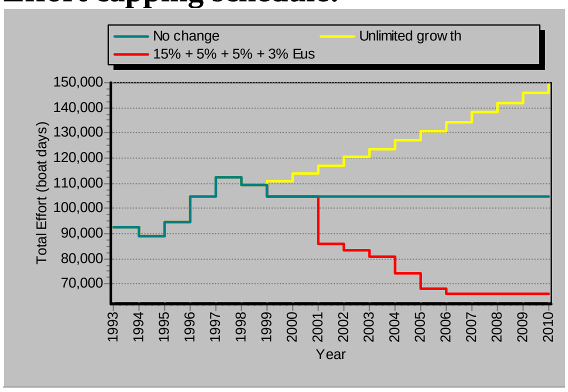
Name	Closures (see map)	Capping (see also figure below)
0. No change (status quo scenario)	Green and blue zones and non-trawled areas starting in 2001	Remain at 1996 level
1. 15% + 5% + 5% + 3% effort units	ditto	Reduction by 15% in 2001, and by 5% in 2004 and 2005. Also a 3% reduction every year from 2001 to the end of 2006 (see *Effort Units* below)
2. Unlimited growth	Green and blue zones only	Exponential growth, roughly 2.5% per year, based on 1988–98 trend

Synopsis

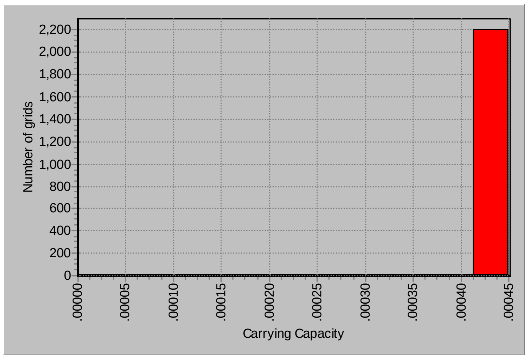
Number of grids: 2207
Period of logbook effort: 1993–1997
Simulation period: 1998–2010
Status quo management:
Recovery values: 0.1, 0.5, 2
Depletion values: 0.4, 0.2, 0.01
Aggregation values: 2
Deterministic or stochastic: Deterministic
Vessel parameters:
- gear width: 25 m
- trawl speed: 3 knots
- hours trawled per day: 10

Historical effort:
- year trawling began: 1956
- level relative to current levels: 33%
- number of years at this level: 25

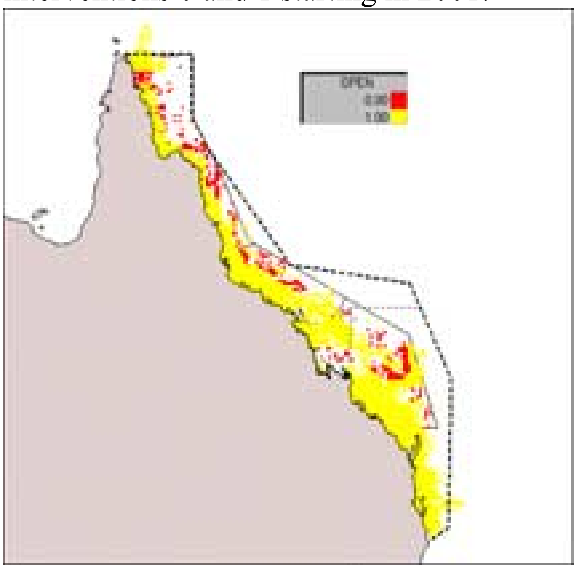
Effort capping schedule:



Carrying capacity histogram. All carrying capacities are the same, and are normalised to sum to 1.



Closures (in red) for management interventions 0 and 1 starting in 2001:



Effort Units and Vessel Characteristics

Scenario 1 involves a 3% reduction in effort per year due to 3% effort unit (EU) reduction. We make the assumption here that the distribution of vessel size is not affected by the removal of effort units. If this is the case, then the average vessel as characterised by the vessel parameters listed in the *Synopsis* is unchanged, and so a boat day still corresponds to the same swept area after removal of effort units.

Since effort unit reduction is aimed at combatting effort creep, the question arises: should we be including effort creep in our model for effort? We should include this if it has an effect on swept area per boat day. Some industry sources have suggested that there has been some increase in trawl speed since 1988. This means there is indeed a component of effort creep that affects swept area. We do not know whether such an increase would be further sustained from 1999 to 2010.

On the other hand, changes in the pattern of trawling due to uptake of GPS technology and the consequent improvement in the efficiency of searching are likely to have increased *aggregation*. The effect of increased aggregation is to reduce overall impact on the benthos, and so oppose the damaging effect of effort creep. Unfortunately we are not able to quantify the increase in aggregation. Furthermore, any structural redistribution of the fleet due to surrender of effort units is likely to have an important effect on average vessel characteristics, but the size and direction of this effect is unknown. In view of all these uncertainties, we have decided not to incorporate effort creep in our scenarios. We feel that it is premature to base scenarios on information about the fleet that is currently fragmentary and incomplete.

The value of 25m we have used for gear width is based on opinions provided by industry representatives on the steering committee. We have found from discussion with industry sources that for some fisheries this is a representative value and for others it is a slight over-estimate. In light of this, we believe it is reasonable to use the 25m value, since it appears to be conservative.

Decision tables

Below are decision tables in 2003 and 2006 for each management intervention relative to the status quo based on 3 indicators and all 9 combinations of r and d. Chosen indicators are mean relative biomass, proportion of grids exceeding 20% initial biomass (Proportion 20) and median relative biomass (Quantile 50).

Differences between management interventions are larger in 2006 than in 2003 because the interventions have been acting for longer. Within each indicator-intervention combination the most vulnerable species group is at the top left and the most resistant is at the bottom right. For ‘Proportion 20’, the changes for depletion rate 0.01 are zero because all grids exceeded 20% initial biomass for all management interventions.

Decision table for end of 2003

Percentage change relative to status quo		Management Intervention					
Indicator		15% + 5% + 5% + 3% Eus			Unlimited growth		
	d / r	0.4	0.2	0.01	0.4	0.2	0.01
Mean Biomass	0.1	1.2	1.1	0.2	-1.1	-1.0	-0.2
	0.5	1.9	1.8	0.2	-1.6	-1.5	-0.1
	2	2.2	1.2	0.1	-1.7	-0.9	0.0
Proportion 20	0.1	0.7	1.1	0.0	-0.8	-0.5	0.0
	0.5	1.2	0.8	0.0	-1.7	-0.8	0.0
	2	0.5	0.0	0.0	-0.4	-0.1	0.0
Quantile 50	0.1	2.0	0.8	0.1	-2.2	-1.1	-0.1
	0.5	1.2	0.6	0.0	-1.2	-0.6	0.0
	2	0.5	0.2	0.0	-0.4	-0.2	0.0

Decision table for end of 2006

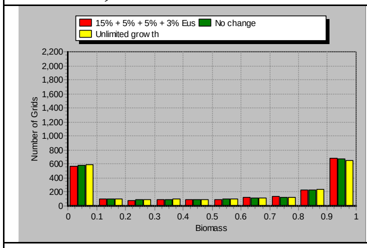
Percentage change relative to status quo		Management Intervention					
Indicator		15% + 5% + 5% + 3% Eus			Unlimited growth		
	d / r	0.4	0.2	0.01	0.4	0.2	0.01
Mean Biomass	0.1	2.8	2.6	0.6	-2.1	-2.0	-0.4
	0.5	4.4	3.9	0.3	-3.0	-2.7	-0.2
	2	4.0	2.0	0.1	-2.7	-1.5	-0.1
Proportion 20	0.1	2.3	2.0	0.0	-2.1	-1.8	0.0
	0.5	3.0	2.1	0.0	-2.4	-2.1	0.0
	2	1.4	0.2	0.0	-1.3	-0.1	0.0
Quantile 50	0.1	5.2	2.8	0.1	-4.8	-2.1	-0.1
	0.5	3.1	1.4	0.1	-2.2	-1.2	-0.1
	2	0.8	0.3	0.0	-0.6	-0.3	0.0

Histograms

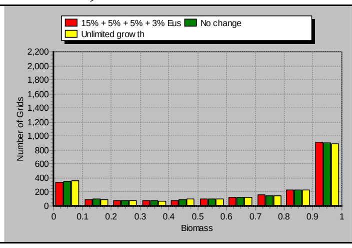
Below are histograms of relative biomass in 2003 and 2006 under each management intervention and all 9 combinations of *r* and *d*. The most vulnerable species group is in the top left panel and the most resistant is in the bottom right panel. All histograms are plotted on the same scale for comparison across species groups.

Relative biomass at end 2003

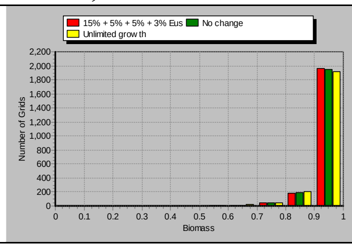
r = 0.1; d = 0.4



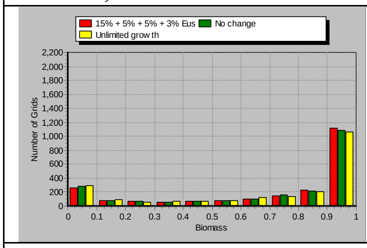
r = 0.1; d = 0.2



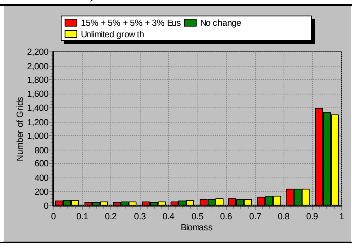
r = 0.1; d = 0.01



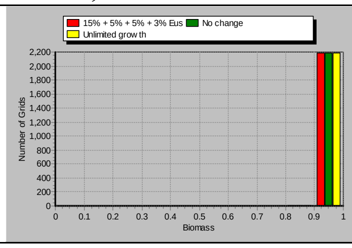
r = 0.5; d = 0.4



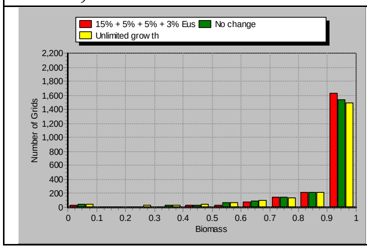
r = 0.5; d = 0.2



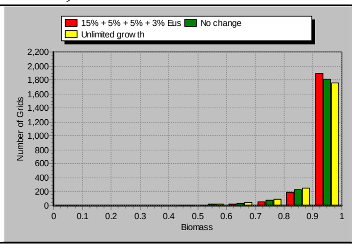
r = 0.5; d = 0.01



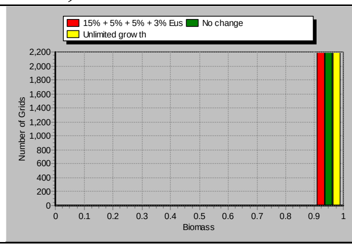
r = 2; d = 0.4



r = 2; d = 0.2

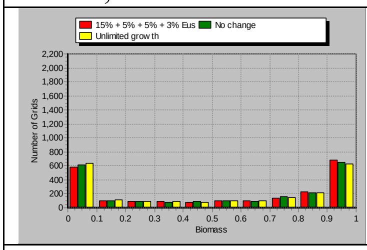


r = 2; d = 0.01

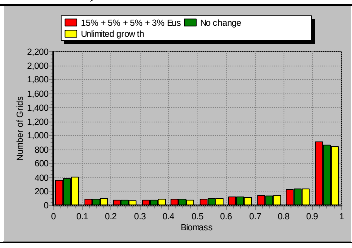


Relative biomass at end 2006

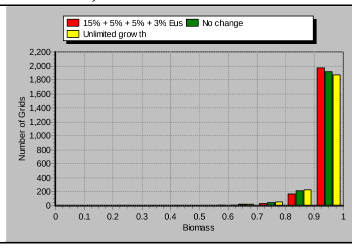
r = 0.1; d = 0.4



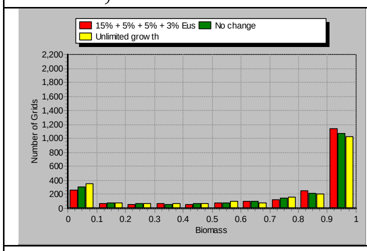
r = 0.1; d = 0.2



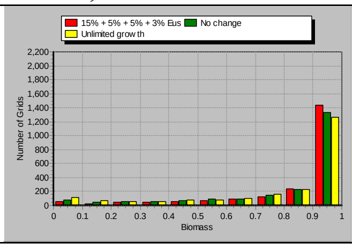
r = 0.1; d = 0.01



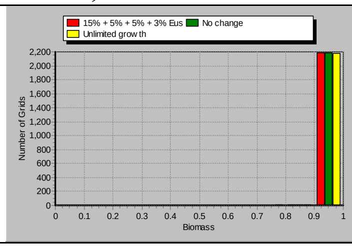
r = 0.5; d = 0.4



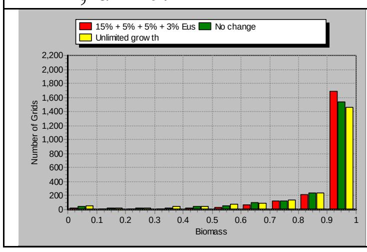
r = 0.5; d = 0.2



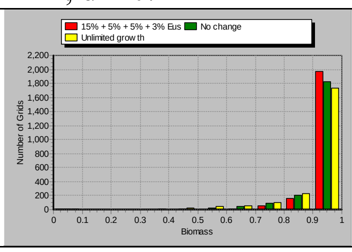
r = 0.5; d = 0.01



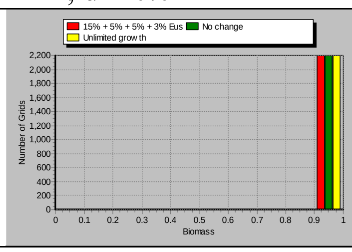
r = 2; d = 0.4



r = 2; d = 0.2



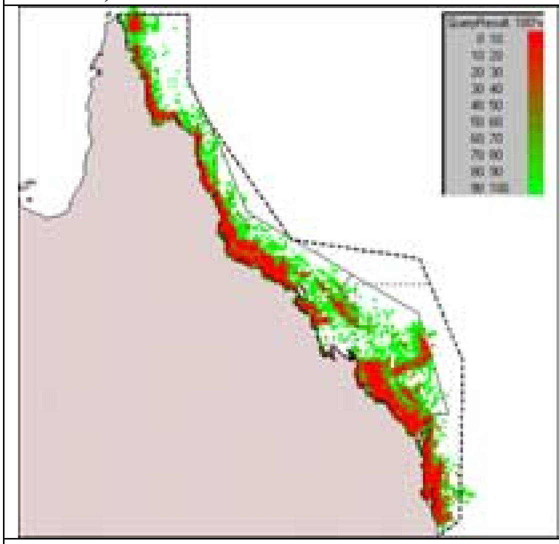
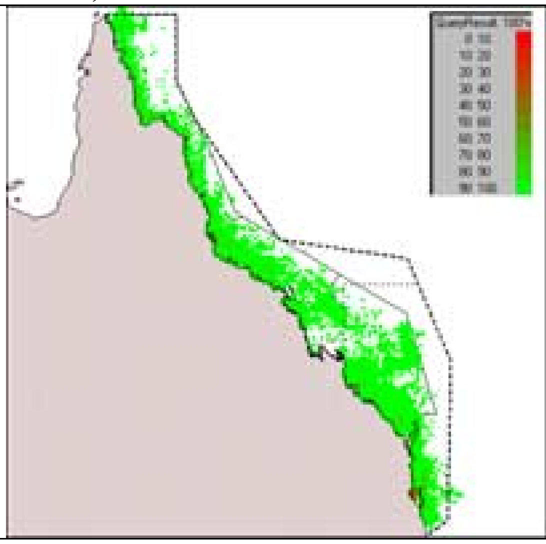
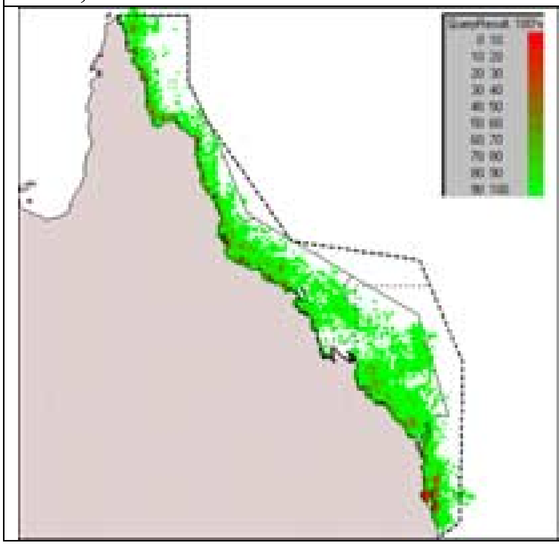
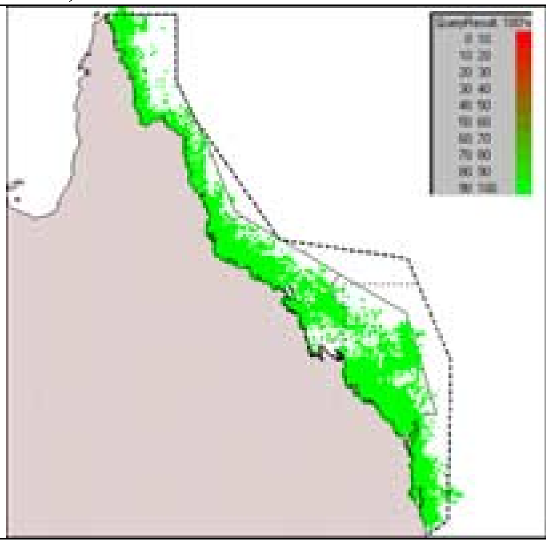
r = 2; d = 0.01



Maps

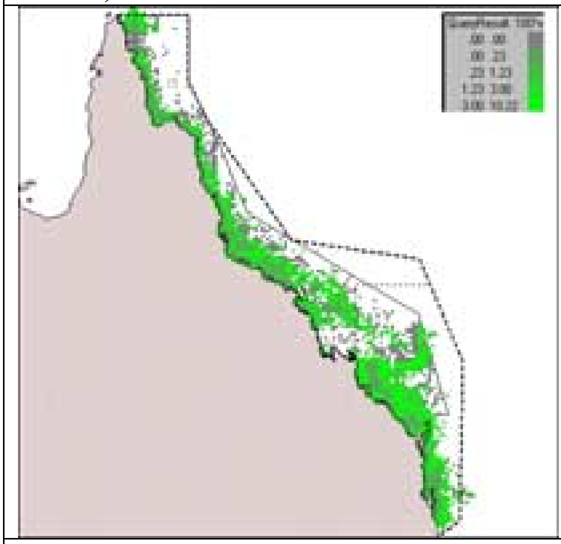
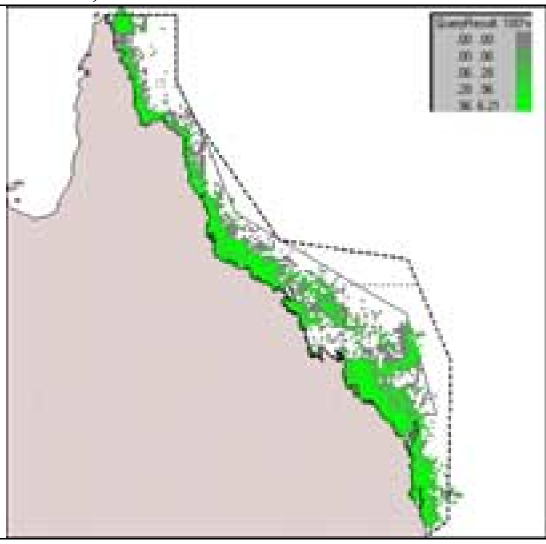
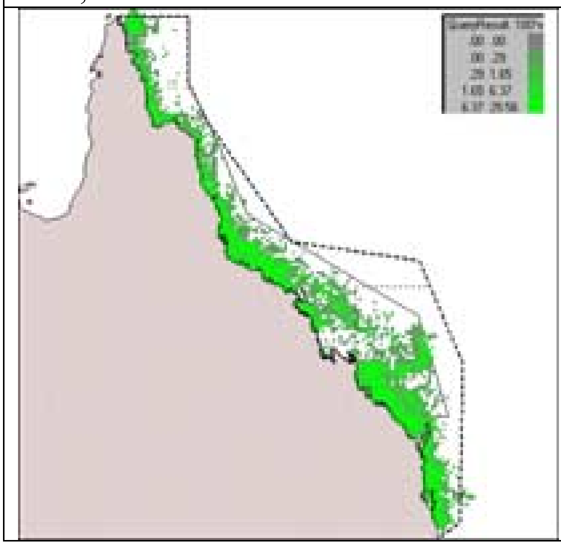
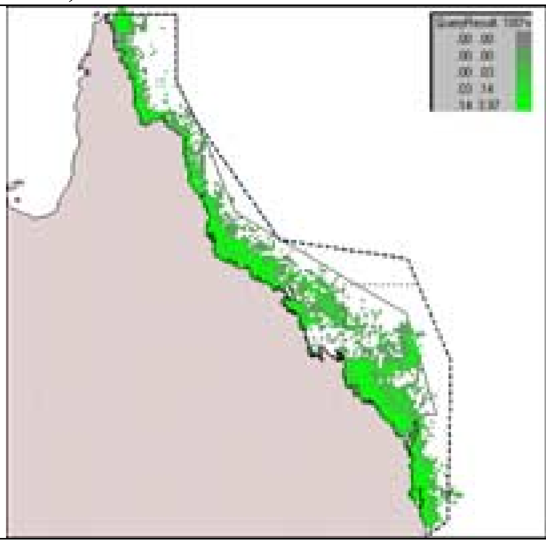
We only show the ‘extreme’ values of *r* and *d*. The most vulnerable species group is in the top left panel and the most resistant is in the bottom right panel.
NB: the range for recovery is 0.1–2 year^{-1} and for depletion is 1%–40%. These ranges are limits on the model, not on reality. There may be organisms that have recovery and depletion rates outside these ranges.

Percentage relative biomass in 2006 for Scenario 1.
All maps have a common colour scale. Green indicates high relative biomass (low impact), red low relative biomass (high impact). The common colour scale aids comparison across species groups but hides the detail in the less vulnerable species group. The pattern of impact for these groups is similar to, but smaller in magnitude than, the pattern for the most vulnerable group.

r = 0.1; d = 0.4	r = 0.1; d = 0.01
	
r = 2; d = 0.4	r = 2; d = 0.01
	

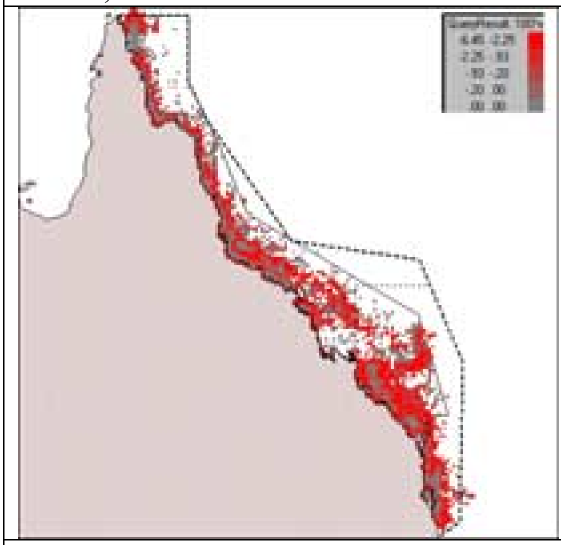
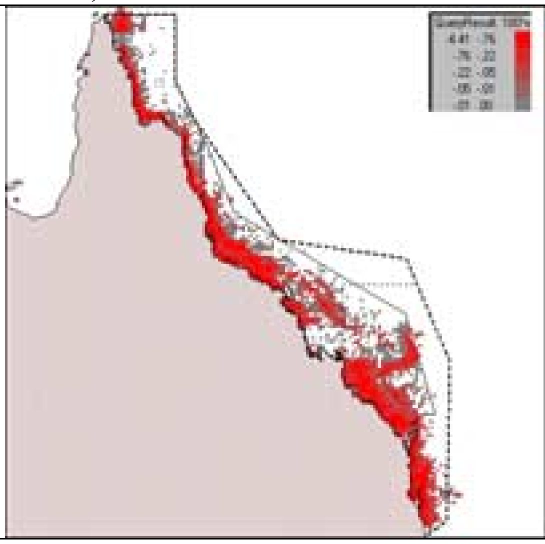
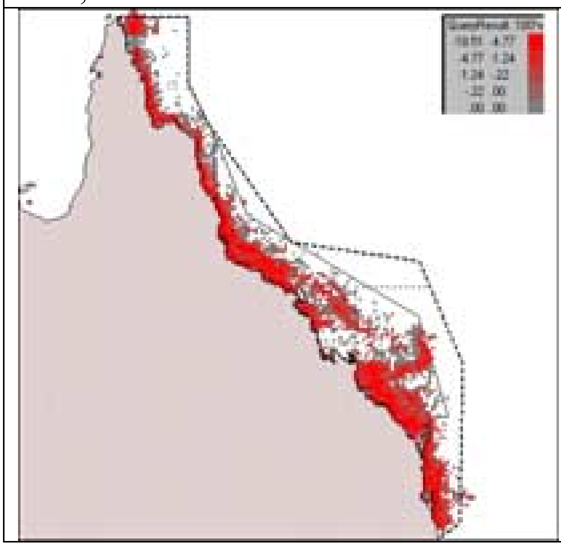
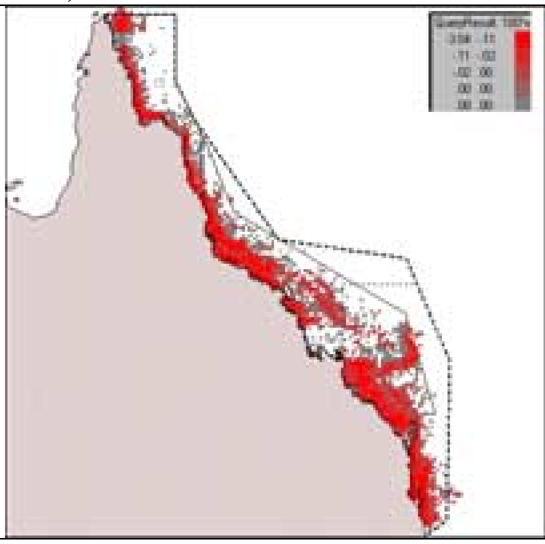
Difference in percentage relative biomass in 2006 between Scenario 1 and the No change scenario.

We use a quantile-based colour scale; that is, there are equal numbers of grids (in this case 20%) in each colour band. The brighter the green, the more recovery or less impact relative to the 'No change' scenario. The colour scale is not common across maps. There is little difference (grey) in areas of very high impact or very low impact (relative biomass ≅ 0 or 1 respectively). The biggest differences are in areas of intermediate impact (relative biomass ≅ 0.5). Refer to the first set of maps in this section.

r = 0.1; d = 0.4	r = 0.1; d = 0.01
	
r = 2; d = 0.4	r = 2; d = 0.01
	

Difference in percentage relative biomass in 2006 between Scenario 2 and the No change scenario.

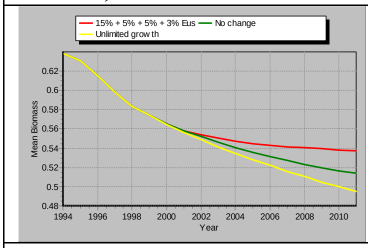
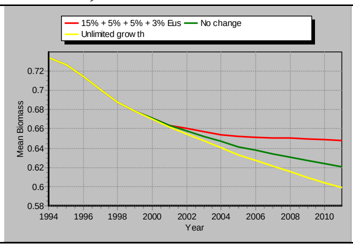
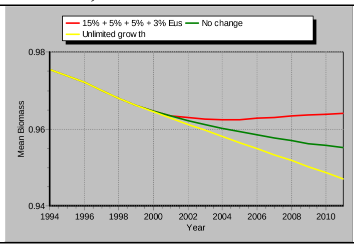
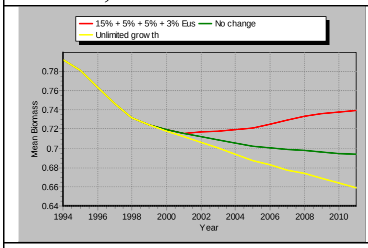
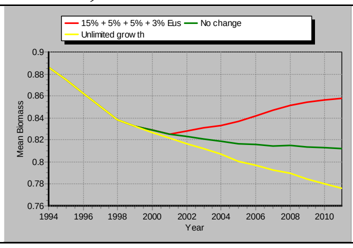
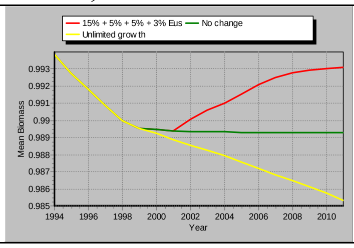
We use a quantile-based colour scale; that is, there are equal numbers of grids (in this case 20%) in each colour band. The brighter the red, the less recovery or more impact relative to the 'No change' scenario. The colour scale is not common across maps. There is little difference (grey) in areas of very high impact or very low impact (relative biomass ≅ 0 or 1 respectively). The biggest differences are in areas of intermediate impact (relative biomass ≅ 0.5). Refer to the first set of maps in this section.

r = 0.1; d = 0.4	r = 0.1; d = 0.01
	
r = 2; d = 0.4	r = 2; d = 0.01
	

Indicator plots

Below are plots of indicator *vs* year for each management intervention and all 9 combinations of *r* and *d*. Chosen indicators are mean relative biomass, proportion of grids exceeding 20% initial biomass and median relative biomass. For each indicator the most vulnerable species group is in the top left panel and the most resistant is in the bottom right panel.

The *y*-axis scales are *not* common across panels. From the beginning of 1993 until the end of 1998 the 3 lines on each panel coincide, because the effort data in all 3 cases are identical. The 'management interventions' diverge after this point. The history of depletion from the assumed beginning of trawling in 1956 to 1993 is not shown.

<table>
<tr><th colspan="3">Mean Relative Biomass</th></tr>
<tr><td>r = 0.1; d = 0.4</td><td>r = 0.1; d = 0.2</td><td>r = 0.1; d = 0.01</td></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
<tr><td>r = 0.5; d = 0.4</td><td>r = 0.5; d = 0.2</td><td>r = 0.5; d = 0.01</td></tr>
<tr><td>
</td><td>
</td><td>
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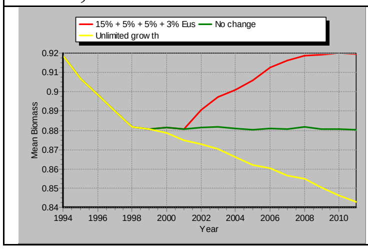
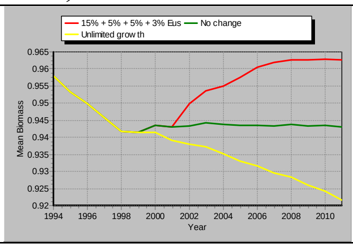
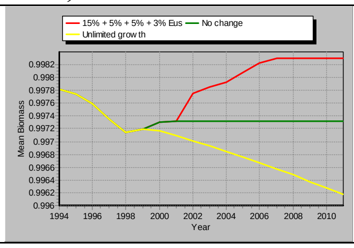
<tr><td>
</td><td>
</td><td>
</td></tr>
</table>

<table>
<tr><th colspan="3">Proportion of grids exceeding 20% Initial Biomass</th></tr>
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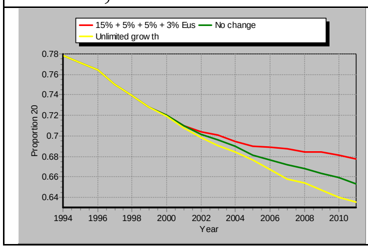
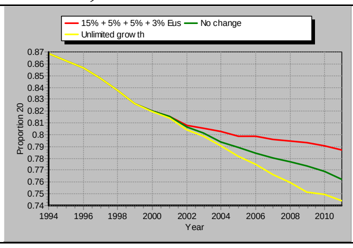
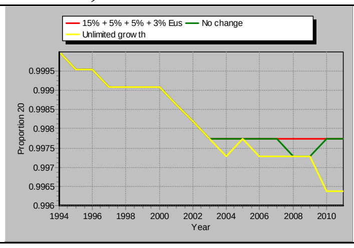
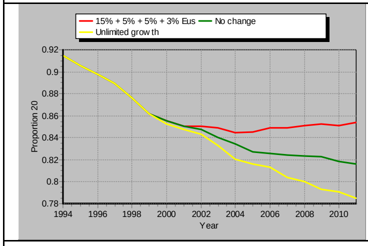
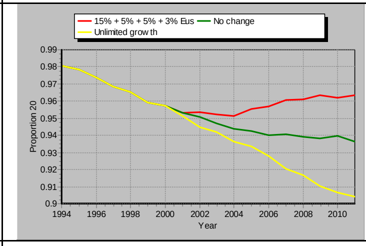
<tr><td>
</td><td>
</td><td>
</td></tr>
</table>

Proportion of grids exceeding 20% Initial Biomass (cont.)

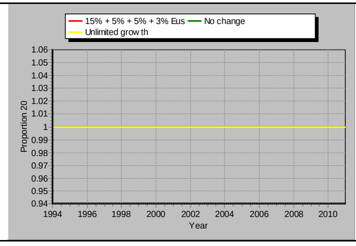
r = 0.5; d = 0.4



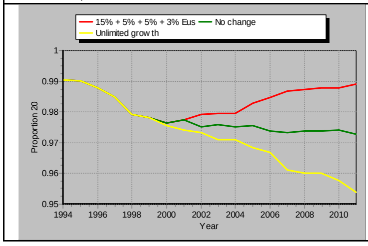
r = 0.5; d = 0.2



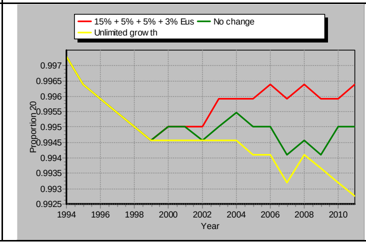
r = 0.5; d = 0.01



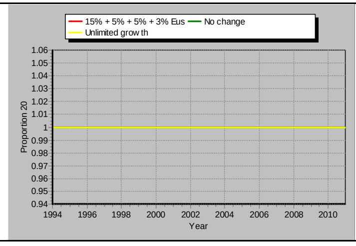
r = 2; d = 0.4



r = 2; d = 0.2

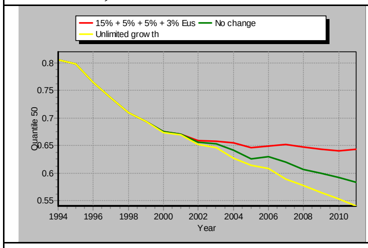


r = 2; d = 0.01

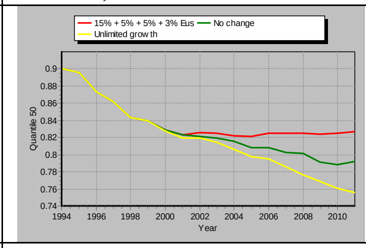


Median Relative Biomass

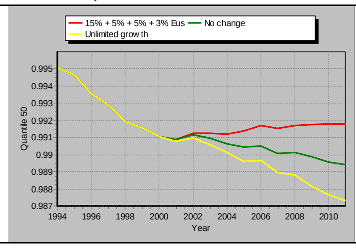
r = 0.1; d = 0.4



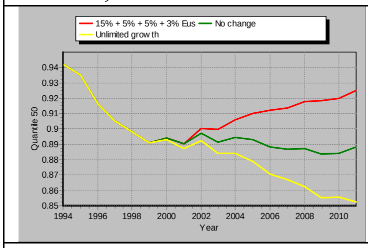
r = 0.1; d = 0.2



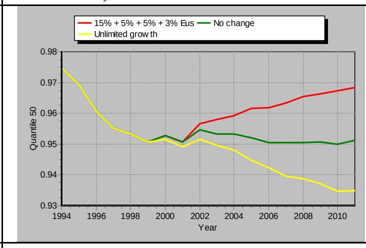
r = 0.1; d = 0.01



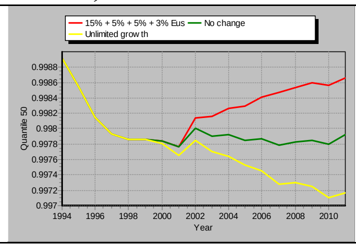
r = 0.5; d = 0.4



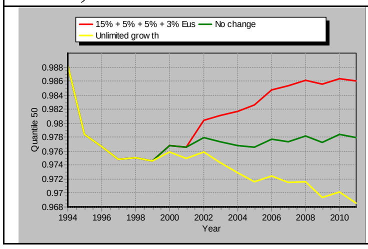
r = 0.5; d = 0.2



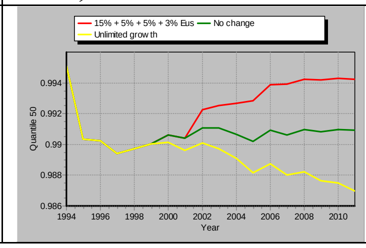
r = 0.5; d = 0.01



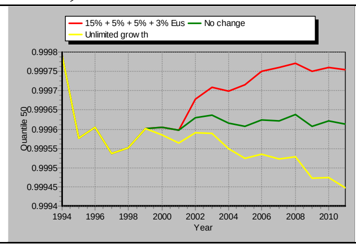
r = 2; d = 0.4



r = 2; d = 0.2



r = 2; d = 0.01



Ultimate steady state

In most cases the indicators for scenarios 0 and 1 appear to settle down to a steady state in which the biomass remains constant. This occurs when the rate of regrowth due to recovery balances the rate of removal by trawling This can only occur if the overall level of effort remains constant, which it does after 2005 for these two scenarios. The ‘unlimited growth’ scenario, if unchecked indefinitely, would ultimately result in zero biomass.

For a grid with long-term effort rate (swept area per year) E and vulnerability group (r, d), the steady state relative biomass b_{ss} is

$$b_{ss} = \max\left(0, 1 - dE \big/ r(1 - \tfrac{1}{2}d)\right).$$

Interestingly, this value is independent of β. From this, it is possible to predict the ultimate steady state for various indicators. Such steady state values are shown in the table below.

Comparison with the indicator plots shows good agreement for those cases that have already reached equilibrium by 2010. Note that these steady state estimates rely on the pattern of trawling remaining the same as it was during 1993–1997.

Steady state indicator value (percent)		Management Intervention					
Indicator		No change			15% + 5% + 5% + 3% Eus		
	d / r	0.4	0.2	0.01	0.4	0.2	0.01
Mean Biomass	0.1	42.6	55.2	94.8	49.5	62.6	96.6
	0.5	68.2	80.8	98.9	75.4	86.8	99.3
	2	88.1	94.3	99.7	92.1	96.3	99.8
Proportion 20	0.1	53.6	67.3	99.5	61.2	75.3	99.7
	0.5	80.9	92.8	100.0	87.4	97.2	100.0
	2	97.8	99.5	100.0	99.2	99.7	100.0
Quantile 50	0.1	38.3	72.6	98.8	61.0	82.6	99.2
	0.5	87.7	94.5	99.8	92.2	96.5	99.8
	2	96.9	98.6	99.9	98.0	99.1	100.0

Appendix 6: Effort allocation based on catch-per-unit-effort data

The rationale behind this approach to effort prediction is that it may be easier to predict for abundance than for effort. If we can find a relationship between abundance and effort, then, given a predicted value for abundance, we can predict effort. In the absence of abundance data, we use catch per unit effort as a surrogate.

The effort data used in the scenario modelling is aggregated trawl data. That is, whether the catch was tiger prawns, endeavour prawns, king prawns, banana prawns, scallops or whiting, the effort is still the number of boat days spent trawling. The reason the fisheries are not differentiated is that the focus of the modelling is the impact on benthos. This effect depends only on the swept area, not the target species. Nevertheless, fishery dependence (e.g. gear differences) can be incorporated by making the depletion rate vary spatially.

If we are to allocate effort based on historical catch per unit effort, it is important to separate different species, and, because of the nature of the effort data, this has to be done spatially. We also have to assume that in each region one species dominates the catch (which does hold for the QECTF to varying degrees). We examined maps of catch per different species and found that this assumption is largely true.

One way of separating regions of different catch per unit effort is to generate a regression tree model with latitude and longitude as the explanatory variables (Breiman et al, 1984). This partitions the fishery into rectangular blocks of roughly homogenous catch per unit effort (**Figure 29**). The best model in the sense of cross-validated pre-

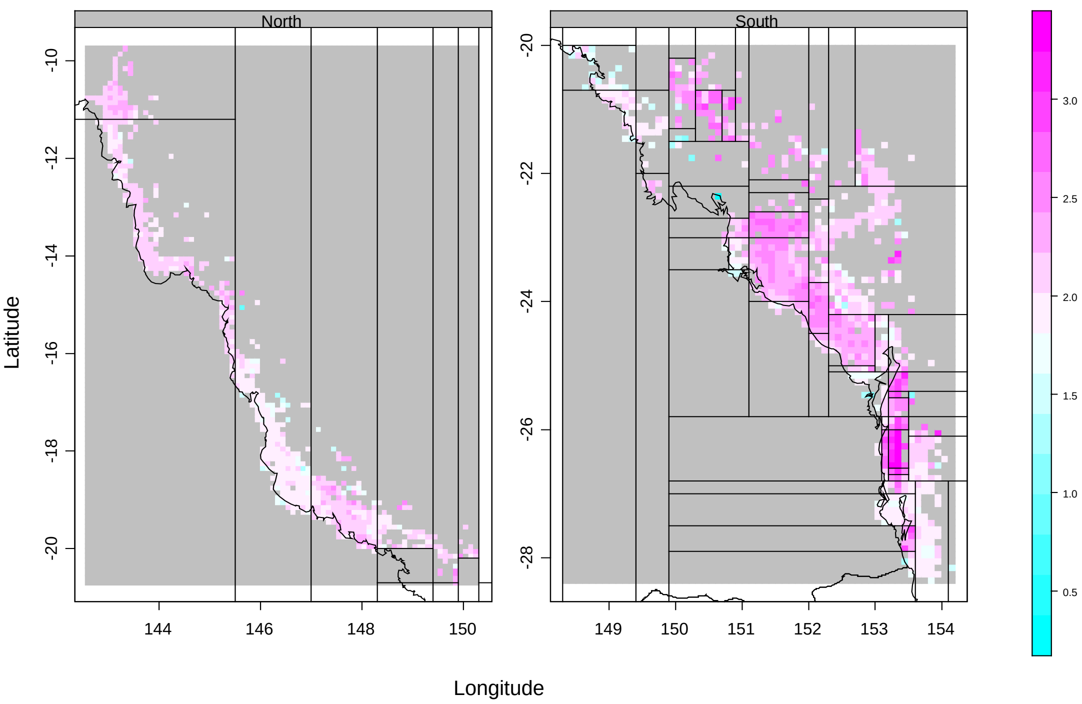


Figure 29. Mean $\log_{10}$ catch per unit effort over 1993–1997. Overlaid is the partitioning on latitude and longitude generated by the tree model. The tree model does a reasonable job of separating areas of differing overall catch per unit effort.

diction error has 60 partitions.

The tree model is constrained to have rectangular partitions, whereas regions of similar catch per unit effort are not in general rectangular. Therefore we have merged adjacent partitions with similar catch per unit effort to form 22 blocky regions (**Figure 30**). We performed the merging 'by hand', taking into consideration the rough species areas delineated in the maps of catch for different species.

Each region is treated separately in the prediction process. We show the relationship between $\log_{10}$ effort and $\log_{10}$ catch per unit effort in **Figure 31**. Each panel corresponds to a different region. There is considerable variation, especially with both variables on the logarithmic scale. There has been substantial separation into regions of different catch per unit effort, although some regions still have quite a wide spread.

The relationship is very complicated so we have modelled it in a flexible way using natural splines with two internal knots (de Boor, 1978). The fitted model is shown by a line. Within each region the variation is roughly constant if we take into consideration the smaller number of points in the tails.

The prediction is carried out as follows. For grid i in region r we sample the $\log_{10}$ catch per unit effort u_{ir} from the distribution $N(u_r, \sigma_u^2)$ where u_r is the mean $\log_{10}$ catch per unit effort for region r and $\sigma_u^2 = 0.3$. Then we sample effort E_{ir} from the distribution of $\log_{10}$ conditional on u_{ir}:

$$\log_{10} E_{ir} \sim N(f_r(u_{ir}), \sigma_E^2),$$

where $\sigma_E^2 = 1.34$ and $f_r(\cdot)$ is the spline function for region r.

The model is still in the experimental stages and there are certainly ways it could be

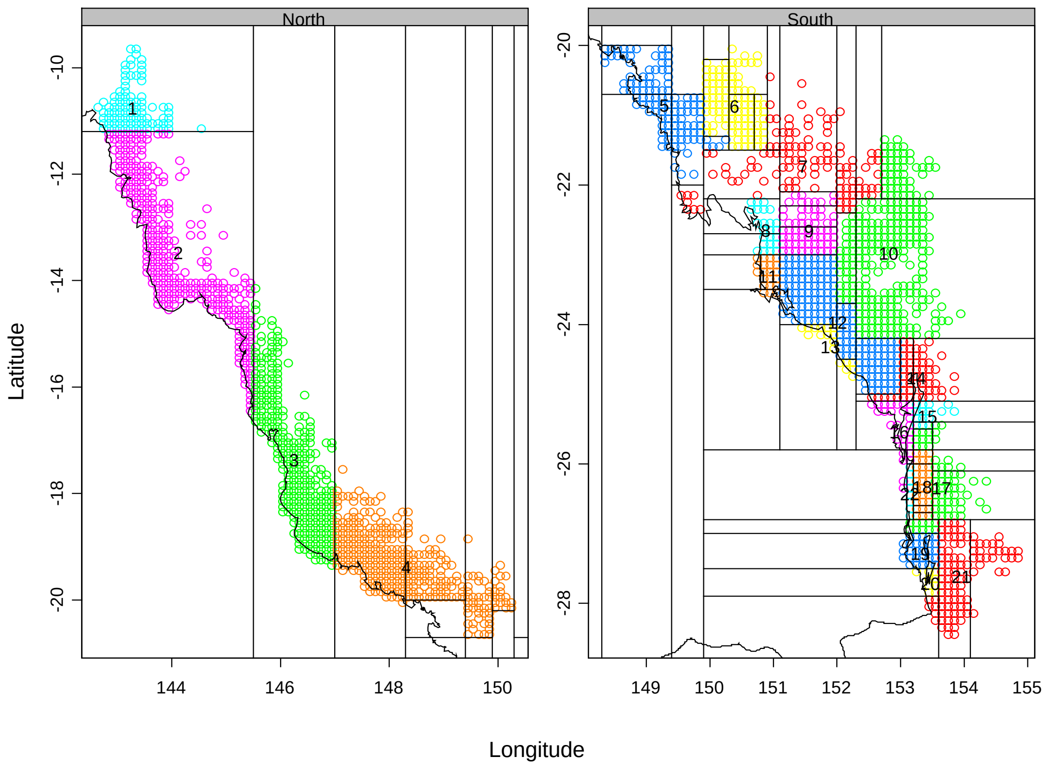


Figure 30. The 22 regions obtained after merging adjacent partitions from the regression tree model. Each region has roughly homogeneous catch per unit effort. Overlaid is the partitioning on latitude and longitude generated by the tree model.

improved. For instance, the prediction of catch per unit effort could be modified to include historical catch per unit effort information for that grid, as well as for the region as a whole. A still more flexible approach could be to use multivariate additive regression splines (Friedman, 1991). Here, instead of approximating catch per unit effort as a range of plateaux, it is possible to achieve a much smoother and so more accurate description.

Appendix 7: Glossary of acronyms

ESRI	Environmental Systems Research Institute, Inc.
FAO	Fisheries and Agriculture Organisation
GBRMPA	Great Barrier Reef Marine Park Authority
GPS	Geographic Positioning System
MPA	Marine Protected Area
NPF	Northern Prawn Fishery
QECTF	Queensland East Coast Trawl Fishery
QFMA	Queensland Fisheries Management Authority
QFS	Queensland Fisheries Service
VMS	Vessel Monitoring System
WHA	World Heritage Area

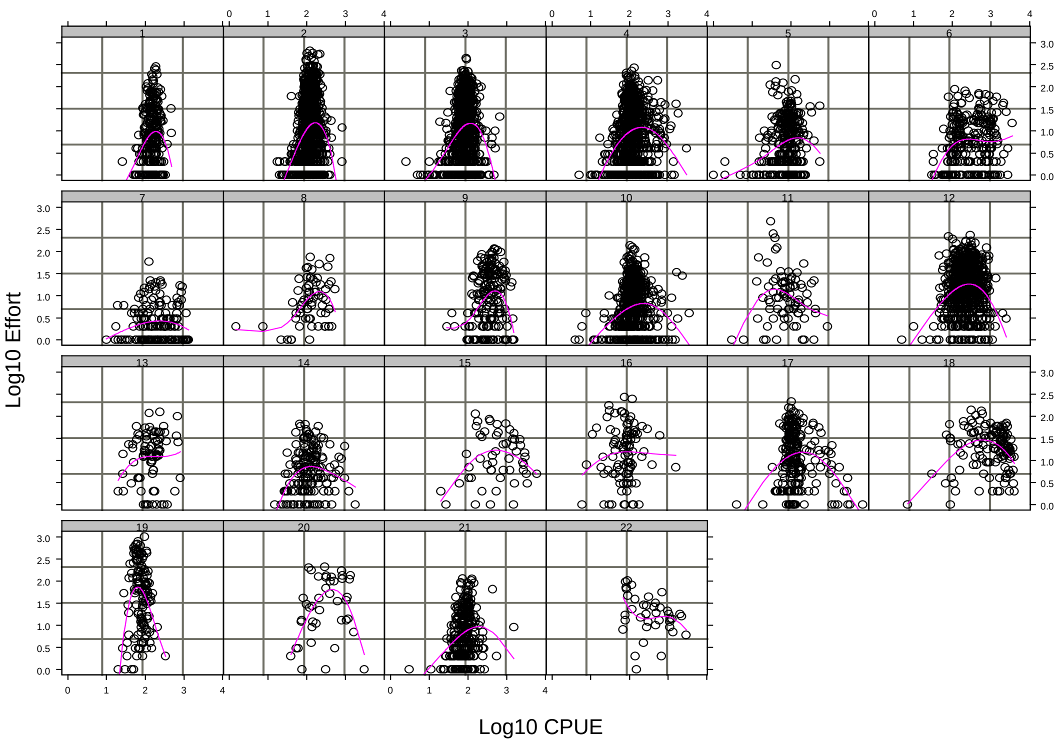


Figure 31. Scatterplots of $\log_{10}$ effort *vs* $\log_{10}$ catch per unit effort. Each panel corresponds to a different one of the 22 regions shown in **Figure 30**. All data for 1993–97 are shown. The spline fit is shown by a solid line.

Part Two

Technical Report

Part Two

Technical Report

Contents

List of Figures

1 Introduction

This technical report provides the derivation of the depletion-recovery differential equation which lies at the core of the model for the Trawl Management Scenario Modelling project. It also provides some results from simulations that can be used as a guide for future runs of the modelling software.

2 Depletion

In this section we derive a differential equation for biomass undergoing depletion from discrete trawl events which follow a statistical distribution. We defer discussion of recovery to a later section.

2.1 Depletion under a general pattern of trawling

We wish to find the rate of change of biomass over a (6-minute) grid in terms of the depletion rate per tow and the rate at which area is swept out by trawling gear. Let us suppose that trawling activity begins at time 0 and that after time t the ratio of total swept area to the area of the grid is $\mu(t)$. Then, on average, every point within the grid has been covered $\mu(t)$ times. However, this is just an average: some points have been covered more that $\mu(t)$ times and some less. The exact distribution of coverage about the mean μ affects the total depletion of biomass over the whole grid. In general, the more uniform the coverage, the higher is the total depletion.

We therefore have to specify a distribution for the number of times a point is covered; that is, we specify the probability $P_t(n)$ that at time t a point has been covered (trawled) n times.

The biomass $B(t)$ over the entire grid is given by the following integral

$$B(t) = \int_A \rho(\mathbf{x})(1-d)^{n_t(\mathbf{x})} dA \tag{1}$$

where d is the fraction of biomass removed per tow, $\rho(\mathbf{x})$ is the initial biomass density at position $\mathbf{x}$, $n_t(\mathbf{x})$ is the coverage at $\mathbf{x}$ after time t, and the integration is over the area of the grid A. Both $\rho(\mathbf{x})$ and $n_t(\mathbf{x})$ are random variables. Let $A_t(k)$

be the area covered k times at time t. Then

$$B(t) = \sum_{k=0}^{\infty}(1-d)^k \int_{A_t(k)} \rho(\mathbf{x})dA. \qquad (2)$$

We also know that the expected value of $A_t(k)$ (with respect to the random trawling process) is

$$\mathrm{E}A_t(k) = P_t(k)A. \qquad (3)$$

If we further assume that the distribution of trawling is independent of the distribution of initial biomass, then

$$\mathrm{E}\int_{A_t(k)} \rho(\mathbf{x})dA = P_t(k)A\mathrm{E}\rho = P_t(k)\mathrm{E}B(0), \qquad (4)$$

and so we have

$$\mathrm{E}B(t) = \sum_{k=0}^{\infty}(1-d)^k P_t(k)\mathrm{E}B(0). \qquad (5)$$

This last expression relates the expected biomass at time t to the expected initial biomass through the probability generating function of the coverage distribution, $g_t(z) = \sum_{k=0}^{\infty} z^k P_t(k)$, so that

$$\mathrm{E}B(t) = g_t(1-d)\mathrm{E}B(0). \qquad (6)$$

This equation states that the proportion of biomass remaining at time t is $g_t(1-d)$.

Because the area of a 6-minute grid is much larger than that of a single trawl, it follows that, by the central limit theorem, the actual total biomass will be close to the expected total biomass. Therefore from now on we drop the expectation symbol.

2.2 Depletion under particular patterns of trawling

Simple patterns: the negative binomial family

The distribution $P_t(n)$ reflects the pattern of trawling: if trawling has been completely random then $P_t(n)$ is a Poisson distribution; if aggregated, $P_t(n)$ could follow a negative binomial distribution; and if regular, $P_t(n)$ may follow a (positive) binomial distribution. Fortunately all three cases belong to a family of distributions that is governed by a single parameter β, which we call the aggregation parameter. For random trawling β is zero, for aggregated trawling β is positive, and for regular trawling β is negative.

For this one-dimensional family of distributions, the probability generating function is

$$g_t(z) = \exp(-\mu(t)\log(1 + \beta(1 - z))/\beta), \tag{7}$$

so that (6) becomes

$$B(t) = e^{-\lambda\mu(t)}B(0), \tag{8}$$

where

$$\lambda = \log(1 + \beta d)/\beta. \tag{9}$$

It is worth remarking that, for the Poisson case when $\beta = 0$, we have $\lambda = d$. For aggregated trawling ($\beta > 0$) $\lambda < d$, and for the regular trawling ($\beta < 0$) $\lambda > d$.

It is instructive to differentiate (8), because then we obtain the following differential equation:

$$\frac{dB}{dt} = -\lambda e(t)B(t), \tag{10}$$

where

$$e(t) = \frac{d\mu}{dt}. \tag{11}$$

The quantity $d\mu/dt$ is the rate at which area (relative to grid area) is swept out, and so we call this the *effort rate* $e(t)$. The quantity λ can be interpreted as the large-scale fractional depletion rate per unit effort rate: it is the large-scale analogue of d. Note that, whereas d describes a *discrete* depletion event (a tow), λ describes a *continuous* process of depletion, hence the dimensions of 'per unit effort rate'.

More complicated patterns: the two-stage model

The negative binomial family of distributions is a convenient starting point for handling aggregation. However, it is also possible to consider more complicated distributions. For instance, parts of the grid may be untrawlable, or trawlers may target certain areas, leaving others alone. The pattern of trawling within a targetted area may be modelled with the negative binomial family. The selection of area to trawl may be modelled by a binomial process. Hence we may suppose that the entire fishery may be modelled as a two-stage process: first a patch of area a is selected; and second, trawling is modelled within that patch according to the negative binomial family.

The first process is binomial and has probability generating function

$$g_{\mathrm{p}}(z) = (pz + 1 - p)^N. \tag{12}$$

Here $p = a/A$ is the probability of a point being within the patch of area a, which was randomly selected from a region of area A. N is the total number of patches. The mean number of patches covering a point is $\mu_p = Np$

The within-patch process is given by the probability generating function

$$g_{\mathrm{wp}}(z) = \exp(-\mu_{\mathrm{wp}} \log(1 + \beta(1 - z))/\beta). \tag{13}$$

Here μ_{wp} is the mean level of coverage within the patch and β is the within-patch aggregation parameter. Poisson trawling corresponds to $\beta = 0$; the case of uniform trawling corresponds to $\beta = -1$ and integer μ_{wp}, which is a special case of the binomial distribution.

Happily, the probability generating function of the combined process is the composition of these two functions:

$$g(z) = g_{\mathrm{p}}(g_{\mathrm{wp}}(z)) = (p \exp(-\mu_{\mathrm{wp}} \log(1 + \beta(1 - z))/\beta) + 1 - p)^N. \tag{14}$$

The coverage mean is

$$\mathrm{E}(n) \equiv \mu = g'(1) = \mu_p \mu_{\mathrm{wp}}, \tag{15}$$

and the variance is

$$\mathrm{Var}(n) = g''(1) + g'(1) - g'(1)^2 = \mu(1 + \beta + (1 - p)\mu/\mu_p). \tag{16}$$

Note that when the within-patch process is aggregated, so is the two-stage process (variance is greater than mean). However, when the within-patch process is regular, the two-stage process may be either regular or aggregated. The proportion of biomass remaining is still given by $g(1 - d)$. The two-stage model reduces to the simple model of the previous section when $N = p = 1$.

As an example, consider the case of a grid, half of which is closed to trawling and the other half is trawled randomly. This case corresponds to $N = 1$, $p = 1/2$ and $\beta = 0$. If the total coverage is μ, then within the trawlable patch the coverage is 2μ. So the proportion of biomass remaining is $g(1 - d) = \frac{1}{2}(1 + e^{-2\mu d})$.

2.3 Interpretation of negative binomial family as a continuous process

We have derived the remaining biomass $B(t)$ in terms of the accumulated swept area $\mu(t)$ at time t. Implicit in our derivation is the assumption that the distribution of coverage is negative binomial not only at time t but also at intermediate times between 0 and t. We have implicitly stated this by writing down a differential equation which applies for all times. In particular we have stated that the time dependency of the distribution is subsumed into μ, but the aggregation of the distribution β is independent of time. We need to check whether such a distribution can exist, and, if so, whether it adequately models the process of trawling itself.

Let us first consider the case of random trawling. If the effort rate is $e(t)$ then the probability of a particular point being trawled within the infinitesimal time interval $(t, t + dt)$ is $e(t)dt$. The number of trawl events over the finite interval $(0, t)$ is a Poisson random variable with mean $\mu(t) = \int_0^t e(t')dt'$. So the Poisson nature of the distribution applies for all times.

We can now generalize this to the negative binomial case. Whereas in the Poisson case, the 'trawl event' that occurs in the infinitesimal time interval $(t, t + dt)$ is a *single* pass of the net, in the negative binomial case, the trawl event may be *one or more* passes. The number of passes per event is a logarithmic random variable with probability generating function $g_{\log}(z) = \log(1-\theta z)/\log(1-\theta)$, where $\theta = \beta/(1+\beta)$. The probability of an 'event' occuring within the infinitesimal time interval $(t, t+dt)$ is $\beta^{-1}\log(1 + \beta)e(t)dt$ (Quenouille, 1949). Under these circumstances, the number of trawl events over the finite interval $(0, t)$ is a negative binomial random variable with mean $\mu(t)$ and aggregation parameter β.

The possibility of multiple passes per event resembles the real process of trawling, where one or more vessels may trawl the same track over again. We should not carry this resemblance too far however. The phenomenon of aggregation is a spatial process, whose details cannot be captured by such a simple statistical model. However, the broader properties of aggregation, namely the distribution of coverage, can be captured to a certain extent by our models.

We do not know whether the two-stage model can be similarly extended to a continuous process. Also, a natural extension of the simple negative binomial model is to make β vary in time. It is certainly possible to make β time-varying in equation (10), but we do not know whether the equation then correctly describes the change in biomass.

3 Recovery

We have so far derived a differential equation for biomass undergoing depletion and no recovery. We obtained a large-scale depletion rate λ which depended on the small-scale depletion rate d and the aggregation parameter β.

We now have to incorporate recovery into the model. We shall find that the differential equation is modified by adding a logistic recovery term with large-scale recovery rate r. However, recovery is measured on the scale of individual organisms or areas on the scale of metres. Let us call this small-scale recovery rate r_s to distinguish it from r. Then we need to show how r depends on r_s. In other words, we need to scale up the small-scale recovery rate, just as we scaled up the depletion rate.

3.1 Recovery on the small scale

Consider the biomass B in a small area on the scale of metres. The biomass undergoes discrete trawl events in which a fixed proportion d of the biomass is removed. The timing of these events is random. During periods between consecutive trawl events we assume the biomass recovers according to the logistic recovery equation

$$\frac{dB}{dt} = r_s B(t)(1 - B(t)/K), \tag{17}$$

where K is the carrying capacity of the small area. This is a special case of equation (47) in the next section, which we can solve analytically. The solution of (17) is the sigmoidal curve shown in (55) with r_s substituted for r.

It will prove convenient to work with *relative biomass* $b(t) \equiv B(t)/K$. The relative biomass is bounded between 0 and 1 and takes its maximum value when the biomass reaches the carrying capacity. The relative biomass at time $t + \Delta t$ in terms of relative biomass at time t is given by

$$b(t + \Delta t) = \frac{b(t)e^{r_s \Delta t}}{1 + b(t)(e^{r_s \Delta t} - 1)}. \tag{18}$$

3.2 A differential equation for the moments of the relative biomass distribution

In the case of depletion only, it was fairly straightforward to derive the evolution of total biomass over time. When we incorporate recovery, however, the derivation becomes much more difficult, because we are now averaging over quite complicated small-scale time histories. We approach the problem by first assuming a small-scale distribution $\pi_t(b_t)$ for the relative biomass b_t at time t. (We use subscripts to avoid unwieldy parentheses.) We then find the distribution after a small time interval Δt, in terms of the distribution at time t. By taking moments of these distributions, and considering the limit as $\Delta t \to 0$, we set up differential equations for the moments of $\pi_t(\cdot)$. The first moment $b_1(t)$ is the mean relative biomass, and the second moment $b_2(t)$ is related to the variance.

The relative biomass distribution at time $t+\Delta t$ in terms of the distribution at t is given by

$$\pi_{t+\Delta t}(b_{t+\Delta t})db_{t+\Delta t} = \sum_{n=0}^{\infty} \frac{P_{\Delta t}(n)}{(1-d)^n}\pi_t(b_t/(1-d)^n)db_t. \tag{19}$$

This states that the relative biomass can end up in the interval $[b_{t+\Delta t}, b_{t+\Delta t}+db_{t+\Delta t}]$ if the relative biomass starts at $b_t/(1-d)^n$, undergoes n depletion events reducing it to b_t, then recovers along the sigmoidal curve to $b_{t+\Delta t}$. $P_{\Delta t}(n)$ is the probability of n events within the time interval $(t, t+\Delta t)$. The factor $(1-d)^n$ in the denominator accounts for the change in width of the initial relative biomass interval with n. Because Δt is small we suppose all events occur at the beginning of the time interval.

The differential deterministic recovery relationship is

$$\begin{aligned} b_{t+\Delta t}(b_t) &= \frac{b_t e^{r_s \Delta t}}{1 - b_t(1-e^{r_s\Delta t})} && (20)\\ &= b_t(1 + r_s\Delta t(1-b_t)) + O(\Delta t^2). && (21)\end{aligned}$$

We can find the kth moment of relative biomass at time $t+\Delta t$ in terms of the kth moment of relative biomass at time t by integrating thus

$$b_k(t+\Delta t) = \int_0^1 b_{t+\Delta t}^k \pi_{t+\Delta t}(b_{t+\Delta t})db_{t+\Delta t} \tag{22}$$

$$= \int_0^1 b_t^k(1 + kr_s\Delta t(1-b_t)) \sum_{n=0}^{\infty} \frac{P_{\Delta t}(n)}{(1-d)^n}\pi_t(b_t/(1-d)^n)db_t + O(\Delta t^2), \tag{23}$$

$$= \sum_{n=0}^{\infty} \int_0^1 z^k (1-d)^{nk} (1 + kr_s \Delta t (1 - z(1-d)^n)) P_{\Delta t}(n) \pi_t(z) dz + O(\Delta t^2), \quad (24)$$

$$= \sum_{n=0}^{\infty} b_k(t)(1-d)^{nk}(1 + kr_s\Delta t) - kr_s \Delta t b_{k+1}(t)(1-d)^{n(k+1)}) P_{\Delta t}(n) + O(\Delta t^2), \quad (25)$$

$$= b_k(t) \mathrm{E}_{\Delta t} \left[(1-d)^{nk} \right] (1 + kr\Delta t) - kr \Delta t b_{k+1}(t) + O(\Delta t^2). \quad (26)$$

$b_k(t)$ is the kth moment of the relative biomass distribution, and $\mathrm{E}_{\Delta t}$ denotes expectation within the period of duration Δt.

We can evaluate the expectations for $k = 1$ and 2:

$$\mathrm{E}_{\Delta t}((1-d)^n) = 1 - \lambda e(t) \Delta t + O(\Delta t^2), \quad (27)$$

$$\mathrm{E}_{\Delta t}((1-d)^{2n}) = 1 - 2(\lambda - \lambda_2) e(t) \Delta t + O(\Delta t^2), \quad (28)$$

where $e(t)$ is the effort rate and

$$\lambda = \log(1 + \beta d)/\beta \quad (29)$$

$$\lambda_2 = \log \left[\frac{1 + 2\beta d(1 + \beta d/2)}{1 + 2\beta d(1 - d/2)} \right] /2\beta. \quad (30)$$

The definition of λ is the same as we saw in equation (9).

It follows then that

$$b_1(t + \Delta t) = b_1(t)(1 - \lambda e(t) \Delta t + r_s \Delta t) - r_s \Delta t b_2(t) + O(\Delta t^2), \quad (31)$$

$$b_2(t + \Delta t) = b_2(t)(1 - 2(\lambda - \lambda_2) e(t) \Delta t + 2r\Delta t) - 2r \Delta t b_2(t) + O(\Delta t^2). \quad (32)$$

Taking the limit $\Delta t \to 0$ we get for the first moment

$$\frac{db_1}{dt} = (r_s - \lambda e(t)) b_1(t) - r_s b_2(t). \quad (33)$$

From the definition of variance, $V(t) \equiv \mathrm{Var}(b) = b_2 - b_1^2$, we have

$$\frac{db_1}{dt} = r_s b_1(t)(1 - b_1(t)) - \lambda e(t) b_1(t) - r_s V(t). \quad (34)$$

This is a remarkable equation. It is a differential equation for the large-scale average biomass in terms of small-scale parameters r_s and (through λ), d. The first term on the right-hand side is the classic recovery term with rate equal to the small-scale recovery rate. The second term is the depletion term that we derived in the last section. The third term provides a correction to the recovery as we now show.

The maximum variance b can have is $b_1(1-b_1)$, because b is bounded. We can therefore rewrite the variance as $V = \phi b_1(1-b_1)$, where $0 \le \phi \le 1$ and is a function of time. The differential equation then becomes

$$\frac{db_1}{dt} = r_s(1-\phi(t))b_1(t)(1-b_1(t)) - \lambda e(t)b_1(t). \tag{35}$$

Thus the large-scale recovery rate is equal to the small-scale rate reduced by a time-varying fraction $\phi(t)$.

To solve this differential equation we need a second differential equation for $\phi(t)$. We obtain this from the differential equation for $b_2(t)$. After considerable manipulation we get

$$\begin{aligned}(2r_s)^{-1}b_1(1-b_1)\frac{d\phi}{dt} &= \\ &b_1(1-b_1)\left[-(1-\phi)((1-\phi)b_1+\phi/2)+\phi(1-\gamma+\gamma_2-3b_1)\right] \\ &+\gamma b_1((1-\phi)b_1+\phi/2)+b_1^2(1-\gamma+\gamma_2-b_1)-\mathrm{E}((b-b_1)^3).\end{aligned} \tag{36}$$

where

$$\gamma(t) = \lambda e(t)/r_s, \tag{37}$$

$$\gamma_2(t) = \lambda_2 e(t)/r_s. \tag{38}$$

3.3 An approximate solution

It does not appear possible to solve the differential equation for any moment b_k, because the right-hand side always involves the next higher moment b_{k+1}. At some stage we have to make an assumption about one of these moments. We could for instance assume that the variance was negligible and ignore the third term in (34). We prefer however to include the variance term. We shall instead assume that the skewness $\mathrm{E}((b-b_1)^3)$ is negligible and set it to zero in (36).

The quantity $\phi(t)$ is really a nuisance quantity: we are not interested in $\phi(t)$ itself, only in its effect on $b_1(t)$. Our plan therefore is to replace it with a constant value chosen so that the differential equation for $b_1(t)$ remains approximately valid. We obtain such a value by solving for the steady state with $e(t) = \bar{e}$, a constant, since then ϕ is constant. Setting $db_1/dt = d\phi/dt = 0$ we find

$$b_{1\mathrm{ss}} = \frac{1}{4}(1-\gamma)(3+\sqrt{1-8\gamma_2/(1-\gamma)}) \tag{39}$$

$$\phi_{\mathrm{ss}} = 1-\gamma/(1-b_{1\mathrm{ss}}). \tag{40}$$

For small d we have, approximately,

$$b_{1\mathrm{ss}} = 1 - \bar{e}d/r_s - \bar{e}d^2/2r_s \tag{41}$$
$$\phi_{\mathrm{ss}} = (\beta+1)d/2. \tag{42}$$

Equation (39) does not have a real solution for $8\gamma_2 > 1-\gamma$. This corresponds to cases where the steady state biomass is small (< 0.2). This seems to imply that the zero skewness assumption breaks down. In fact there are technical difficulties leading to instability for cases where $r_s \approx \bar{e}d$. It does not appear possible to obtain an analytical form for the biomass for these cases. On the other hand, equation (41) is well behaved, provided d remains small and β is not too large. Because of this, we use (42) as the constant for adjusting the recovery.

So we have for the large-scale recovery

$$r = r_s(1-\phi_{\mathrm{ss}}), \tag{43}$$

which, to the same level of approximation (small d), is equivalent to

$$r = r_s(1-d/2)\log(1+\beta d)/\beta d. \tag{44}$$

Finally we replace equation (35), which has time-varying recovery, with the following form with constant large-scale recovery:

$$\frac{db_1}{dt} = rb_1(t)(1-b_1(t)) - \lambda e(t)b_1(t). \tag{45}$$

Reintroducing the biomass B and carrying capacity K for the entire grid we have

$$\frac{dB}{dt} = rB(t)(1-B(t)/K) - \lambda e(t)B(t). \tag{46}$$

The derivation of (44) may seem less than compelling, especially since (44) is not the only expression than reproduces (43) for small d. Nevertheless, we have found quite good agreement between the solution of (46) and output from simulations of detailed biomass evolution. The agreement extends over a range of values of r_s, d, β and $e(t)$, even beyond the validity of (42). We describe the simulation work in a later section.

4 The large-scale depletion-recovery equation

The large-scale depletion-recovery equation is tractable to a certain degree: we describe some of its properties. The equation is

$$\frac{dB}{dt} = rB(t)(1 - B(t)/K) - \lambda e(t)B(t), \tag{47}$$

where $B(t)$ is the biomass at time t, $e(t)$ is the effort rate, λ is the large-scale depletion rate per unit effort rate, r is the large-scale recovery rate and K is the carrying capacity. These are *large-scale* equations because they are based on an effort model at the grid level. In order to make this equation soluble we have to provide an initial condition. We assume that the biomass at time $t = 0$ prior to trawling is equal to the carrying capacity:

$$B(0) = K. \tag{48}$$

4.1 Analytical solution

The differential equation (47) can be solved analytically. It has solution

$$B(t)/K = \frac{B(0)\exp(rt - \lambda\mu(t))}{K + rB(0)\int_0^t \exp(rt' - \lambda\mu(t'))dt'}, \tag{49}$$

where the cumulative effort μ is defined by

$$\mu(t) = \int_0^t e(t')dt'. \tag{50}$$

In the absence of recovery (49) reduces to

$$B(t) = B(0)e^{-\lambda\mu(t)}, \tag{51}$$

which is simply exponential decay.

We can get a qualitative understanding of the long-term behaviour of the system by replacing $e(t)$ by its long-term average $\bar{e}$. Then

$$\lim_{t\to\infty} B(t)/K = \max(1 - \lambda\bar{e}/r, 0), \tag{52}$$

so that, if the depletion rate or effort is too large, or the recovery is too slow, the species dies out, otherwise it survives at a biomass reduced by relative amount $\lambda\bar{e}/r$. If $e(t)$ is not in fact constant, but oscillates about $\bar{e}$, then $B(t)/K$ also oscillates about the long-term mean shown in (52).

Recursive formulation

Equation (49) expresses the solution at time t in terms of the initial state at time 0. It will sometimes be convenient to express the solution at time t in terms of the solution at some earlier time t_1. This can be useful in a time-stepping implementation where, for reasons of efficiency, the time step cannot be made arbitrarily small. The recursive solution is

$$B(t)/K = \frac{B(t_1)\exp(r(t-t_1) - \lambda\mu_1(t))}{K + rB(t_1)\int_0^{t-t_1}\exp(rt' - \lambda\mu_1(t'))dt'}, \tag{53}$$

where $\mu_1(t) = \mu(t_1+t) - \mu(t_1)$ is the cumulative effort from t_1. This is simply the same as equation (49) with the time origin at t_1.

Evolution over a period of constant effort

If $e(t) = e_1$, a constant, over the interval $(0, t)$ then

$$B(t)/K = \frac{B(0)\exp((r-\lambda e_1)t)}{K + B(0)(\exp((r-\lambda e_1)t) - 1)/(1-\lambda e_1/r)}. \tag{54}$$

The same result could be obtained by using several time steps across the time period; but this form eliminates the need for time steps.

An important special case of (54) is when $e_1 = 0$, which describes recovery along the sigmoid

$$B(t)/K = \frac{B(0)e^{rt}}{K + B(0)(e^{rt} - 1)}. \tag{55}$$

Evolution over a period of linearly increasing effort

If $e(0) = e_1$, $e(t) = e_2$ and $e(t')$ is linear over the interval $(0, t)$ then

$$B(t)/K = \frac{B(0)\exp(rt - \lambda\mu(t))}{K + rB(0)\sqrt{\frac{2\pi t}{\lambda\Delta e}}\exp\left(\frac{t(\lambda e_1 - r)^2}{2\lambda\Delta e}\right)\left[\Phi\left(\sqrt{\frac{t}{\lambda\Delta e}}(\lambda e_2 - r)\right) - \Phi\left(\sqrt{\frac{t}{\lambda\Delta e}}(\lambda e_1 - r)\right)\right]} \tag{56}$$

where $\Delta e = e_2 - e_1$ and $\mu(t) = (e_1 + e_2)t/2$. Cumulative effort is quadratic over the interval, $\mu(t') = e_1 t' + \Delta e t'^2/2t$. $\Phi(\cdot)$ is the cumulative density function of the standard normal. The expressions in the denominator can become difficult to compute for large e_1; in that case the following alternative form can be used:

$$B(t)/K = \frac{B(0)\exp(rt-\lambda\mu(t))}{K + rB(0)\sqrt{\frac{2\pi t}{\lambda\Delta e}}\left[W\left(\sqrt{\frac{t}{\lambda\Delta e}}(\lambda e_1 - r)\right) - e^{-(\lambda\bar{e}-r)t}W\left(\sqrt{\frac{t}{\lambda\Delta e}}(\lambda e_2 - r)\right)\right]} \tag{57}$$

where $\bar{e} = (e_1 + e_2)/2$ and $W(x) = e^{x^2/2}(1 - \Phi(x))$. Again this form eliminates the need for time steps.

4.2 Numerical Implementation

The analytical properties described in the previous section allow us to formulate numerical solutions in either integral or differential form. The integral form is exact and highly efficient. The differential form can be made exact, but it is also simpler and more flexible.

Integral form

If we assume that $\mu(t)$ is piece-wise constant or piece-wise linear, then the integral in (49) can be evaluated analytically. In the following we assume $j = 1, 2, \ldots$ is the number of years after some origin, e_j is the effort in the jth year and $\mu_j = \sum_{i=1}^{j} e_i$ is the cumulative effort after j years. The piece-wise constant model implies that all the fishing effort occurs at the beginning of the year, whereas the piece-wise linear model implies the effort is uniform throughout the year.

The biomass after j years, B_j, is given by

$$\frac{e^{rj-\lambda\mu_j}}{K + \sum_{i=1}^{j} e^{ri-\lambda\mu_i}(1-e^{-r})} \qquad \text{constant} \tag{58}$$

and

$$\frac{e^{rj-\lambda\mu_j}}{K + \sum_{i=1}^{j} e^{ri-\lambda\mu_i}(1-e^{\lambda e_i - r})/(1-\lambda e_i/r)} \qquad \text{linear} \tag{59}$$

Note that setting $e_i = 0$ in the linear case produces the constant case, and that when $r = 0$ both cases are the same. Differences between the two cases are important only for species with rapid recovery (large r) or for large time steps.

Differential form

The simplest way of solving the depletion equation is to convert the differential equation into a difference equation thus:

$$B(t+\Delta t) = B(t) - \lambda e(t)B(t)\Delta t + rB(t)(1 - B(t)/K)\Delta t, \tag{60}$$

where Δt is the time step. By making Δt small enough, we can achieve any desired accuracy.

For a fixed Δt the time stepping form can be made exact by using the recursive form (53), with (t_1, t) replaced by $(t, t + \Delta t)$.

The differential form is more flexible than the integral form because it allows for time variation in r and λ. Such variation could be systematic or random. For instance, random variation can be introduced by simply adding a random amount to r at each time step and using (60) with that adjusted value. The integral formulation, with its assumption of fixed r and d, cannot cater for this.

5 Simulation Studies

In this section we describe four topics where we have used simulation. We use simulation for two reasons: first, to verify our models, and second, to provide feasible ranges for model parameters or calibrate the model. In the first topic, we simulate the detailed process of depletion and recovery at the subgrid level, aggregate the results and compare them with results from the simpler large-scale model. Secondly, we investigate how stochastic variation in the depletion rate from tow to tow scales up to variation in the large-scale depletion rate. Thirdly, we attempt to simulate real trawling using a stochastic spatial process, in order to check the validity of the negative binomial family. And fourthly, we report on simulations involving real trawl pattern data that provide a feasible range for the aggregation parameter β. The first and third topics concern verification and the second and fourth concern calibration.

5.1 Checking the large-scale depletion-recovery differential equation

We need to check that the large-scale depletion-recovery equation accurately reproduces the large-scale change in biomass. We do this by simulating the detailed process of depletion and recovery at the subgrid level and aggregating the results up to the grid scale. The simulation is carried out as follows: Partition the trawled grid into $N = 1000$ equal cells, and set the biomass to 1 in each cell. For each cell $i = 1, \ldots, N$ sample the number of tows n_i (usually 0 or 1) within a certain time step Δt from the appropriate distribution as described in earlier sections. Then deplete the biomass by factor $(1-d)^{n_i}$ and then allow it to recover for time Δt according to equation (18). At each time t compute the mean remaining biomass $b(t) = N^{-1}\sum_{i=1}^{N} b_i$. Call this result $b^{(1)}(t)$. Repeat the whole process for a suitably large number of simulations, here $n_{\text{sim}} = 100$, obtaining $b^{(2)}(t), \ldots, b^{(n_{\text{sim}})}(t)$. We can then compare these multiple simulations with the results from the model.

Initially we assumed a constant rate of effort $\bar{e}$. We ran simulations for a range of values of r_s (0.05, 0.1, 0.2, 0.3), $\bar{e}$ (0.5, 1, 2, 4, 8), β (0, 1, 2, 5) and d, such that the approximate steady state relative biomass b_{simple} ($\equiv 1 - \lambda\bar{e}/r_s$) took the values (0.1, 0.3, 0.5, 0.7, 0.9). It is interesting first to look at the results for the simple model assuming $r = r_s$. This model arises if we ignore the variance term in (34). Under this model the steady state relative biomass equals b_{simple}.

Figure 1 shows the residuals of the simulated steady state biomass from b_{simple}. We estimated the steady state biomass as the median biomass over the final ten years of a sufficiently long run, the duration being inversely proportional to $|r_s - \bar{e}d|$. The true steady state value is generally overestimated. The kinks in some of the curves for small b_{simple} is an artefact caused by the steady state not being reached.

The residuals from the preferred model with r given by (44) are shown at an expanded scale in Figure 2. The fit is greatly improved. The positive residuals for small b_{ss} are due in part to the simulated vales being too large, those runs having not reached convergence.

We have focussed on the model fitting the eventual steady state. We should also check how well the model tracks the simulations over time. We show this for various cases in Figure 3 for $\beta = 0$ and in Figure 4 for $\beta = 5$.

So far all these examples have been for constant effort. We now check that the model works for more realistic effort patterns. We analysed effort data for the period

1993–1997 in all 30-minute grids in the Queensland East Coast Fishery. We assumed the effort within each grid to be lognormally distributed and we found the mean and variance of log effort within each grid cell. The 75th percentile of the distribution of means was 0.56 (900 boat days) and the corresponding standard deviation on the log scale was 0.17. We simulated an effort sequence by sampling from the lognormal distribution with the same mean and standard deviation. We then used this effort sequence to simulate biomass depletion with various depletion/recovery parameters. The results are shown in Figure 5 for $\beta = 0$ and in Figure 6 for $\beta = 5$.

The agreement between the simulations and the model is quite satisfactory. Case (b) corresponds to the critical case when recovery and depletion rates balance. This is difficult to model when $e(t)$ is constant (see bottom of Figure 3). Here, however, the variation of $e(t)$ stabilizes the model.

5.2 Variation in depletion rate among tows

The results of the depletion experiment (Poiner et al, 1998, chapter 7) show that the catches from one tow to the next are highly variable. This is partly because subsequent tows did not precisely cover the same ground. But it also may be due to variation in the depletion rate from one tow to the next.

We can simulate the effects of variation in d for a range of effort, aggregation and mean depletion. Because our focus is on depletion, we do not consider recovery in this simulation. This simplifies the problem greatly.

We perform the simulation as follows. Partition the trawled grid into $N = 1000$ equal cells. For each cell $i = 1, \ldots, N$ sample the number of tows n_i from the appropriate distribution which depends on the total effort μ as described in earlier sections. For each tow m in cell i, sample d_{im} from the Beta distribution with mean μ_d and variance $\mu_d(1-\mu_d)\phi$ where $\phi \in [0, 1]$. Find the remaining biomass in cell i as $b_i = \prod_{m=1}^{n_i}(1 - d_{im})$, where we have assumed the initial biomass is 1. Compute the mean remaining biomass $b = N^{-1}\sum_{i=1}^{N} b_i$, and call this result $b^{(1)}$. From equation (51), the effective large-scale depletion rate is then given by $\lambda^{(1)} = -\log(b^{(1)})/\mu$. We repeat the whole process for a suitably large number of simulations, here $n_{\mathrm{sim}} = 100$, obtaining $\lambda^{(2)}, \ldots, \lambda^{(n_{\mathrm{sim}})}$.

We then have a sample from the distribution of λ. Taking the mean $\bar{\lambda}$ of this sample gives us an estimate of the expectation of λ. When d is fixed, λ is given by (9); let us call this value λ_{f}. Then $\bar{\lambda}/\lambda_{\mathrm{f}}$ gives a measure of the bias in λ introduced by variation in d. Figure 7 shows that there is very little bias in λ, since $\bar{\lambda}/\lambda_{\mathrm{f}}$ is close to 1.

The main effect of variation in d is to introduce variation in λ, as seen in Figure 8. In this Figure we have plotted the variance of $\lambda/\lambda_{\mathrm{f}}$, which is an estimate of the coefficient of variation. This quantity varies in a straightforward way with ϕ. There is some dependence on μ and Ed, but only very weak dependence on β. The simulations suggest square root coefficients of variation in the range 0–10% are appropriate for λ.

5.3 Spatial trawl track simulation

In this section we attempt to simulate real trawling using a stochastic spatial process, in order to check the validity of the negative binomial family.

Method

We have developed a program that simulates trawling over a rectangular grid. We assume all tows are straight so that they cover an elongated rectangle. The trawl coverage is accumulated on a rectangular grid; that is, for each tow, the count on those grid points lying inside the rectangle is incremented by 1. Because the geometry is simple, this operation can be performed very efficiently. Obviously the finer the accumulator grid, the more accurate is the representation of coverage; however, for a 40m tow width, we have found that a 30m grid spacing is adequate.

Around this simple framework it is possible to build up different types of trawling patterns. Two such patterns are completely random trawling and aggregated night-time trawling. In completely random trawling the central location (x_c, y_c) and orientation θ of the tow are sampled from uniform distributions thus:

$$X_c \sim U(x_{\min} - l/2, x_{\max} + l/2) \tag{61}$$
$$Y_c \sim U(y_{\min} - l/2, y_{\max} + l/2) \tag{62}$$
$$\Theta \sim U(0, \pi) \tag{63}$$

Here $(x_{\min}, y_{\min})$ and $(x_{\max}, y_{\max})$ are the south-west and north-east corners of the rectangle being trawled (typically a 6-minute grid), and l is the length of a trawl (e.g. 2.7km). Notice the sampling rectangle extends a distance $l/2$ ouside the trawling rectangle. This is to allow for tows entering the area from outside, and so it eliminates edge effects. If we only sampled inside the trawling rectangle, then areas near the boundary would be undersampled relative to areas near the centre.

In aggregated night-time trawling tows occur in groups of n tows per night, where all tows target the same transect. We may also assume a preferred direction of trawling (eg NW–SE) which could be due to the prevailing wind or to orientation of a reef edge. Alternatively the orientation can be random. The centre of the first tow of the night is selected in the same way as for random trawling (edge effects need to be eliminated here too). The orientation θ is sampled thus

$$\Theta \sim \mathrm{Binom}(NW, SE) + U(-\delta, \delta) \qquad \text{(first tow)} \tag{64}$$

in the case of a preferred direction, and thus

$$\Theta \sim U(-\pi, \pi) \qquad \text{(first tow)} \tag{65}$$

in the case of random direction. At the end of a trawl we assume the boat turns round within a circle of radius R, and the start point of the new trawl is randomly selected from inside that circle. The orientation θ of the new trawl is selected from a uniform distribution centered on θ_{prev}, the direction to the start of the previous trawl:

$$\Theta \sim U(\theta_{\mathrm{prev}} - \delta, \theta_{\mathrm{prev}} + \delta) \qquad \text{(subsequent tows)} \tag{66}$$

The overall trawl effort is determined from the total number of increments of the grid. If the grid has M cells, then to simulate an overall effort level of 100% coverage, we run the simulation until the grid sum $\sum_{i=1}^{M} n_i$ just exceeds M, where n_i is the count in cell i. We cannot base the effort on number of tows, because many of these lie partially outside the trawling rectangle.

Results

We ran simulations under the preferred-direction model with 4 correlated tows per night, each of length 10km and turn-around parameters $\delta = 3^\circ$ and $R = 0.5$km. Figure 10 shows an example of one of these runs in progress after covering 8% of the grid. We made runs with these approximate coverage levels: 50%, 100%, 150% and two runs at 200%. By combining runs, we can build up all coverages from 50% to 700% in increments of 50%. Most of these levels can be obtained in more than one way: for instance 300 = 200 + 100 = 150 + 100 + 50. Figure 9 (*left*) shows histograms of trawl coverage over the 333^2 30m cells in the 10km grid for each level of effort. The distribution shifts to the right for higher levels of effort.

On the right in Figure 9, we have plotted the variance of coverage V against mean coverage μ. For a negative binomial model with parameter β we should find $V = (1 + \beta)\mu$. Indeed the variance is very closely proportional to the mean with slope 1.40, which implies $\beta = 0.4$. This is quite a low amount of aggregation because there are only 4 correlated trawls per night. If the simulation were continued to very high levels of coverage, β would tend to 0 ($V = \mu$) as the independence between nights dominates the correlation within nights.

It is interesting to see how the aggregation parameter depends on the trawling pattern parameters R, l, δ and n. We have run simulations over a range of values of μ (1, 2, 4), R (0.5, 0.75, 1.0), δ (0°, 1°, 3°, 5°, 10°) and l (3, 4, 6, 8, 12). In order to keep the correlated swept area comparable we have constrained n so that $nl = 48$km, i.e. 48km are towed per night. Results are shown in Figure 11. Not all combinations of parameters are shown because the simulations take a long time to run. The dependencies are quite complicated, but aggregation depends most strongly on δ. When there are many short tows per night and the error in turn-around angle is small, the aggregation is highest. The aggregation is further increased if the vessel has a tight turning circle (small R). Increasing μ without increasing the amount of correlation always reduces the aggregation. As before, the independence between nights ultimately dominates the correlation within nights.

Although we have talked about correlation 'within nights', this is only a matter of interpretation. A correlated set of tows could represent returns to the same place by one or more vessels over the duration of a night or over several years.

5.4 Calibration from VMS and GPS plotter data

Hall et al. (1999) have used a combination of vessel monitoring system (VMS) data and geographic positioning system (GPS) data to estimate the aggregation of prawn trawling in the Gulf of Carpentaria. They obtained coarse-scale data for the entire fleet (VMS locations every two hours) and fine-scale data for a few vessels (GPS trawl tracks for a single day). From the fine-scale data it was possible to compute ground coverage at the metre scale.

Their aim was to find the pattern of coverage for the entire fleet. However, they only had GPS plotter data for a subset of the fleet. To overcome this limitation, they scaled up the trawl patterns by the following two-stage simulation approach: First, sample (without replacement) a position from the VMS data. Second, sample (with replacement) a set of daily tracks from the GPS data and overlay these tracks so that the centroid coincides with the VMS position. Repeat the process until the desired level of total effort is reached.

By incrementing counts on a grid in a similar way to the simulation of the previous subsection, they obtained histograms of coverage that followed a negative binomial distribution reasonably well.

They considered two grids: one had a random spatial distribution (with a leaning towards regularity) and the other had an aggregated distribution with most VMS positions occuring in one corner. Not surprisingly, simulations on the aggregated grid generated higher values of β (2–5) than on the random grid (1–2). These simulations demonstrate how aggregation can arise from the combination of fine-scale patterns in the track of a single vessel and of intermediate-scale clustering due probably to features on the sea bed such as rough bottom.

An earlier study by Rijnsdorp and Buijs (1996) on beam trawling in the North Sea also found aggregation at larger scales (10 miles). However, they found the pattern within 1.6km squares, based on smaller squares of side 0.16km, was approximately random, i.e. $\beta = 0$.

6 Discussion

The Trawl Management Scenario Modelling project has at its core the differential equation (47). We have shown in this technical report how the equation is derived. The derivation is quite elegant in the absence of recovery, and the statistical process underlying the model is reasonably similar to the real process of trawling. When we included recovery we had to average over an ensemble of time histories. We arrived at a remarkable large-scale equation (34) which looked like a first guess for a depletion-recovery equation ($r = r_s$) except for an extra variance term. We interpreted this extra term as an adjustment or correction to the recovery term, and, by solving the equation for the second moment in the steady state, we found the magnitude of the adjustment, finally arriving at (47).

We have also shown how the large-scale parameters r and λ of (47) are related to the small-scale parameters r_s and d and the aggregation parameter β. Estimates of d have already been reported in Poiner et al (1998). We have some idea of the range of β from Hall et al (1999) and of its dependency on trawl pattern characteristics from the trawl track simulations. We expect the outcomes of the recovery dynamics project (Pitcher et al., 2000) to provide estimates of r_s.

All the scenario runs of the modelling software are based on equation (47). The implementation in the current version of the program (11/07/00) is the simple differential form (60).

The trawl scenario modelling software allows for random variation in λ; the simulation work on tow-to-tow variation provides guidance for choosing suitable ranges for the variance of λ. Future work of interest would be to simulate stochastic recovery in order to calibrate the variance of r in terms of the variance of r_s.

7 References

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Pitcher, C R, Burridge, C Y, Wassenberg, T, Smith, G P, Ellis, N, Fry, G, 2000, *Recovery of seabed habitat from the effects of impact of prawn trawling in the far northern section of the Great Barrier Reef: Final Report to GBRMPA on Year 1 Research.* CSIRO Division of Marine Research Report, 234 pp.

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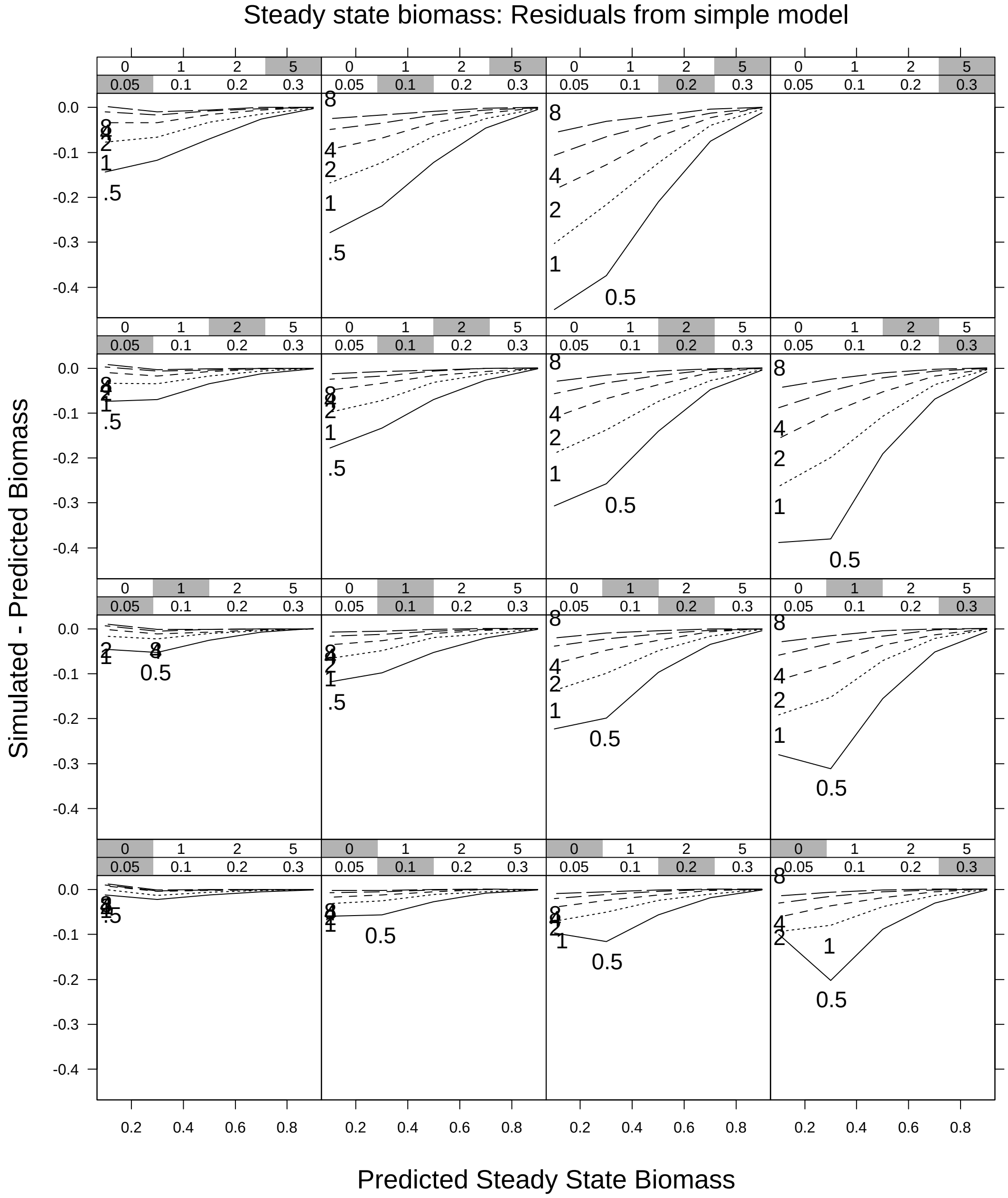

Figure 1: Difference between simulated steady state biomass and steady state biomass predicted from the simple model $r = r_s$. Each panel corresponds to a different value of $r_s = (0.05, 0.1, 0.2, 0.3)$ and $\beta = (0, 1, 2, 5)$, as given by the highlighted strips at the top. Within each panel the x axis is b_{simple} so that depletion rate *decreases* from left to right. Curves are labelled by the constant effort rate $\bar{e}$.

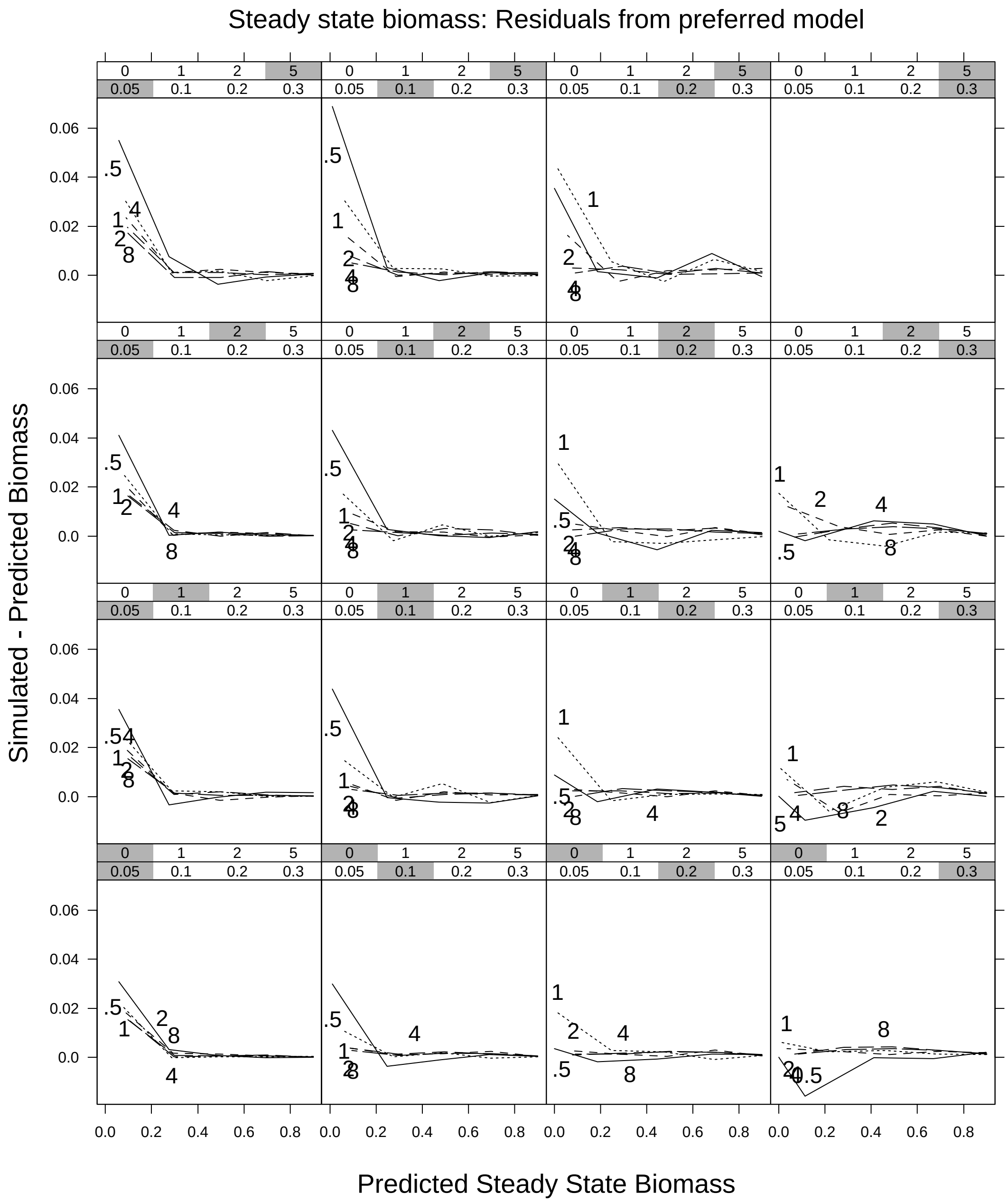

Figure 2: Difference between simulated steady state biomass and steady state biomass predicted from the preferred model with $r = r_s(1 - d/2)\log(1 + \beta d)/\beta d$. The labelling is the same as in Figure 1, but the vertical scale has been expanded.

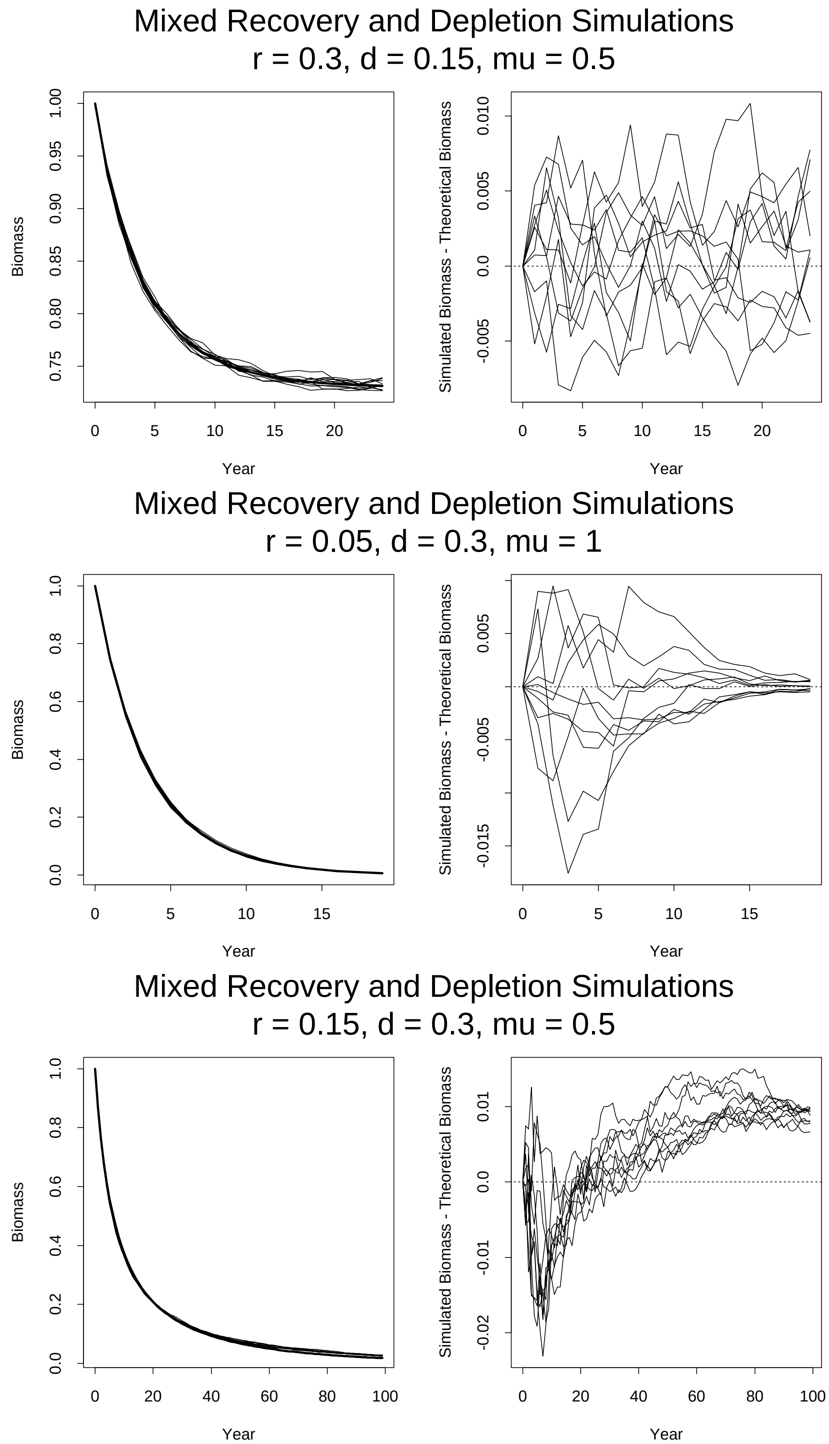

Figure 3: Evolution of 10 biomass simulations for various parameter values for random trawling ($\beta = 0$): (*top*) $r_s > \bar{e}d$, leading to eventual steady state $b_{\text{ss}} > 0$; (*middle*) $r_s < \bar{e}d$, leading to eventual extinction; (*bottom*) $r_s = \bar{e}d$, a critical case which is modelled less accurately. (Note also the slow decay rate for this case.) The left hand graphs show the simulated biomass with predicted biomass in bold. The right hand graphs show the difference of the simulated biomass from the predicted biomass.

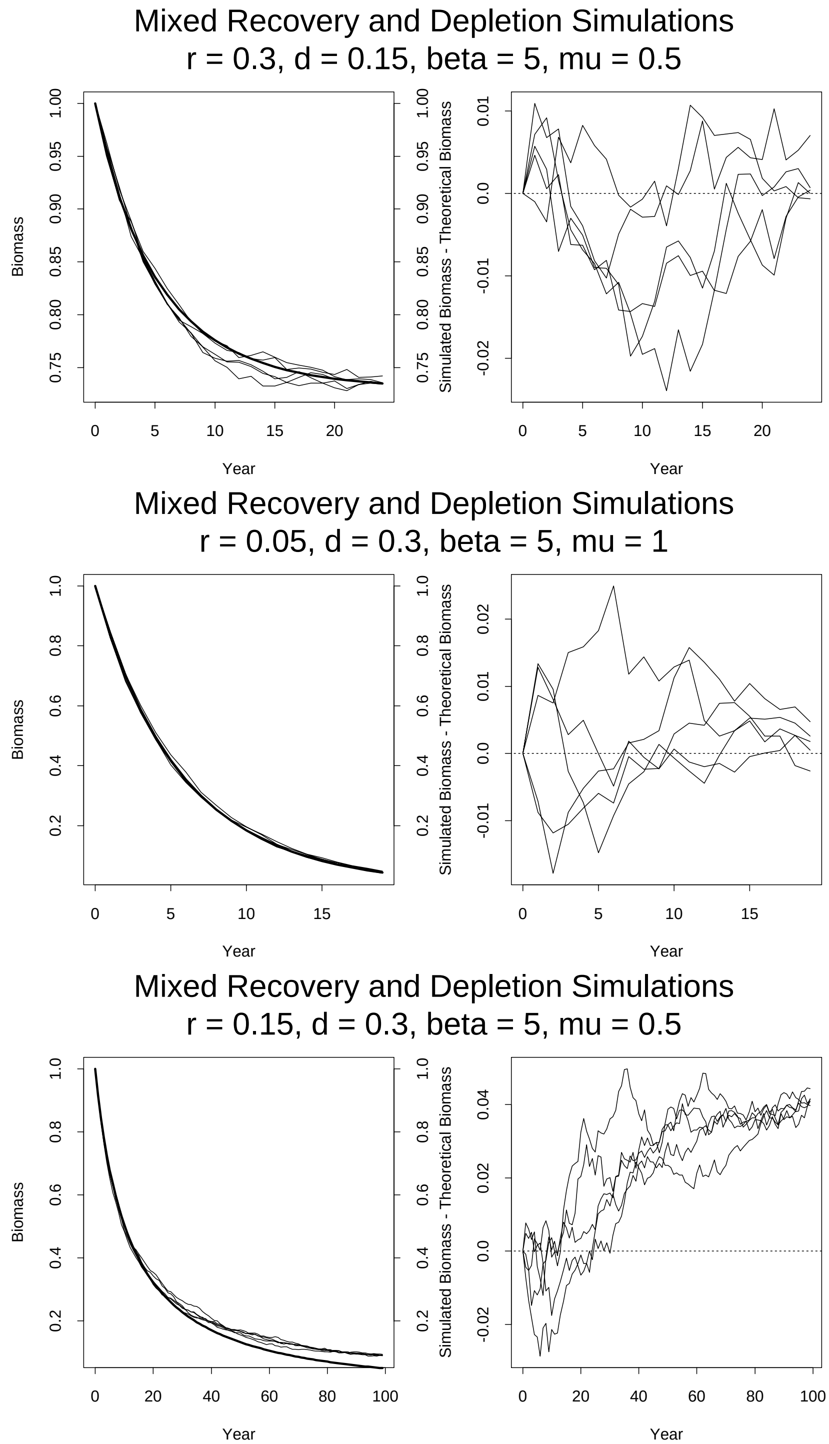

Figure 4: Evolution of 10 biomass simulations for various parameter values and moderately aggregated trawling ($\beta = 5$): (*top*) $r_s > \bar{e}d$, leading to eventual steady state $b_{\rm ss} > 0$; (*middle*) $r_s < \bar{e}d$, leading to eventual extinction; (*bottom*) $r = \bar{e}d$, a critical case which is modelled less accurately. (Note also the slow decay rate for this case.) The left hand graphs show the simulated biomass with predicted biomass in bold. The right hand graphs show the difference of the simulated biomass from the predicted biomass.

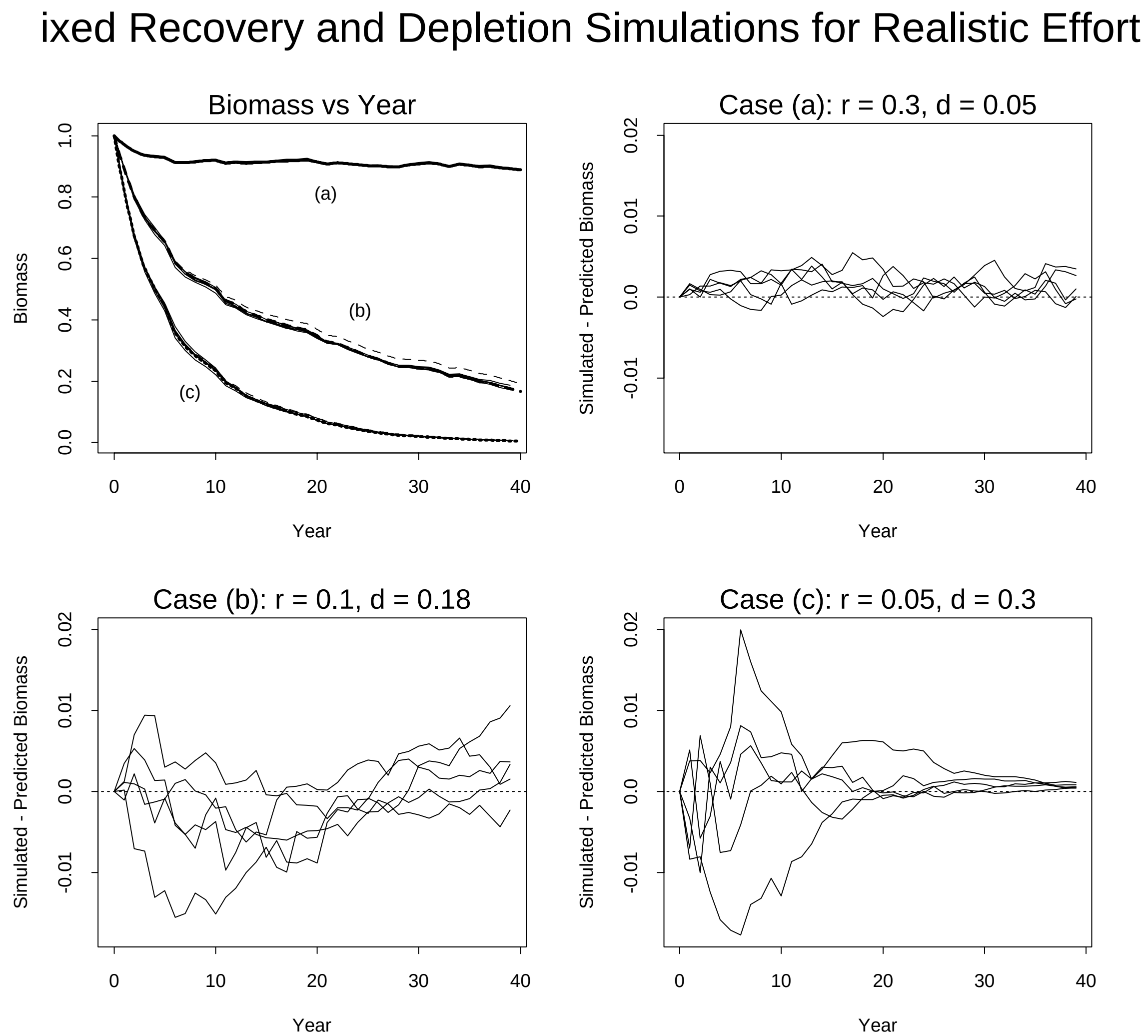

Figure 5: (*top left*) Evolution of 5 biomass simulations for a realistic effort pattern with long-term mean $\bar{e} = 0.56$ for the case of random trawling ($\beta = 0$). The 3 cases are: (a) $r_s > \bar{e}d$, (b) $r = \bar{e}d$, and (c) $r < \bar{e}d$. Also shown are the predicted biomass from the preferred model (*bold solid line*) and the simple model (*dashed line*). The other graphs (*right and bottom*), which are on the same scale, show the difference of the simulated biomass from the predicted biomass using the preferred model.

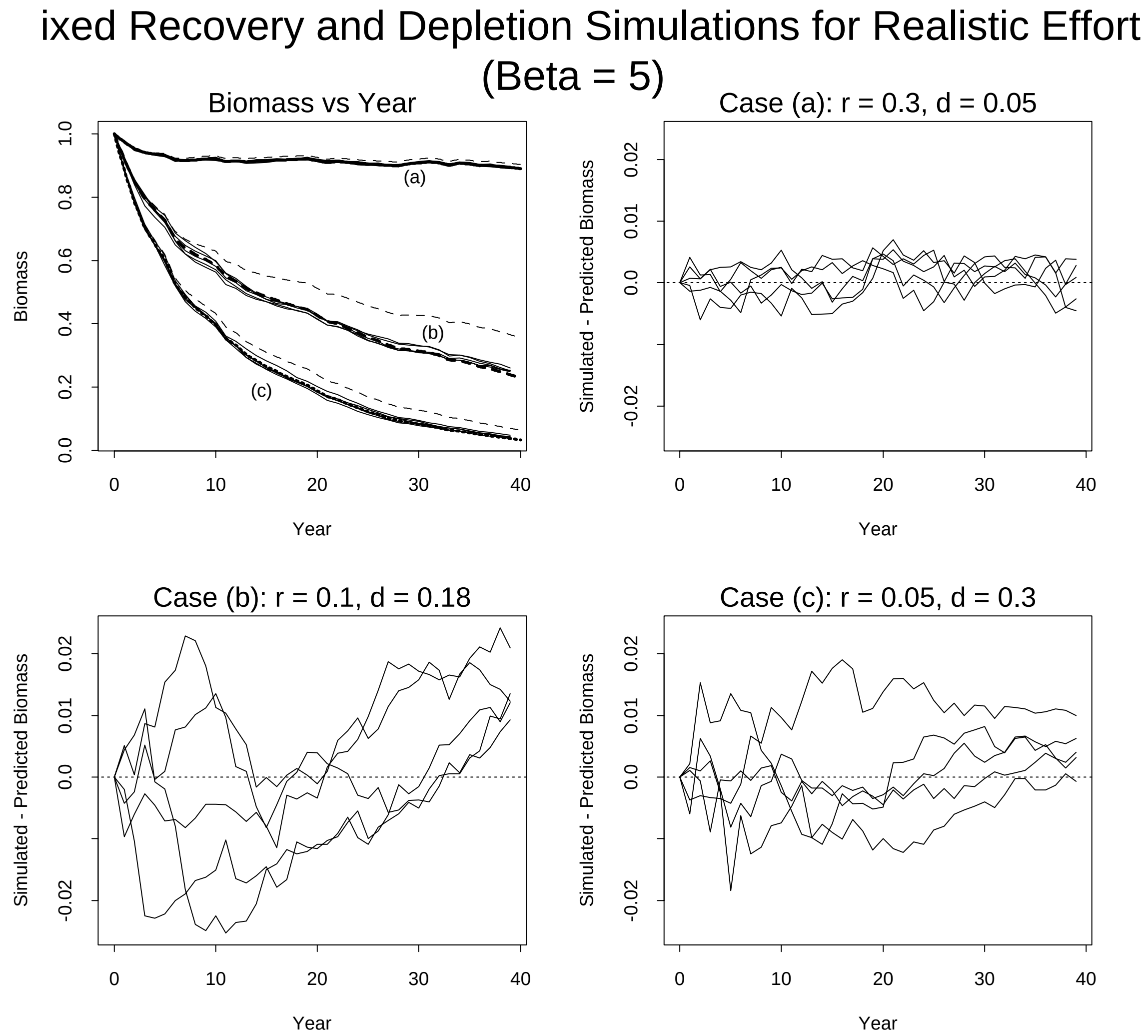

Figure 6: (*top left*) Evolution of 5 biomass simulations for a realistic effort pattern with long-term mean $\bar{e} = 0.56$ for the case of aggregated trawling ($\beta = 5$). The 3 cases are: (a) $r_s > \bar{e}d$, (b) $r_s = \bar{e}d$, and (c) $r < \bar{e}d$. Also shown are the predicted biomass from the preferred model (*bold solid line*) and the simple model (*dashed line*). The other graphs (*right and bottom*), which are on the same scale, show the difference of the simulated biomass from the predicted biomass using the preferred model.

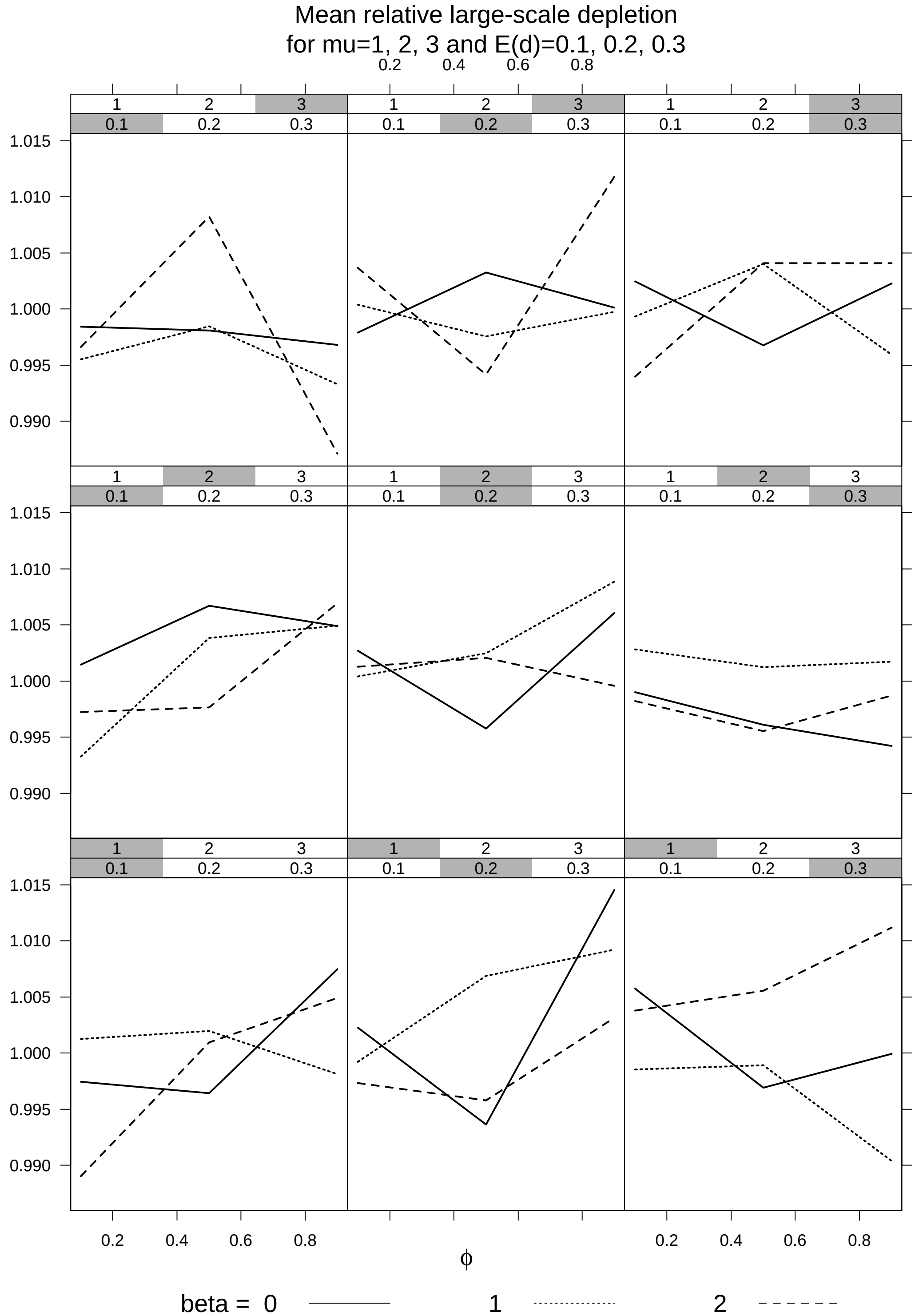

Figure 7: Mean over 1000 simulations of the large-scale relative depletion rate λ against variance parameter ϕ of the distribution of d. The value of λ is relative to the case where d is fixed, i.e. $\phi = 0$. Each panel corresponds to a different value of $\mu = (1, 2, 3)$ and $\mathrm{E}d = (0.1, 0.2, 0.3)$, as given by the highlighted strips at the top. Points with the same value of β are joined by lines.

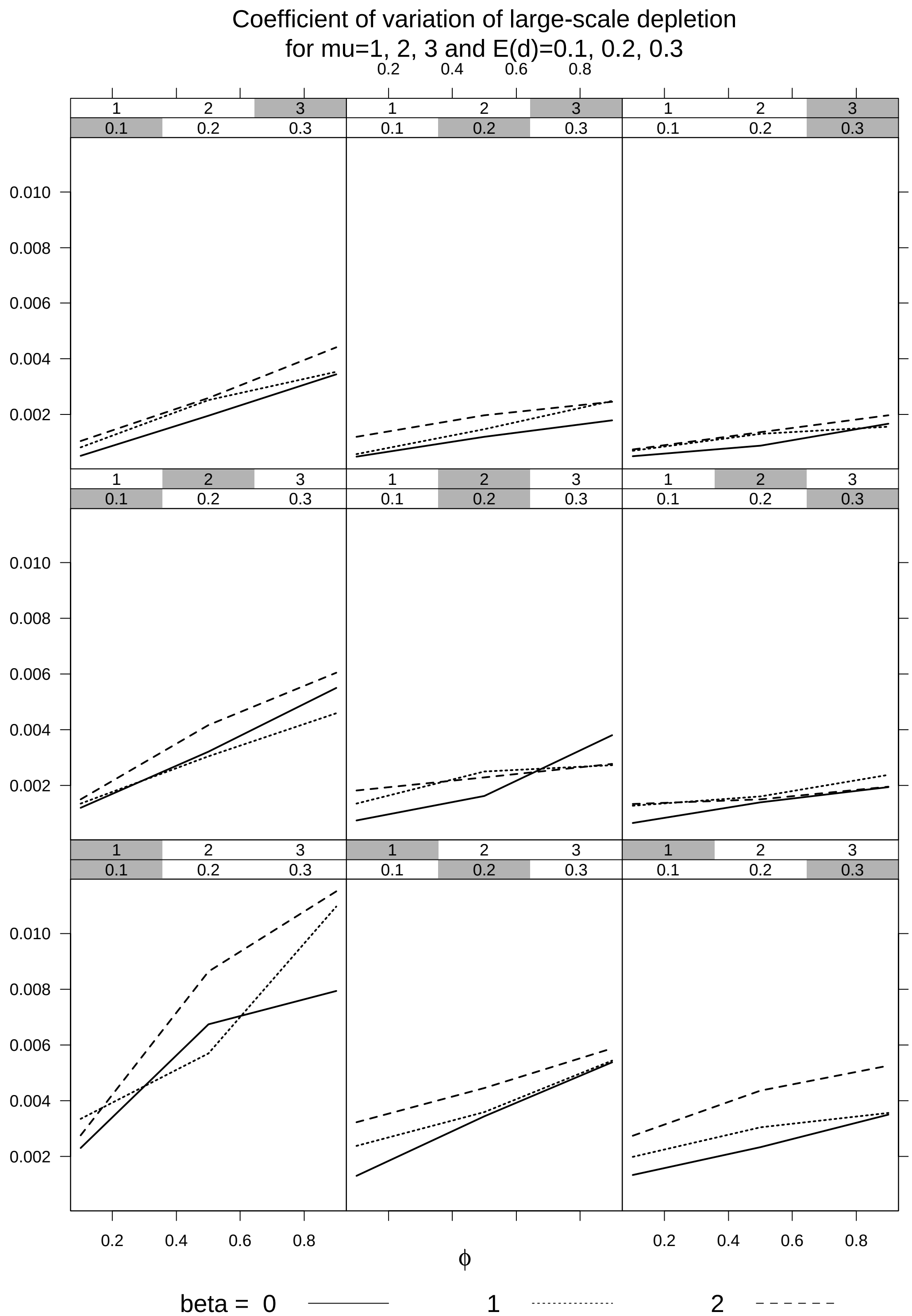

Figure 8: Coefficient of variation over 1000 simulations of the large-scale relative depletion rate λ against variance parameter ϕ of the distribution of d. Each panel corresponds to a different value of $\mu = (1, 2, 3)$ and $\mathrm{E}d = (0.1, 0.2, 0.3)$, as given by the highlighted strips at the top. Points with the same value of β are joined by lines.

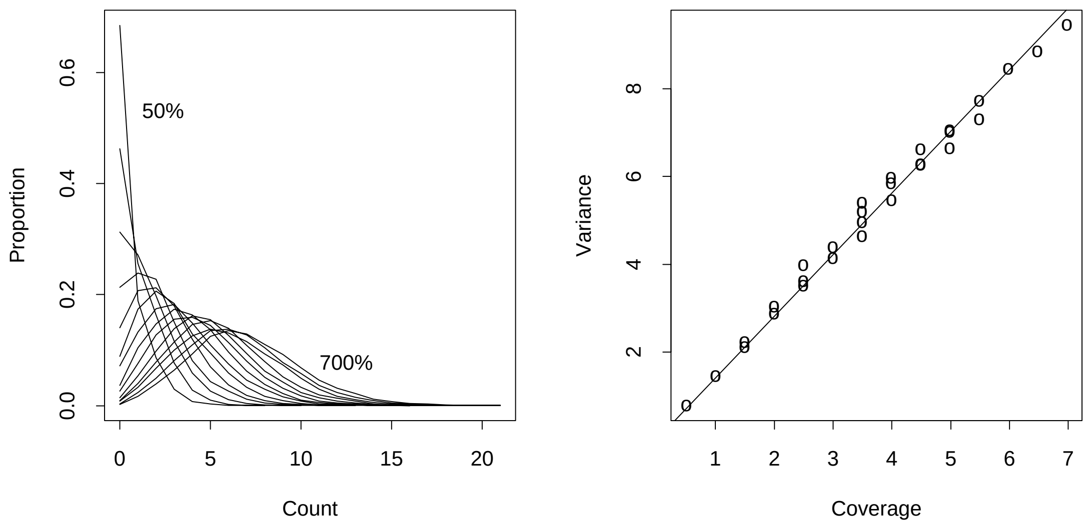

Figure 9: (left) Empirical distributions of coverage for levels of effort 50% to 700% by increments of 50%. (right) Variance-mean relationship for coverage.

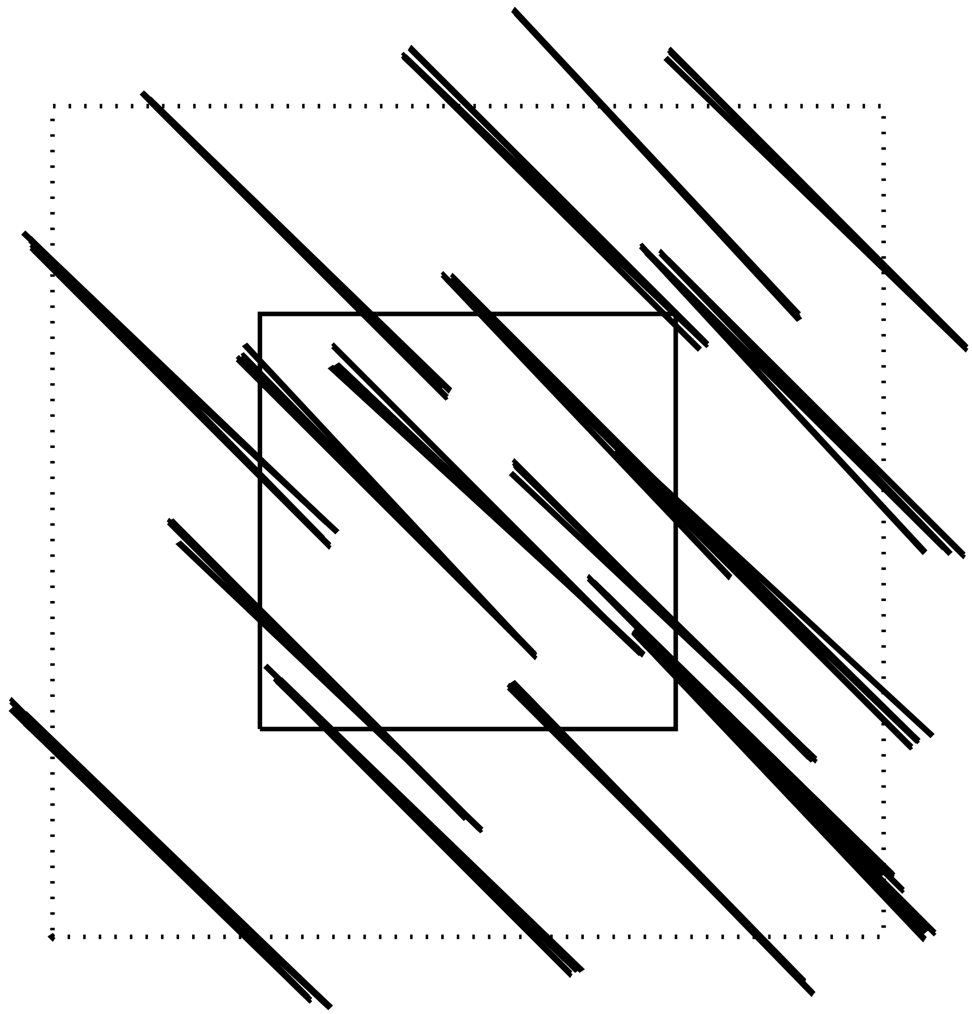

Figure 10: Simulation of 10km tows. The tow centres (of the first trawl per night) are sampled uniformly inside the dotted square. The coverage is measured inside the smaller solid square. Here the coverage is 8%.

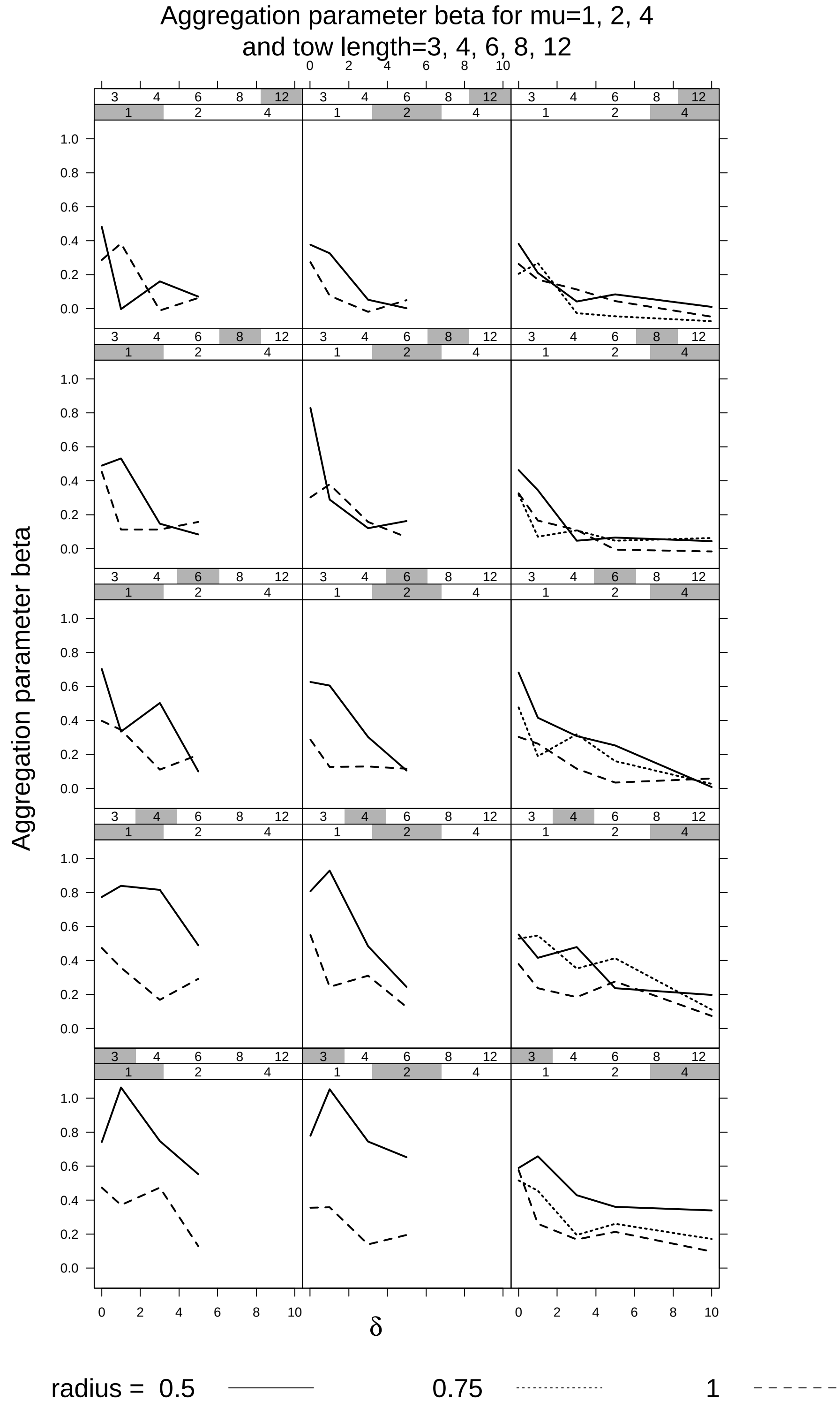

Figure 11: Mean over 3 or 4 simulations of the aggregation parameter β against δ. Each panel corresponds to a different value of $\mu = (1, 2, 4)$ and tow length $l = (3, 4, 6, 8, 12)$, as given by the highlighted strips at the top. Number of tows per night is $48/l$. Points with the same value of radius R are joined by lines.