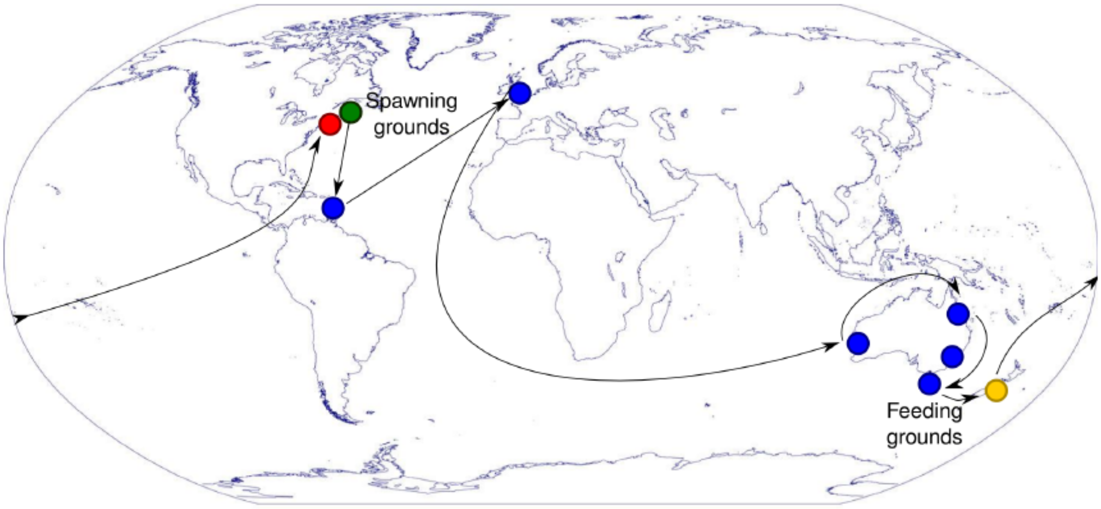
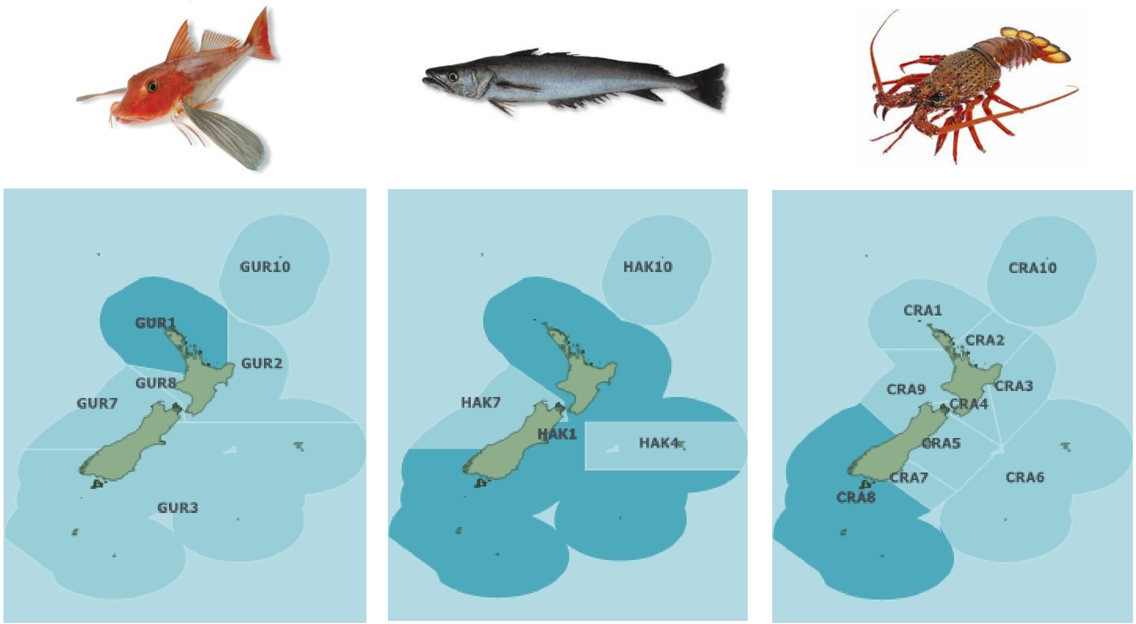
Approaches to stock assessment when data and time are limited

Nokome Bentley



WORLD CONFERENCE ON STOCK ASSESSMENT METHODS



~100 species
~600 quota management areas

NZ Ministry for Primary Industries

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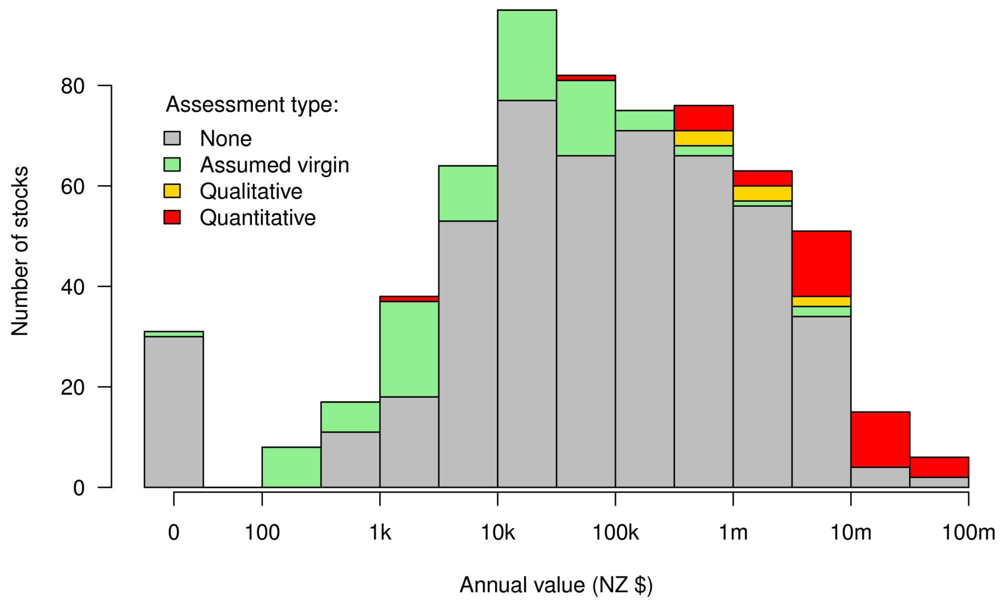
Since we are going to be spending the rest of the day discussing data-poor stock assessments, I thought that I would start off with a brief motivating example.

As with many jurisdictions, New Zealand has a large number of species which are harvested. Unlike many jurisdictions, virtually every commercially fished species is under the Quota Management System. For each species, there up to ten Quota Management Areas.

Currently, there are around 100 species in the Quota Management System, and a total of about 600 Quota Management Areas.



No formal assessment: 80% by number
65% by TAC
51% by value

Bentley & Stokes (2009) Contrasting paradigms for fisheries management decision making: how well do they serve data-poor fisheries? Marine and Coastal Fisheries 1:391–401

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This is an old graph which I know at least some of you have seen before. I have not had the time to update it, it its based on 2008 data. But I have dusted it off because I think it illustrates the situation well.

I have put each of the 600 odd quota management areas into bins according to their approximate annual value shown on a log scale. Each fishstock is then coloured according to their type of stock assessment:fully quantitative (shown in red), qualitative assessment (for example based on trends in catch-per-unit-effort, shown in yellow) and those that are assumed to be at or close to virgin (usually because there has been little fishing) shown in green. The remainder, shown by this grey area are those Fishstocks for which we have no real scientific assessment of stock status

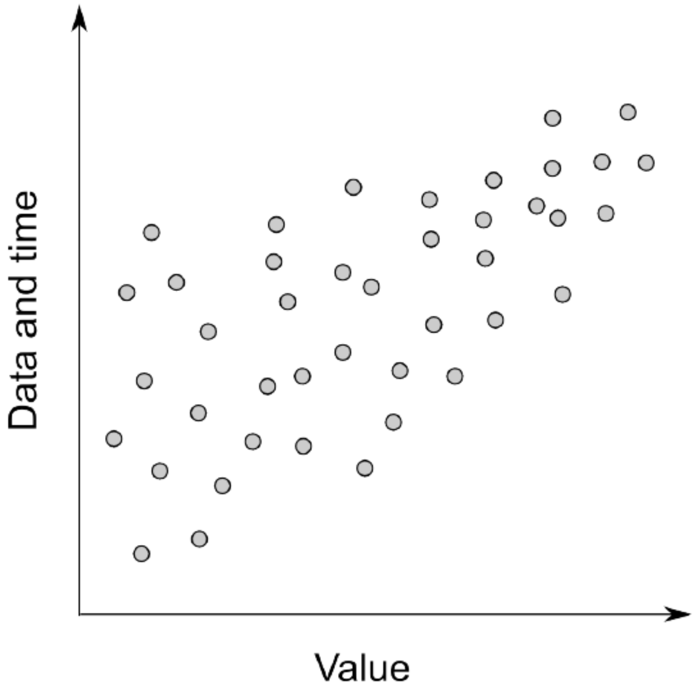
You can see that the majority of stocks with an annual value over $1 million dollars have formal assessments and in most cases these will be done regularly and to a high standard.

But the key message provided by this graph is that although the stocks with no assessment are low in value they collectively represent 80% by number, 65% by weight and 51% by value.

I suspect that if you were to repeat this analysis for other jurisdictions you would find similar pattern: the stocks of lowest value lack assessments, but collectively their value can be substantial.

Low value fisheries are usually both **data-poor** and **time-poor**

data-poor fishery ≈ time-poor scientists



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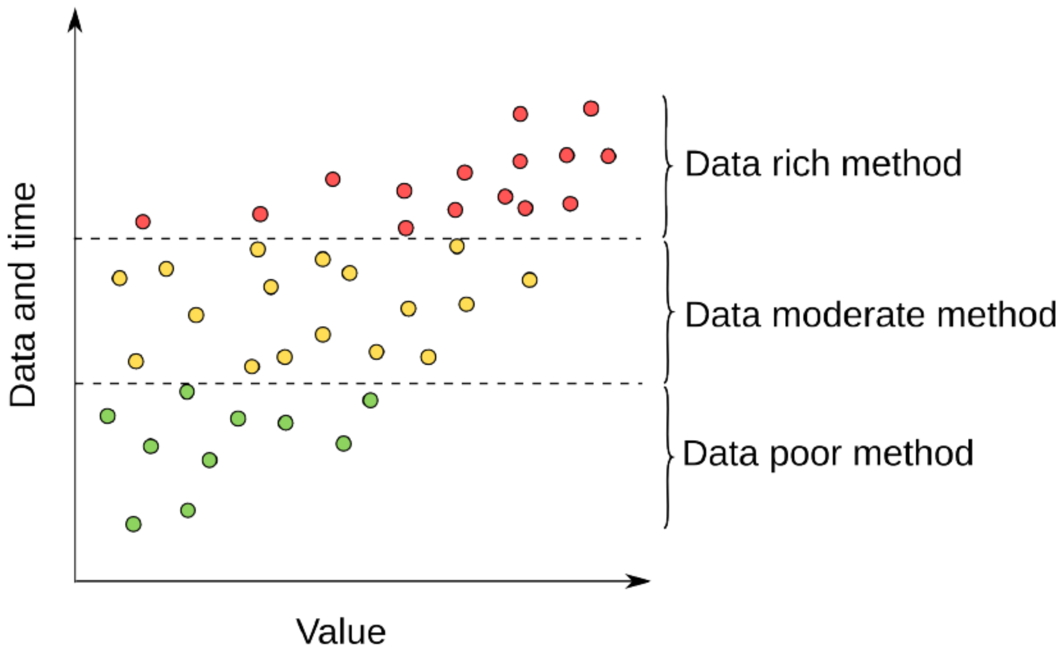
Generally then, a stock that is data-poor is one that is low in value. And because it is low in value there is usually limited time available to do a stock assessment.

So, when we are discussing how to assess data-poor fisheries, I think it is important that we acknowledge that, usually, we will also have time-poor fisheries scientists.

In some ways, this is implicit in our approach to data-poor stocks, but I think that it is worthwhile making it explicit because, time-poverty may affect the stock assessment approach as much as data-poverty.

Approaches

Approach A: **different models** for different tiers



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So, how should we approach stock assessments where we have both limited data and limited time?

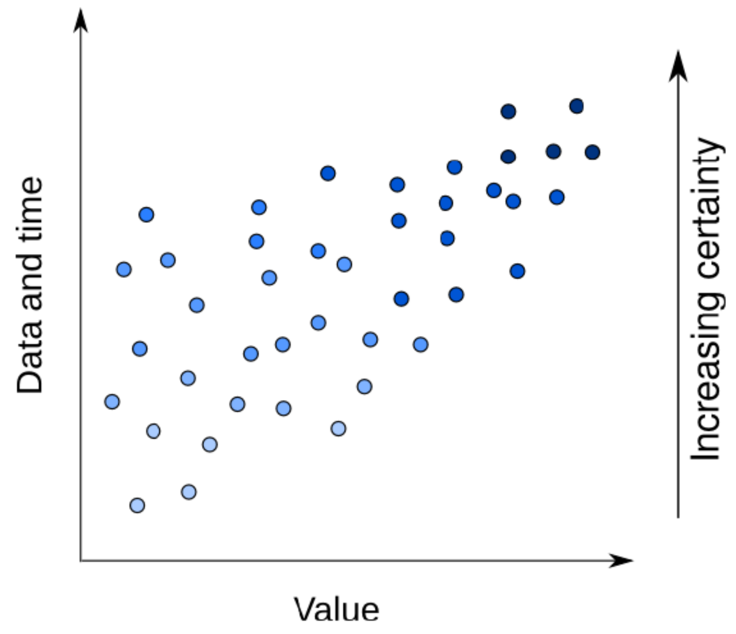
One option is to say that data-limited stocks require fundamentally different methods for stock assessment. Perhaps then, we need to define tiers of data richness and see which method performs best in each tier.

One issue with this approach is that for a stock at the top of one of these tiers we are not necessarily making the most of the data that we have available for it.

Also, we might end up finding that a stock gets stuck in one of these tiers instead of moving up this continuum in terms of data availability.

Approaches

Approach B: **same models**,
continuum of data & time richness, continuum of certainty



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An alternative approach is to say lets just use the same models for all stocks regardless of whether they are data-poor or data-rich.

After all, there is no fundamental biological difference between data-poor stocks and data-rich stock other than that data-poor stocks tend to be smaller in size.

The same *models* of population dynamics can be applied to these stocks it is simply that we will have less certainty in our results because we have less data.

One potential advantage of this approach is that it is based on a continuum of data-richness and for a particular stock, as more data becomes available we simply move up the continuum in terms of certainty.

Approaches — A more useful dichotomy

Strategic estimation	Tactical estimation
More complicated More integrated More statistical	Less complicated Less integrated More empirical

Focus on estimating...

Stock status (B_t/B_0) Reference points (e.g. B_{msy}) Parameter uncertainty	Current biomass (B_t) Current exploitation rate (F_t) Forecast biomass (B_{t+1})

Within management procedure approach the basis of...

operating models to **guide** strategic fisheries management decision making	**management procedures** which **define** tactical fisheries management decision making ...or more ad hoc decision making

Punt (2008) Refocusing Stock Assessment in Support of Policy Evaluation. 5th World Fisheries Congress p. 139–152. with additions 7

Perhaps we don't need to choose between these approaches, perhaps both has their place.

In a 2008 paper, Andre Punt suggested that we need to distinguish between two types of stock assessment models based on their *purpose* rather than their data requirements: strategic models and tactical models.

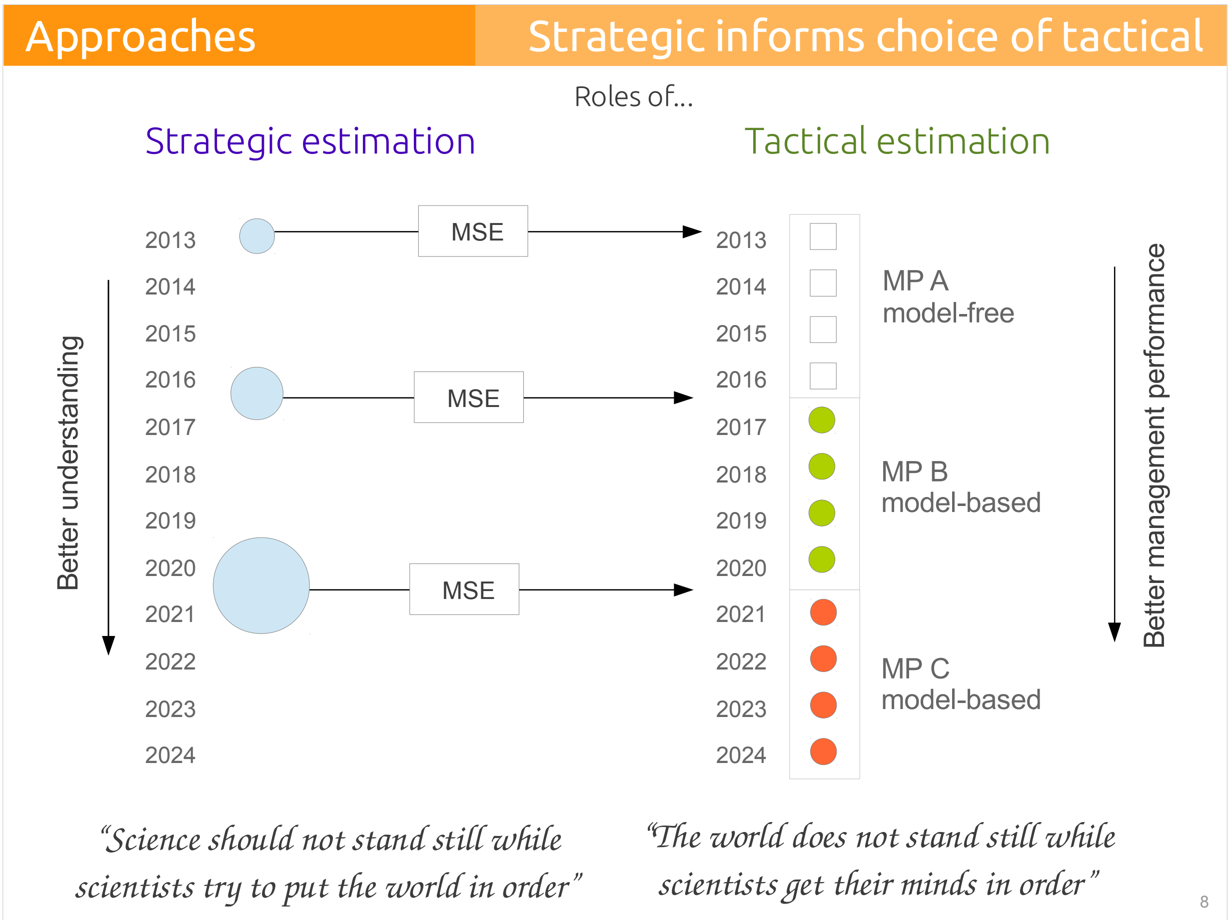
Strategic estimation involves methods that are more complicated, more integrated and more statistical whereas tactical estimation is usually simpler, relies on fewer data sets and can be more empirical.

Strategic estimation is the type of stock assessment methodology which we have become familiar with for data rich stocks. It is focussed on estimating stock status, the current biomass over virgin biomass, and reference points like Bmsy. It also places an emphasis on estimating parameter uncertainty.

In contrast, tactical estimation is focussed on estimating things like current exploitation rate and short term forecast. Despite being less sophisticated these estimation methods may actually be more robust at estimating these variables than a fully integrated assessment.

Within the management procedure approach, strategic estimation acts as a basis for operating models to test alternative management procedures. And tactical estimation can form the basis of model-based management procedures.

The dichotomy between strategic and tactical fisheries estimation is orthogonal to data richness. That is, both data-poor and data-rich stocks can have both strategic and tactical estimation approaches applied to them.



The vital aspect of this dichotomy between strategic and tactical estimation is that we need **both**.

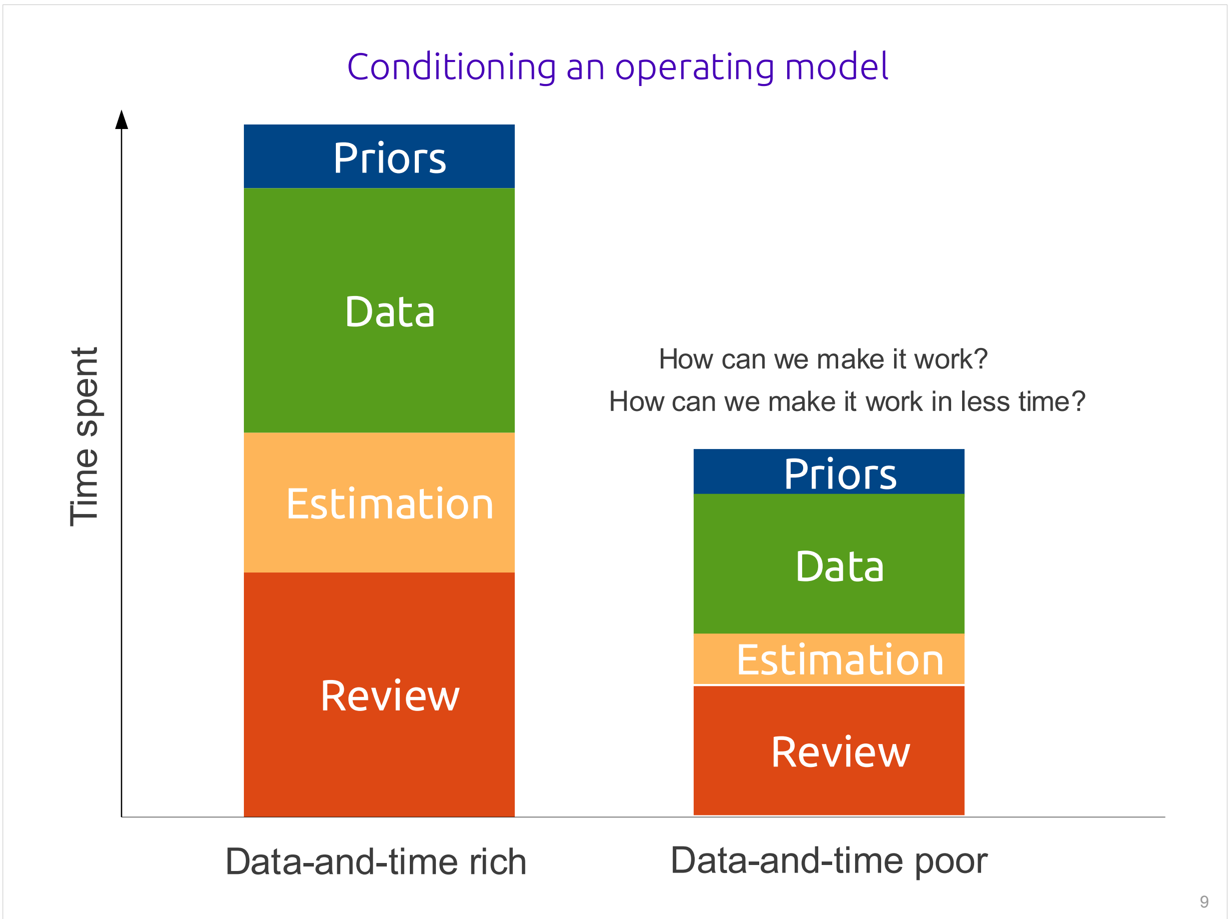
Under the management procedure paradigm we do relatively intensive strategic estimation that forms the basis of our operating models in a management strategy evaluation(MSE). The MSE then informs the choice of management procedure.

The management procedure defines the annual crank-the-handle process to generate a tactical management action. We might start off with a empirical, model-free management procedure of the type that Helena, Doug and others have described already. Or, we might move towards one that includes some form of tactical estimation using simple stock assessment models.

For this conference, the key aspect of this diagram is that the two aspects of fisheries estimation are separated. They move forward in parallel. On one side our understanding of fisheries improves, on the other the management of the fishery improves. In many ways, stock assessment has been trying to do these two things at the same time, and perhaps not doing a very good job as a consequence.

At the start of this conference, Sidney Holt gave us a quote: “The world does not stand still while scientists get their minds in order”. In some ways, this is the mantra of tactical estimation. But we can turn this quote around as a justification for strategic estimation and say, “Science should not stand still while scientists try to put the world in order”

Since this is a conference about stock assessment, in the rest of this talk, I am not going to be talking about management procedures or MSE at all. I want to focus on strategic estimation and how we can do if for data-poor stocks.



So, in the rest of this talk I want to examine how we can go about doing strategic estimation. That is conditioning an operating model for use in an MSE.

I am not going to be talking about models per se. As I have eluded to earlier I see that when doing strategic estimation we should use the same model as we do for data rich stocks.

I am going to explore how we might be able to adapt each of these phases of a stock assessment for data and time poor stocks.

```
 28  0.28862 -2.26513e+04 | 29 -0.02185  1.11525e+04 | 30 -0.55631  1.86506e+03
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32 variables; iteration 891; function evaluation 1000
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Var    Value     Gradient    |Var    Value     Gradient    |Var    Value     Gradient
  1  0.12007  9.17489e+04 |  2 -0.03675  5.96381e+03 |  3 -0.02603  9.10302e+03
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  7  0.02218  1.59789e+03 |  8  0.08644  4.23414e+03 |  9  0.05304  1.50819e+03
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Hessian does not appear to be positive definite
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I call this the Black Screen of Death. It is a screen that many of you will be familiar with, this age structured model has failed to converge, we have a parameter on the bound, and a Hessian that is not positive-definite.

At this stage many of us will start doing things like adjusting our likelihoods, fixing parameters, down-weighting data and other naughty things to get that damn Hessian to be positive definite.

It is one example of the challenges we face when trying to apply data-rich stock assessment methods to data poor stocks.

“The Working Group rejected
the assessment due
to the paucity of data”

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And this is what you might call the White Screen of Death.

Once you have done all that work trying to do a data-poor assessment the peer reviewers give you a big fat F for fail.

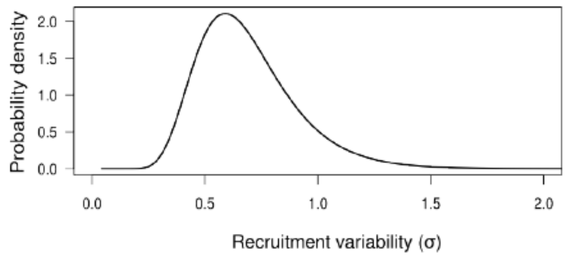
You go away with you head down and vow never to do a data-poor stock assessment again.

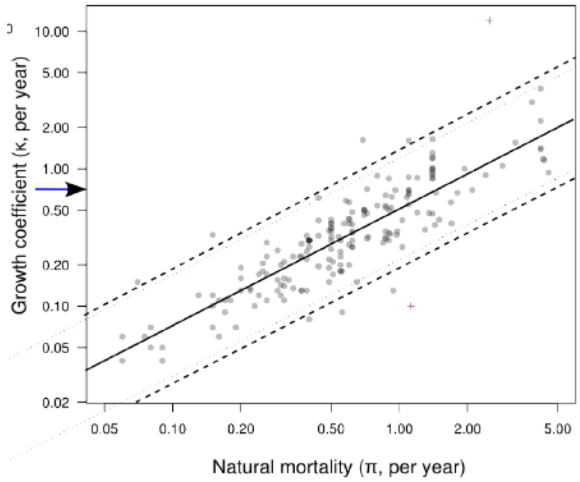
And, more importantly, fisheries managers don't get a quantitative basis for managing the stock.

I suspect, that many data-poor stock assessments never see the light of day because of a fear of rejection at the peer-review stage. In many ways we have set a high bar with data rich stocks on what we consider to be acceptable limits on uncertainty.

Priors — Borrowing and imputing knowledge

- A key means of **injecting knowledge** into data-poor assessments
- Provide a method for "**taking from the rich to give to the poor**"
- Using the **same models** as data-rich stocks will facilitate this
- Univariate priors have been used extensively for at least a decade
- Multivariate priors provide for **probabilistic imputation "filling in the gaps"** where we know one thing but not another





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For data-poor fisheries, Bayesian priors provide a key means of injecting existing knowledge into the estimation process.

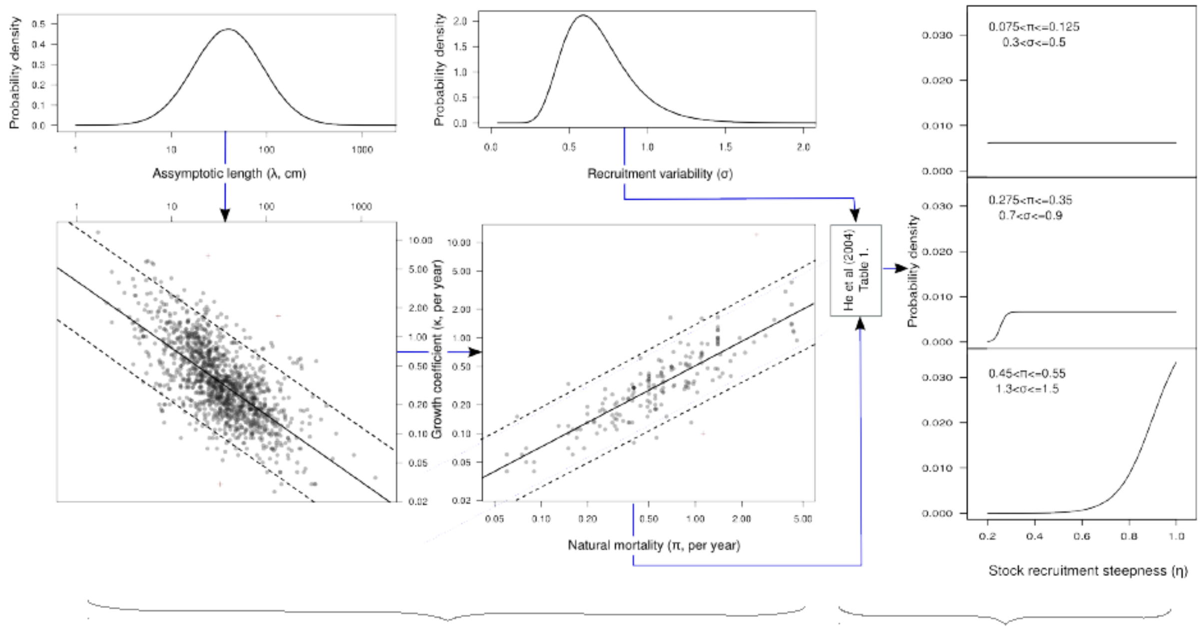
Put another way, they provide a method for "taking from the data-rich to give to the data-poor".

It is worthwhile noting that using the same models for data-poor and data-rich stocks facilitates this transfer of knowledge because the parametrisations will be shared.

Univariate prior probability distributions are widely used in stock assessments. While these will continue to be an important form of prior, for data-poor stocks there is perhaps even greater value in the priors on bivariate and multivariate relationships between parameters.

For data-poor stocks multivariate relationships offer a form of imputation, filling in the gaps of what we don't know using what we do know. Importantly, priors provide a way of probabilistically making those imputations.

Priors — Multivariate priors



Parameter estimates & meta-analyses

Life history theory & evolutionary simulation

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We can take this further and look at the multivariate relationships between population dynamics parameters.

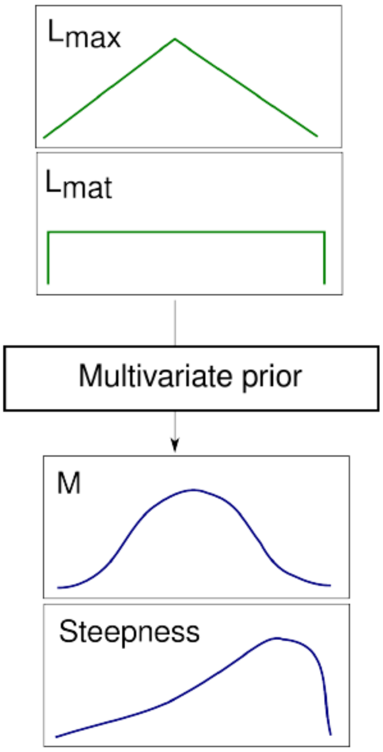
This is a Bayesian network that developed for some population dynamics parameters. For those of you are not familiar with the term Bayesian Network it is really akin to a series of linked correlations between variables, in this case population dynamics parameters.

The main thing to note about this is that we don't need to rely just on meta analyses to develop these types of multivariate priors.

This part of the Bayesian network comes from some work done by He and other where they develop a multivariate prior for steepness based on population persistence theory.

Priors — A library of priors?

Case-specific priors



In a time-limited assessment we need to **rapidly use priors**

Need a **library** of **peer-reviewed** univariate and multivariate priors

Implemented as software library and integrated into assessment packages

Act as defaults with **ability to override** when case-specific priors available or wanted (e.g. on M)

In a time-limited assessment we need to rapidly use priors. We don't have a lot of time spare to go back to the literature or do our own meta-analyses.

I think that we, as a stock assessment community, need a library of peer-reviewed univariate and multivariate priors which we could quickly make use of in our data-poor assessments.

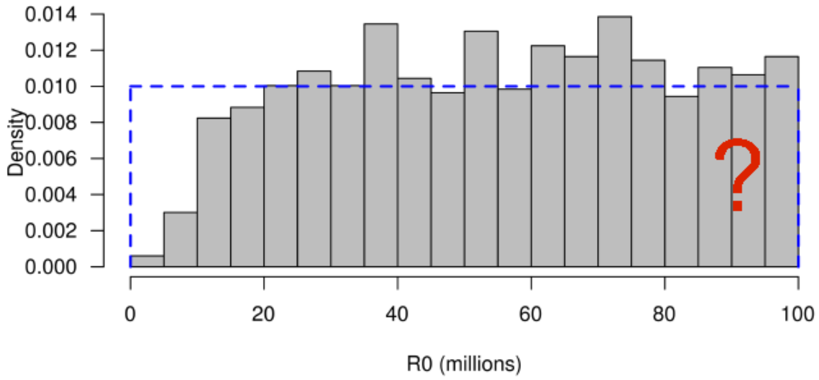
Ideally, this library of priors would be implemented as software library and ultimately integrated into assessment packages like Stock Synthesis.

I don't think we want to impose a standard set of generic priors, but they could at least act as defaults with ability to override them when case-specific priors are available or desired.

Priors — Priors on scale (K) parameters

Can we also put **priors on "scale" (carrying capacity) parameters?**

Catch history alone informs the **lower bound** of B_0, K, R_0 :



Posterior on R0 in 1973 when only catch history was available

What information do we have to **inform the upper bound** of B_0?

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So far the priors that I have been discussing, and which have been the focus of research to date, are priors on what we might call "rate" parameters, those that define the temporal dynamics of the stock.

But a key challenge in stock assessment, particularly for data-poor stocks is estimating what we might call "scale" parameters, such as carrying capacity and virgin unfished biomass.

Catch history is actually quite informative for the lower bound of these parameters. For example, if there has been 50 years of catch in excess of 10,000 t we can say with some confidence that virgin recruitment is at least 10, 000 t. In this way, catch history informs the lower bound on scale parameters.

This example, shows a posterior distribution for R0 generated from a sampling-importance-resampling algorithm with a delay-difference model driven by a catch history. No data has been fitted to but a constraint that the exploitation rate has not exceeded 0.99 is applied. As you can see, this contraint excludes low values of R0.

However, we often lack information on the upper bound of scale parameters and this is where a prior might be particularly useful.

Priors — Scale (K) parameters

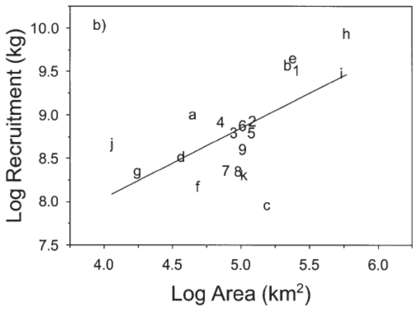
Usually **ignore what we know about habitat**. Focus on temporal contrast to inform estimates of B_0

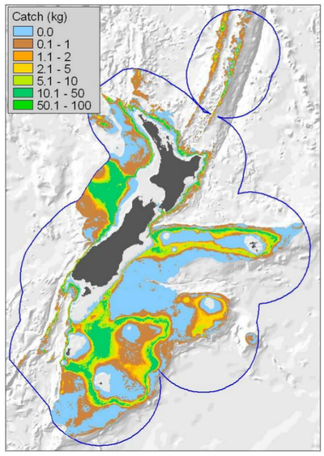
Spatial contrast may provide a means of defining priors on B_0

Hierarchical meta-analyses and **habitat suitability models** to develop priors on B_0*/Habitat* e.g. using RAM Legacy

Allows data on **depth, temperature, primary productivity, benthic community data** etc to inform stock-specific prior

Priors on B_0 are **likely to be diffuse** but, for data-poor stocks, probably **better than nothing**: upper bound 10,000t or 1,000,000t?





Leathwick et al (2008) Predicted catch per standardised tow from a habitat suitability model for Ribaldo (*Mora moro*).
MacKenzie et al (2003) Spawner-recruit relationships and fish stock carrying capacity in aquatic ecosystems. Mar Ecol Prog Ser 248: 209–220

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One way to generate priors for carrying capacity might be to use what we know about the spatial scale of habitat. Traditionally in stock assessment we have relied heavily on temporal contrast in data sets to inform estimates of B0.

Spatial contrast in data may provide a means of defining priors. For example, hierarchical meta-analyses and habitat suitability models could potentially be combined to define priors on B0 per unit of effective habitat for species, genera or functional niches of fish.

Again, such priors would allow for imputation for data-poor stocks by providing a means for stock specific data on habitat to be used to generate a stock specific univariate prior on carrying capacity.

Developing such priors would not be a trivial task. It would rely on compilation of numerous data sources and require extensive analyses.

The resulting priors are likely to be diffuse and probably more suited to demersal species with restricted movement. However, for data-poor stocks the ability to inject additional data in the form of effective habitat areas is likely to be helpful.

Data | Understanding your data

Understanding the data you put into any assessment:

Essential
Time consuming
Case specific

Efficiencies from **automating data processing and presentation** but will always require significant proportion of time

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A key aspect of any stock assessment, be it data-rich or data-poor, is the data you put in to it.

Regardless of the stock assessment methodology, understanding the data that is being used will always be essential, time consuming and case specific. In this regard there are few, if any, short cuts.

Certainly there are efficiencies to be gained from automating data processing and presentation, however gaining a full understanding of the potential biases in the data will always require a significant proportion of the time in a stock assessment.

It is true that in a data poor context, there is less volume of data to deal with, but often that data will be of lower quality and arguably requires more thorough grooming and pre-analysis.

Just because we may be using less data intensive stock assessment techniques does not mean that we can excuse ourselves of the task of understanding potential biases in our data and how that may be deceiving the estimation process.

Data — Using soft data

Focus has been **fitting to "hard" data** e.g. survey time series, age compositions

When you are data-poor you start to look at **"soft" data**:

- i.e. subjective **"priors" on model variables** rather than on parameters
- e.g. beta prior on stock depletion in Depletion-based Stock Reduction Analysis
- e.g. uniform prior on change in biomass between two years
- e.g. normal prior on mean length of catch based on poor quality data 50 years ago

Injection of additional data that may **otherwise be ignored**

Trade-off between making use of all information and **adding junk** - requires care in **how informative/diffuse priors** are.

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Having said that, one area where gains may be possible for data-poor stocks is in the use of what we might call "soft data".

Traditionally, stock assessments have focussed on fitting to hard data such as survey time series of biomass estimates or age and length compositions.

However, in the data-poor context and given the theme of using as much of the data that is available, we have started to look at more subjective, more qualitative data to inform the estimation process.

In essence these amount to "priors" on model output variables. Formally, they are likelihoods, because priors are what we use for model input parameters. However, they are similar to priors in the way that they allow for subjectivity in their definition.

An example of this approach is seen in DB-SRA in its "prior" on depletion.

While such an approach may be unnecessary in the data-rich situation in data-poor assessments it is important because if allows the use of information that would have otherwise been ignored.

However, as with the definition of priors on parameters, care is required and there is a tradeoff between adding useful information and simply "making stuff up".

Estimation

Dominated by formal likelihoods, quasi-Newton minimisers and Hastings-Metropolis MCMC

Alternative algorithms **may** be **more robust** and **less temperamental** in data-poor situations

Alternatives for **fitting to data**. e.g.

- Approximate Bayesian Computation (ABC) and "Synthetic likelihood"
- Fit to **summary statistics** of the data rather than entire data set

Alternatives for **sampling posterior distributions** e.g.

- Sampling-importance-resampling (SIR)
- Adaptive MCMC

Applications and simulation studies required to see if these help

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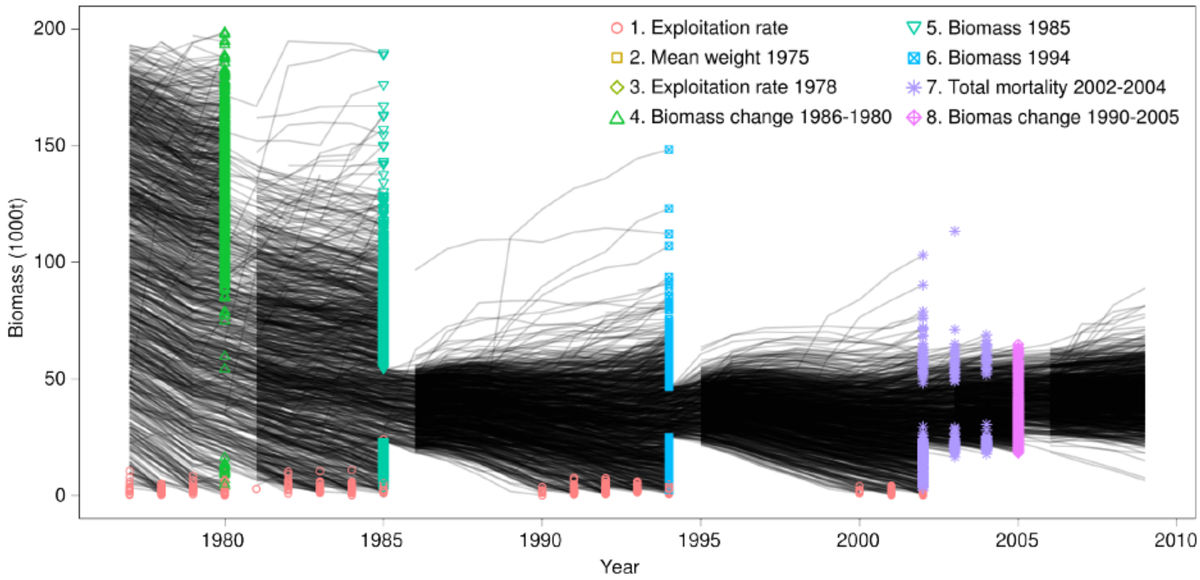
Over the past two decades the algorithms that we use in stock assessment estimation have been dominated by formal likelihoods, quasi-Newton minimisers and Hastings-Metropolis MCMC.

While these seem to serve data-rich stocks well, new, alternative algorithms for parameter estimation may be more robust and require less tuning in data-poor situations.

In particular, Approximate Bayesian Computation and Wood's Synthetic Likelihood, which fit to summary statistics of data, rather than to entire data sets, may prove to be more robust when data is of poor quality.

Similarly, alternatives to Hastings-Metropolis MCMC for sampling posterior distributions, have been used recently for data-poor stocks.

Further real world applications as well as simulation studies are required to see if these alternatives offer benefits to estimation in data-poor contexts.



Bentley & Langley (2012) Feasible stock trajectories: a flexible and efficient sequential estimator for use in fisheries management procedures CJFAS 69: 1–17

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This is an example, of applying some alternative estimation algorithms.

In this example, we took a relatively data-rich stock and threw out some of the data or condensed it down to summary statistics. In doing so, we artificially created the type of "data-random" situation which we commonly come across – a fishery with bits and pieces of different types of data.

We used a sequential SIR algorithm and defined constraints imposed by the various bits of data in a approach that is similar to Approximate Bayesian Computation or Synthetic Likelihood.

Not only did we find this to be an efficient approach to incorporating disparate sources of information, it also illuminated aspects of the estimation process that may not have been evident with traditional algorithms.

Review

Peer review of any assessment:

Essential
Time consuming
Case specific

Efficiencies possible in automated **production and presentation of diagnostics**

Onus on **analyst** to present **comprehensive but concise diagnostics** and **indicate what really matters**

Onus on peers to **learn what really matters**

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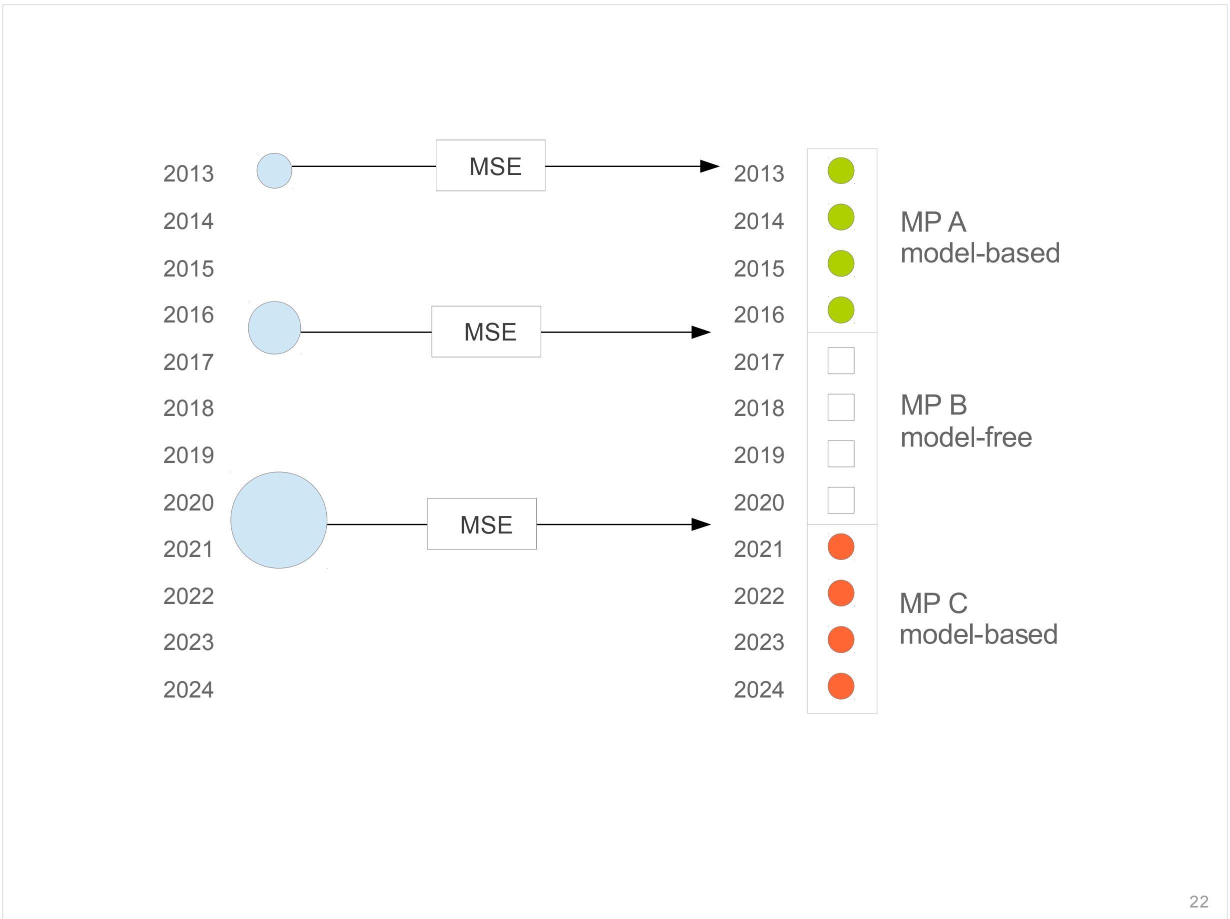
Peer review should be a part of all stock assessments.

This is a copy-and-paste of my data slide because as with understanding your data, peer-review is always going to be essential, time consuming and case specific.

Again, there are efficiencies to be had from the automated production and presentation of diagnostics.

Particularly in a data-poor context there is an onus on the analyst to present a comprehensive but concise set of diagnostics and to indicate the aspects of the assessment that really matter or which the methodology is particularly sensitive to.

There is also an onus on reviewers to learn what aspects of the methodology and results really matter.



I have very briefly gone through some key aspects of stock assessment methodology and looked for ways in which we can improve its application to data-poor stocks. I have suggested that for some of those aspects, such as understanding the data used and peer-review, there is perhaps little scope for reducing the time required for an assessment.

However, I want to come back to this slide and remind you that the real time and cost savings come in only doing strategic estimation **occasionally**.

In the intervening time, we use a management procedure which may involve the types of tactical estimation methods for data-poor stocks that we will see in today's talks.

WARNING

"Data-poor" methods may be used as an **excuse to under fund** data collection and stock assessment

Improper use could lead to suffocation

These **are not magic bullet end points** that will solve the world's fisheries management problems

These **are pragmatic approaches** to robust fisheries management along the pathway to better understanding

Non-use could lead to insanity

I am going to end off with a warning.

There is a real risk that if we overplay the benefit of data-poor methods that those who fund fisheries research will see them as an excuse to under-fund both data collection and stock assessment.

To borrow a phrase "Improper use could lead to suffocation".

There are a number of steps that we as a community can take to mitigate against that. These include using simulations to demonstrate the management benefits of additional research and monitoring.

But perhaps the most effective thing we can do is not present our work as magic bullet endpoints but rather as pragmatic approaches for providing robust fisheries management along the pathway to better understanding of our fisheries.

Support for aspects of this work gratefully received from
(in alphabetical order) ….

Ministry for Primary Industries
Manatū Ahu Matua

Seafood New Zealand

SEAFOOD INNOVATIONS LTD

TRIDENT SYSTEMS

TROPHIA

Thanks again to steering committee!

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BOSTON
WCSAM 2013
WORLD CONFERENCE ON STOCK ASSESSMENT METHODS

Catch-Only Methods: Cure or Placebo

Jim Berkson, Ph.D.
NMFS RTR Program at the University of Florida

NOAA FISHERIES @ UF UNIVERSITY of FLORIDA

Luiz Barbieri, Ph.D.
FWC - Florida Marine Research Institute

The opinions being presented in this talk are those of the authors and do not necessarily represent the views of either author’s agency.

An aside:

Sgt. Rick Remalia

Traditional treatment for pain involves drugs such as opiates:

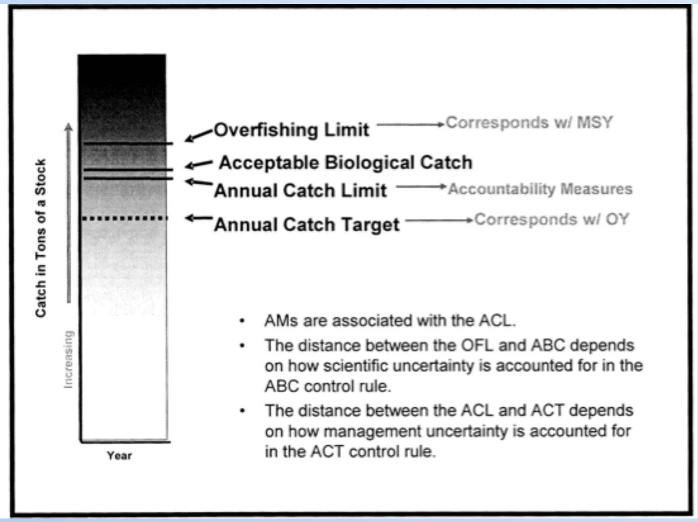
- Side effects
- Drug interactions
- Leads to addiction/abuse
- Long term cost

To be continued

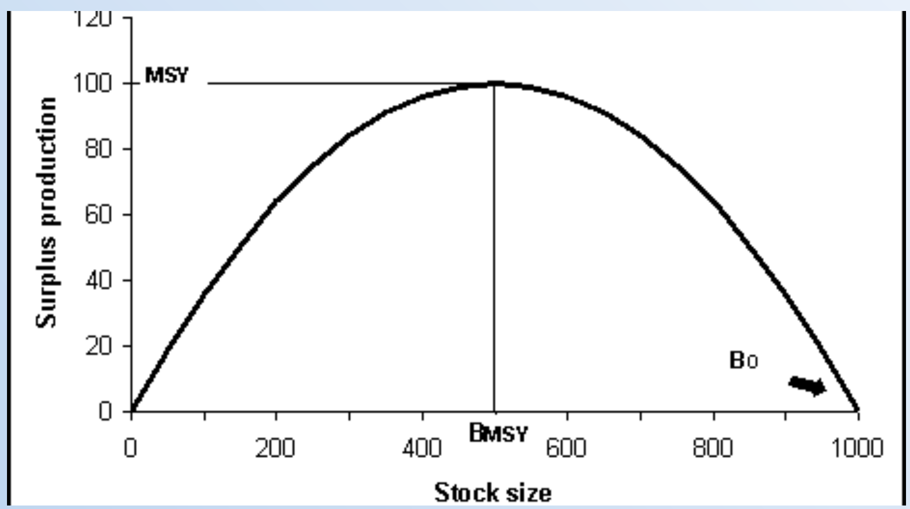
Photo from Wikipedia.com

Photo from blog.innergateaccupuncture.com

MSY is the starting point for Annual Catch Limits (ACLs) in the U.S.



National Standard 1



FAO

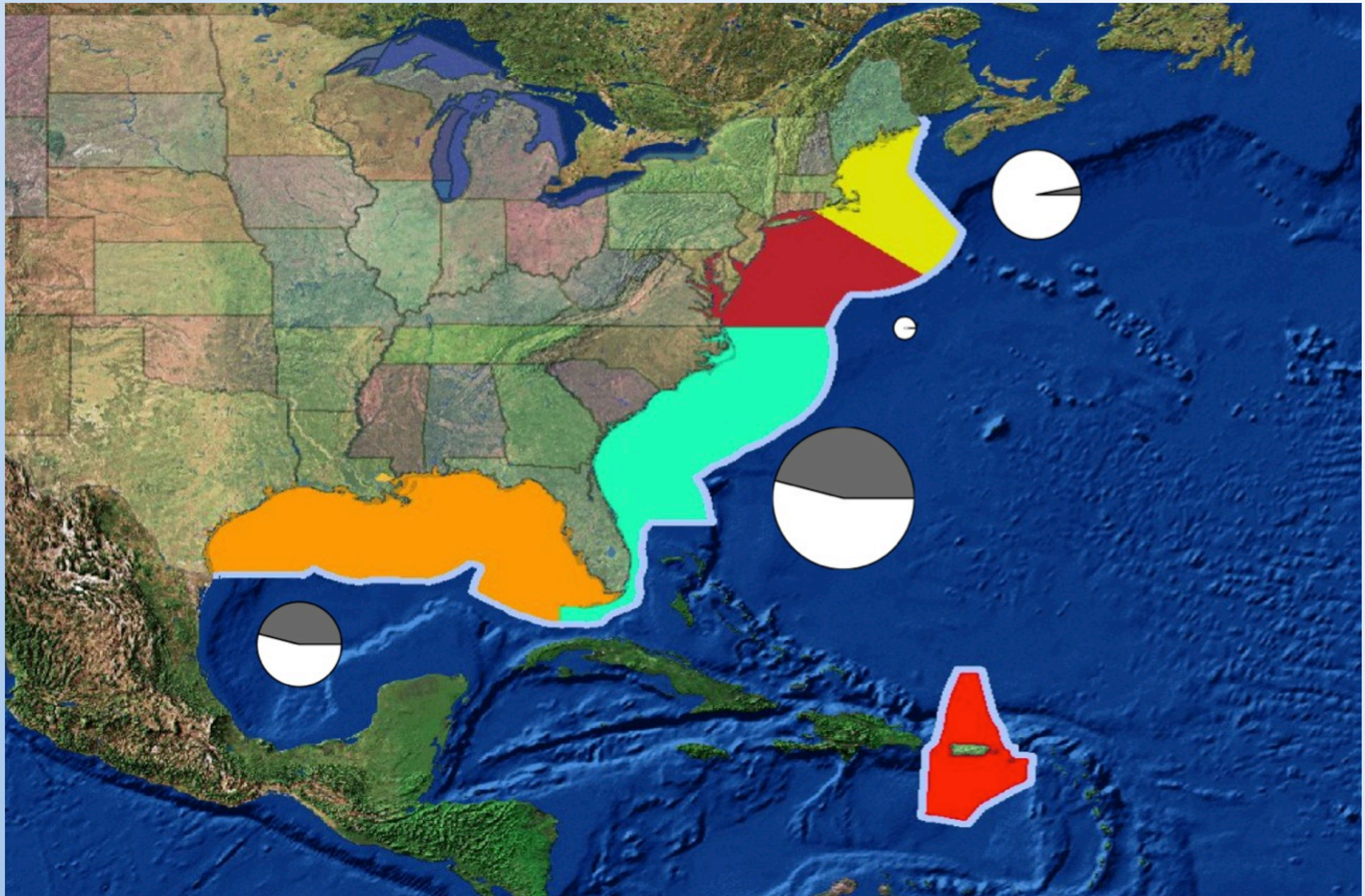
MSY + Catch-Only Stocks = Challenge

(our obligatory equation)

Magnitude of challenge is proportional to number of catch-only stocks involved

Status of catch-only stocks in the U.S.

Fishery Management Council	# Stocks managed by ACLs	# of ACLs used for management	# of ACLs involving catch-only methods	% of ACLs involving catch-only methods
Mid-Atlantic	10	10	0	0%
New England	39	33	1	3%
North Pacific	100's	62	10	16%
Pacific	147	40	9	23%
Gulf of Mexico	37	24	11	46%
South Atlantic	62	37	17	46%
Western Pacific	100's	101	57	56%
Caribbean	100's	67	67	100%
TOTAL	100's	374	172	46%



Proliferation of Catch-Only Methods

- Scalar approaches (Restrepo et al., 1998)
- Depletion-Corrected Average Catch (MacCall, 2009)
- Depletion-Based Stock Reduction Analysis (Dick & MacCall, 2011)
- ORCS Working Group Approach (Berkson et al., 2011)
- Catch-MSY Method (Martell and Froese, 2012)
- New methods continue to be developed
  - (e.g., Thorson et al., *In Prep.*)

Methods either:

- Involve a summary statistic of the catch over a specified time period (scalar approach)

OR

- Require *additional* information not available for most catch-only stocks, such as
  - Full time series of the catch
  - An estimate of stock depletion

Evaluation of Methods
(excerpts)

- Wetzel and Punt (2011)
  - DBSRA and DCAC highly sensitive to depletion parameter.
- Wiedenmann et al. (2013 – *in press* – NAJFM)
  - Stocks with slow or medium life histories with a history of overexploitation were particularly challenging.
  - Conservative control rules were required to produce probabilities of overfishing < 0.5 when information was biased.
- Carruthers et al. (*In prep)*
  - Only methods that accounted for depletion provided good performance at low stock sizes.

Methods applied to catch-only stocks in the US

Fishery Management Council	# of ACLs involving catch-only methods	% of ACLs involving catch-only methods	Methods Used
Mid-Atlantic	0	0%	---
New England	1	3%	Scalar/ DCAC
North Pacific	10	16%	Scalar
Pacific	9	23%	Scalar, DCAC, DBSRA, Other
Gulf of Mexico	11	46%	Scalar
South Atlantic	17	46%	Scalar
Western Pacific	57	56%	Scalar
Caribbean	67	100%	Scalar/ ORCS WG Method
TOTAL	172	46%	

Recap

- Catch-Only stocks are a part of 46% of all ACLs in the US.
  - The Southeast, Caribbean, and Western Pacific have the greatest number and percentage.
- Methods that utilize supplemental information perform better overall.
  - Methods are getting more sophisticated.
  - These will likely remain applicable to a small proportion of catch-only stocks.

Back to our aside:

In treated patients:

- 1/3 report that the pain goes away
- 1/3 report that the pain diminishes
- 1/3 report no improvement

The military is now using alternative medical techniques such as acupuncture.

Sgt. Rick Remalia

"The first treatment where … I've actually seen a really big difference"

Photo from army.mil
Photo from NPR.org
Stats from stripes.com

How are these two systems similar?

- Military – noted for being reluctant to change.
  - Changed paradigm, allowing their doctors to think/act/treat differently to benefit the system.
- Fisheries policymakers may want to do the same.
  - Change the paradigm away from MSY-based ACLs for all stocks, allowing their stock assessment scientists to think/act/treat differently to benefit the system.

If not MSY-based ACLs, then what?

- Many alternatives including:
  - Space-based management (Marine Protected Areas)
  - Effort-based management
  - Territorial user right fisheries
- Answers are not straight forward.
  - Fishery-specific
  - Social/Economic/Political considerations
- Large role for stock assessment scientists in developing and testing the likely effects of alternatives

Acknowledgments

- NPFMC
  - Dave Witherell
  - Pat Livingston
- PFMC
  - John Devore
  - Owen Hamel
- WPFMC
  - Marlowe Sabater
  - Paul Dalzell
- GMFMC
  - Steven Atran
- NEFMC
  - Chris Kellogg
- MAFMC
  - Mike Wilberg
  - Rich Seagraves
  - John Boreman
- SAFMC
  - John Carmichael
  - Mike Errigo
- CFMC
  - Graciela Garcia-Moliner

- UF – Berkson Lab
  - Katyana Vert-Pre

Evaluating data-limited methods of setting catch-limits

Tom Carruthers

University of British Columbia

Carruthers, T.R., Punt, A.E., Walters, C., McCall, A., McAllister, M.K., Dick, E.J., Cope, J.

Paper submitted to Fisheries Research

4.04

Data is not information, information is not knowledge, knowledge is not understanding, understanding is not wisdom.

Clifford Stoll

Life is made up of a series of judgments on insufficient data, and if we waited to run down all our doubts, it would flow past us.

Learned Hand

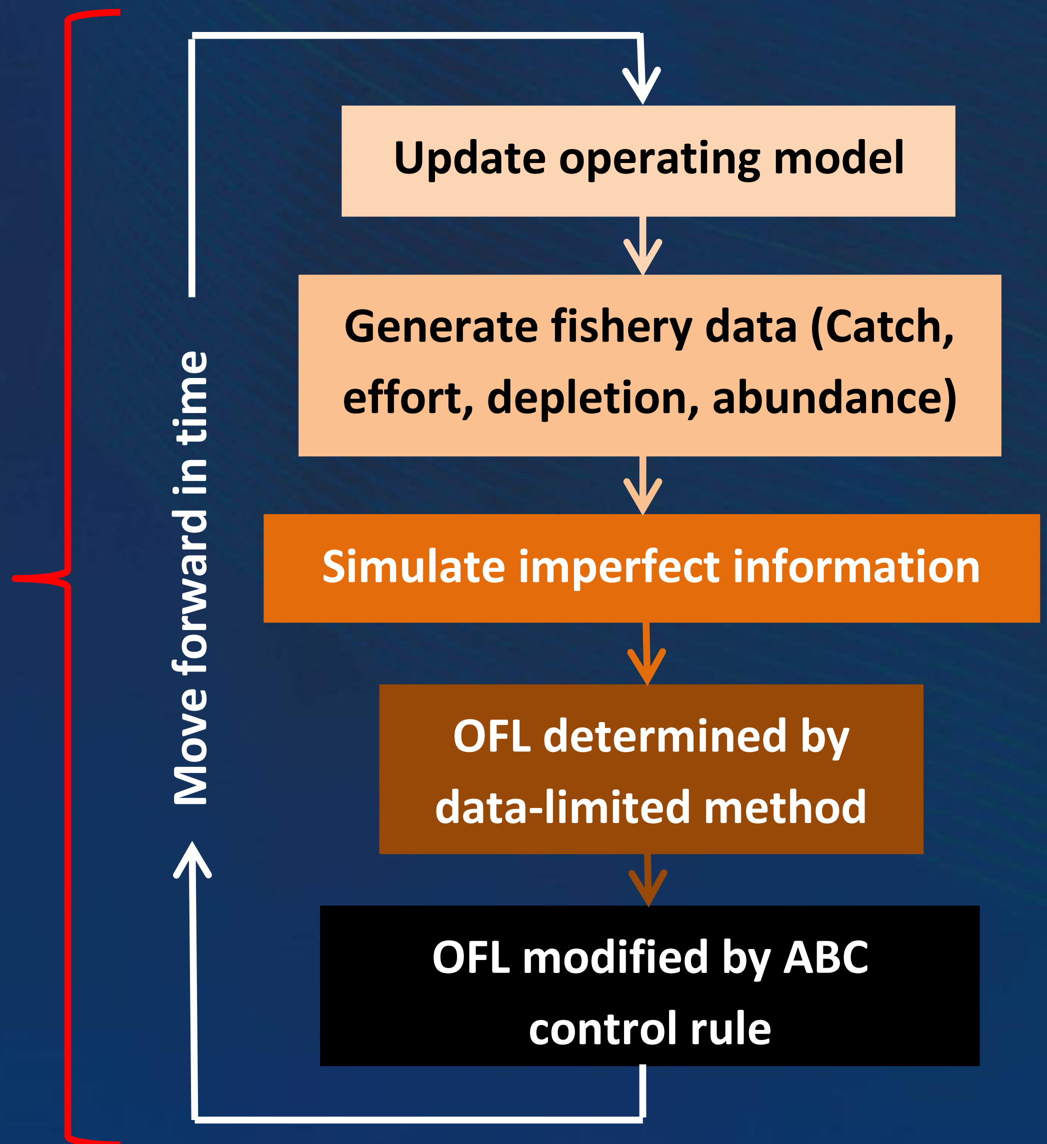
Objectives

Based on data-limited methods, life-history types and broad objectives of the U.S. fishery management system we aimed to quantify:

- the performance of different data-limited methods for setting catch-limits over a range of life-history types
- value of information

Management Strategy Evaluation

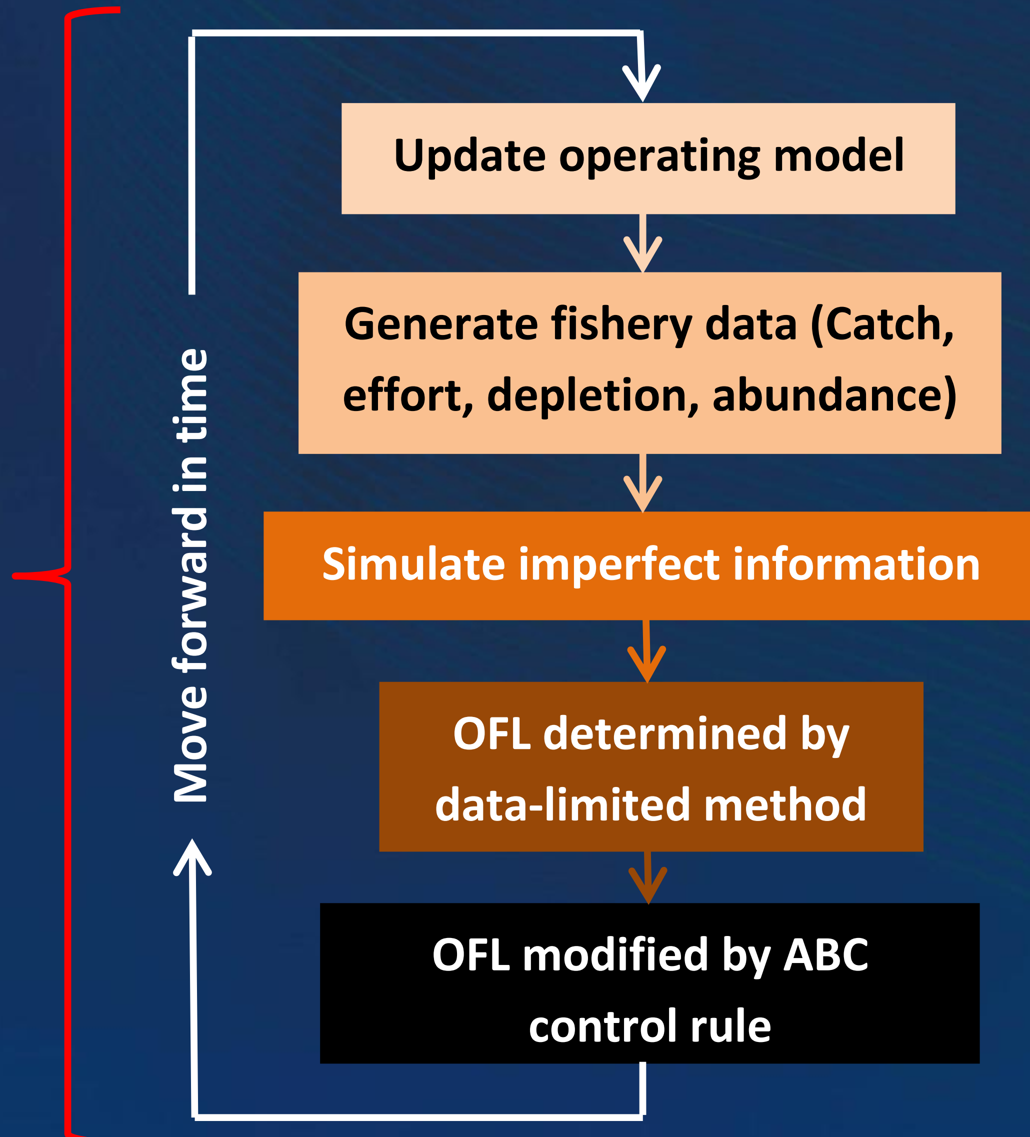
To be specified:



Management Strategy Evaluation

To be specified:

- Operating models
- Data-limited methods
- Imperfect information
- Performance metrics



1. Operating models

Six life-history types or 'stocks', n = 10 000

	M	Steepness	$CV_{recruitment}$
Mackerel	0.2	0.45	0.5
Butterfish	0.8	0.55	0.9
Snapper	0.09	0.65	0.6
Porgy	0.22	0.4	0.55
Rockfish	0.18	0.75	0.4
Sole	0.06	0.55	0.5

These are mean values: parameters were sampled from uniform ranges typically with a CV of 20%

2. Data-limited methods for setting the overfishing limit (OFL)

- DB-SRA (Dick and MacCall 2011)

  depletion, M, B_{MSY}/B_0, F_{MSY}/M, catch, age at 50% maturity

- DCAC (MacCall 2009)

  depletion, M, B_{MSY}/B_0, F_{MSY}/M, catch

- F_{MSY}/M ratio (*e.g.* 0.5, 0.75, 1)

  $B_{current}$, M, F_{MSY}/M

- Life-history analysis (Beddington & Kirkwood 2005)

  $B_{current}$, length-at-first capture, K_{vonB}

- Catch percentiles (OFL = median of historic catches)

  catch

OFL = F_{MSY} * $B_{current}$

3. Imperfect information

Log-normal (mean = 1) CV's for multipliers

	Bias	Imprecision
M	0.5	
F_{MSY}/M	0.8	
B_{MSY}/B_0	0.2	
K_{vonB}	0.2	
Length at 1st capture	0.5	
Catch		0.05 - 0.3
Depletion	1	0 - 2
$B_{current}$	1	0 - 2

4. Evaluating performance

The Magnuson-Stevens Act (MSA) National Standard 1 (NSG, 2009) requires that "conservation and management measures shall prevent overfishing while achieving, on a continuing basis, the optimum yield from each fishery"

Implied are two reference quantities:

- Probability of overfishing
- Yield

Performance

$B < 0.5\ B_{MSY}$

	Mackerel		Rockfish	
	P_{OF}	Yield	P_{OF}	Yield
Median catch 10 Yrs	89	12	95	5

POF = % probability of overfishing   Yield = % of 'optimal yield'

Performance

$B < 0.5 \, B_{MSY}$

	Mackerel P_{OF}	Mackerel Yield	Rockfish P_{OF}	Rockfish Yield
Median catch 10 Yrs	89	12	95	5
DB-SRA 40% depletion	81	16	38	24
DCAC 40 % depletion	77	19	36	24
DB-SRA	13	64	5	48
DCAC	78	27	59	37
Life History Analysis	56	58	50	64
$F_{MSY}/M = 0.5$	27	64	14	57
Delay-Difference	20	38	4	26
Current Catch	82	18	90	9

POF = % probability of overfishing

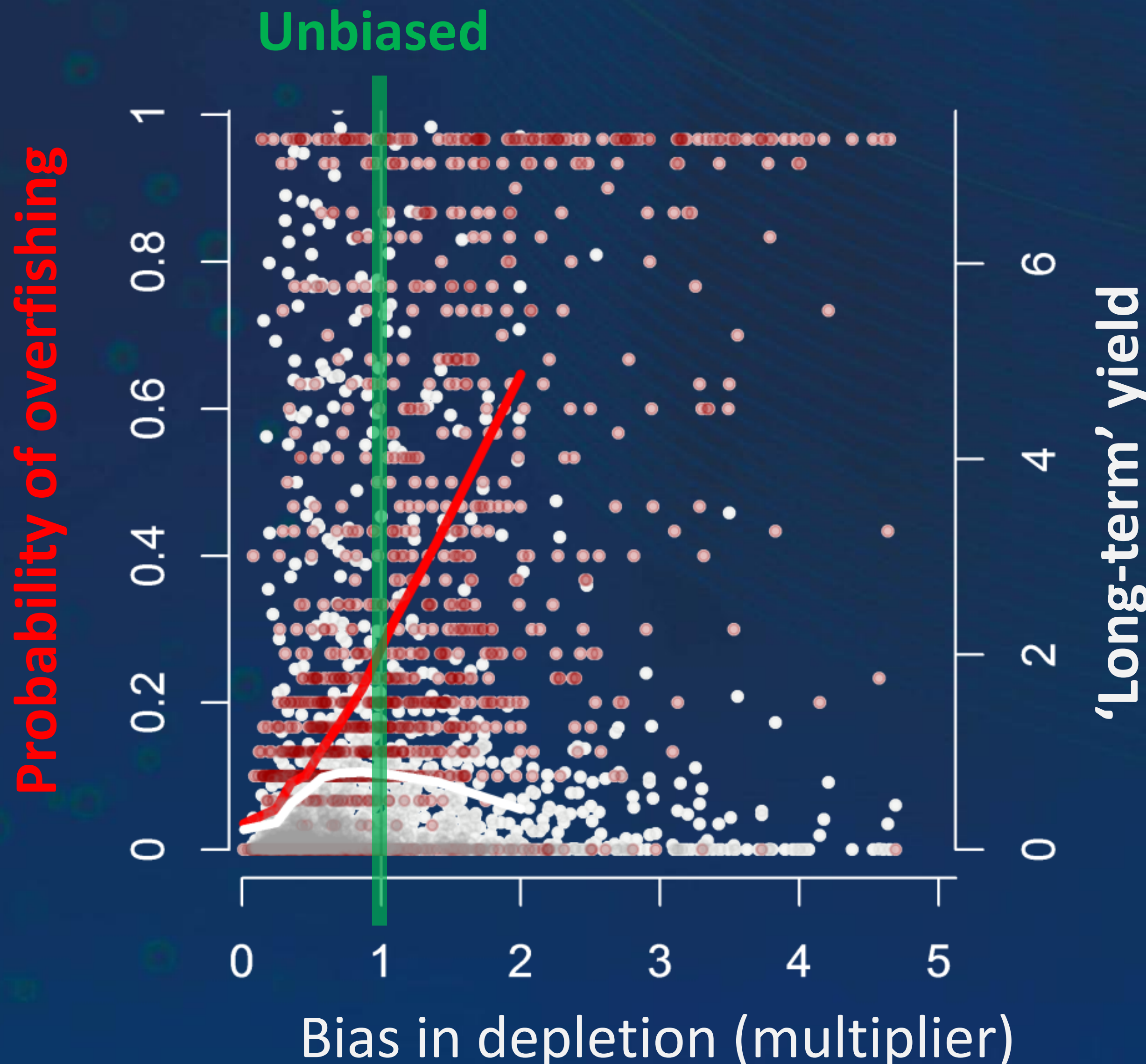
Yield = % of 'optimal yield'

Performance

	$B < 0.5\ B_{MSY}$				$0.5\ B_{MSY} < B < B_{MSY}$			
	Mackerel		Rockfish		Mackerel		Rockfish	
	P_{OF}	Yield	P_{OF}	Yield	P_{OF}	Yield	P_{OF}	Yield
Median catch 10 Yrs	89	12	95	5	63	53	83	32
DB-SRA 40% depletion	81	16	38	24	22	59	3	28
DCAC 40 % depletion	77	19	36	24	13	56	1	27
DB-SRA	13	64	5	48	22	65	8	56
DCAC	78	27	59	37	21	68	12	61
Life History Analysis	56	58	50	64	47	63	47	66
$F_{MSY}/M = 0.5$	27	64	14	57	17	59	11	56
Delay-Difference	20	38	4	26	33	46	11	45
Current Catch	82	18	90	9	56	51	74	37

POF = % probability of overfishing   Yield = % of 'optimal yield'

Sensitivity to imperfect information / value of information (DB-SRA and the mackerel stock)



Value of information

Standard deviation in yield among 10 percentile 'blocks' of each input

Mackerel

	Obs err
Median Catch - 10 Yrs	1

Value of information

Standard deviation in yield among 10 percentile ‘blocks’ of each input

Mackerel

Mackerel	Obs err	Dep bias	Dep CV	FMSY/M	BMSY/B0	M	50% Mat	Bcur bias	Bcur CV	Von B K	L 1st Cap
Median Catch - 10 Yrs	1										
DB-SRA 40% depletion	1			1	1	8	1				
DCAC 40 % depletion	1			0	1	7	1				
DB-SRA	1	22	5	4	3	5	1				
DCAC	0	7	1	1	1	3					
Life History Analysis								31	1	5	2
$F_{MSY}/M = 0.5$						8		19	0		
Delay-Difference	2										

Value of information

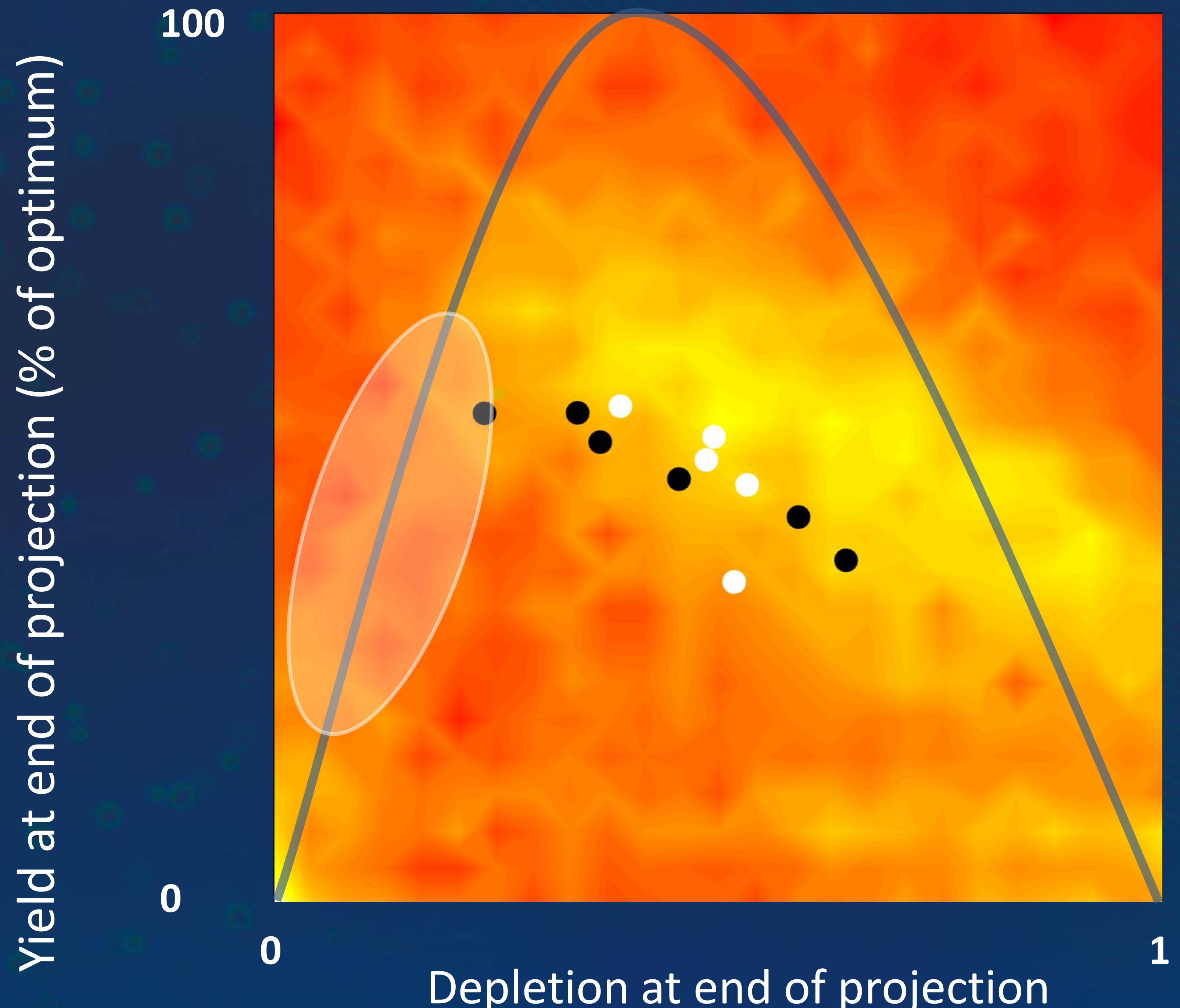
Standard deviation in yield among 10 percentile ‘blocks’ of each input

Mackerel

	Obs err	Dep bias	Dep CV	FMSY/M	BMSY/B0	M	50% Mat	B bias	B CV	Von B K	L 1st Cap
Median Catch - 10 Yrs	1										
DB-SRA 40% depletion	1			1	1	8	1				
DCAC 40 % depletion	1			0	1	7	1				
DB-SRA	1	22	5	4	3	5	1				
DCAC	0	7	1	1	1	3					
Life History Analysis								31	1	5	2
FMSY/M = 0.5						8		19	0		
Delay-Difference	2										

Rockfish

	Obs err	Dep bias	Dep CV	FMSY/M	BMSY/B0	M	50% Mat	B bias	B CV	Von B K	L 1st Cap
Median Catch - 10 Yrs	1										
DB-SRA 40% depletion	0			1	0	10	1				
DCAC 40 % depletion	0			0	0	9	1				
DB-SRA	2	30	9	3	4	13	6				
DCAC	0	13	1	3	2	4					
Life History Analysis								29	4	4	4
FMSY/M = 0.5						12		25	2		
Delay-Difference	1										


100
0
Yield at end of projection (% of optimum)
0
1
Depletion at end of projection

Conclusions (1/2)

- Setting catch limits to historical catch percentiles performs similarly to using current catch

- Well-informed delay-difference models could perform worse than data-limited methods (imprecise survey + F_{MSY}/M) due to the assumption of temporally stationary productivity / fishing efficiency

- Often, more precautionary buffers (lower ABC lead to both higher yields and lower probability of overfishing

Conclusions (2/2)

- Often stocks assigned 'data-limited' status have a greater number of data available that could provide large increases in management performance

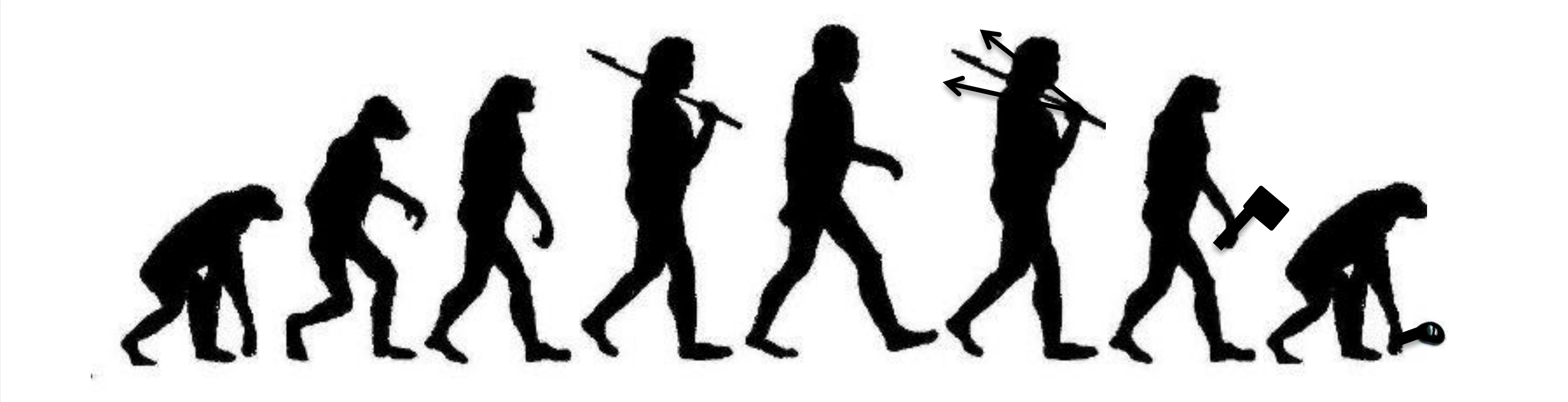
- Spatial effects were not important in these simulations of data-limited methods

Next

Extend MSE to new data-limited methods and control rules based on: catch curve analysis, SPR, relative abundance / CPUE

Acknowledgements

- Chris Legault, Jim Berkson
- TRC is grateful for the support of the Gordon and Betty Moore foundation
- Thanks for to the WCSAM team for sponsoring my attendance



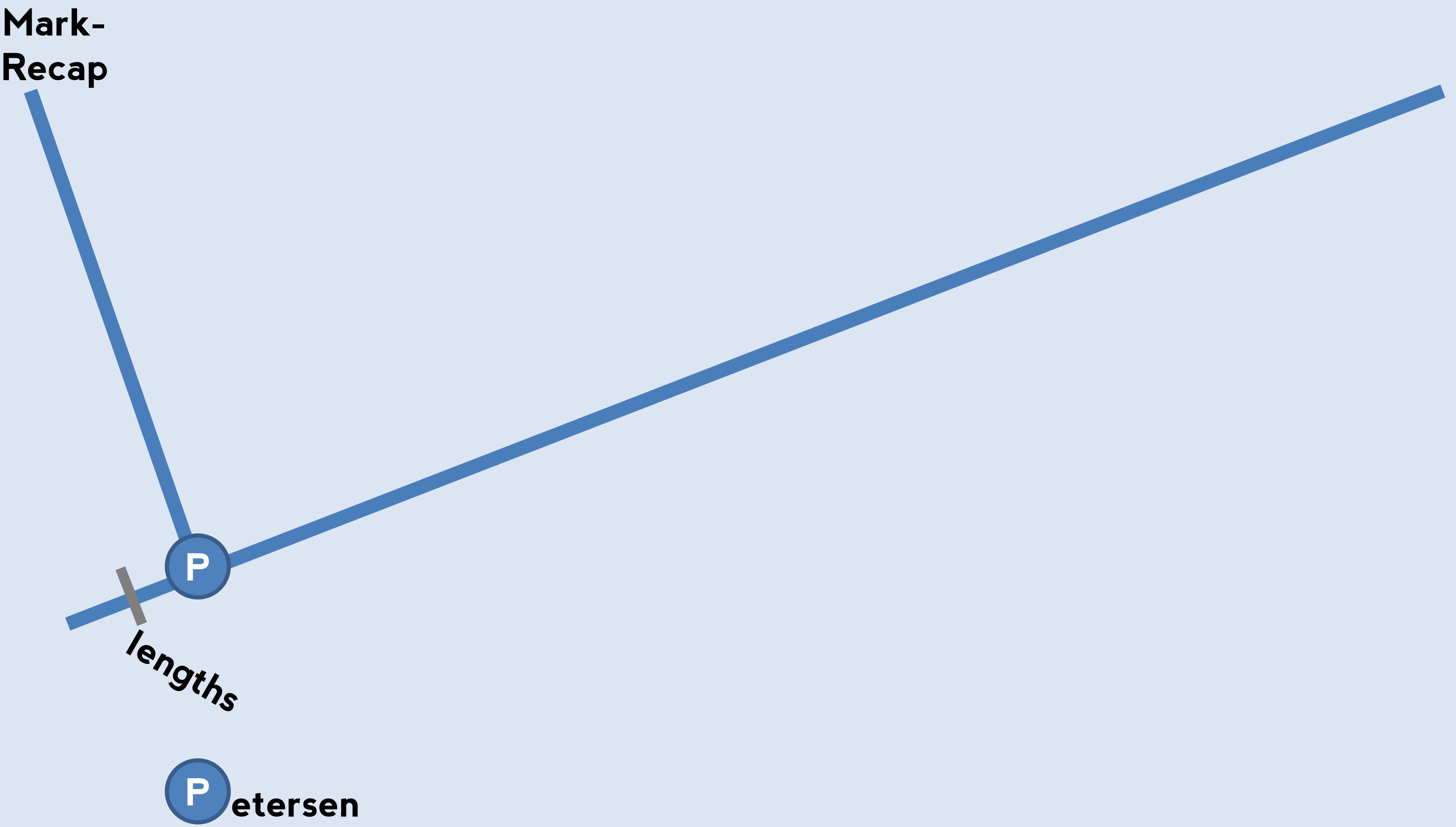
The (d)evolution of stock assessments off the U.S. west coast: from data-poor to data-less poor and back.

Jason M. Cope

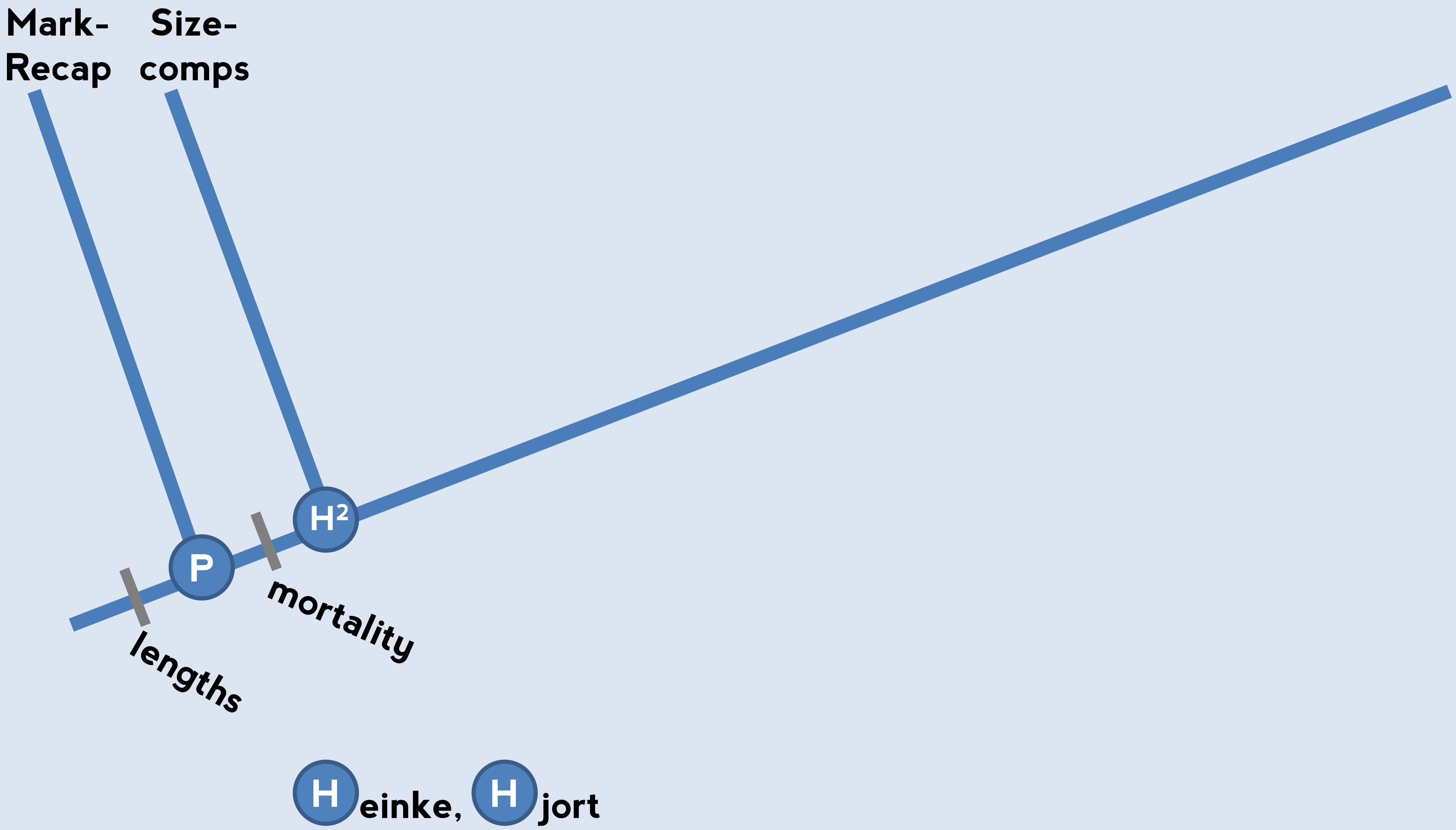
E.J. Dick

Chantell R. Wetzel

Evolution of fisheries models



Evolution of fisheries models



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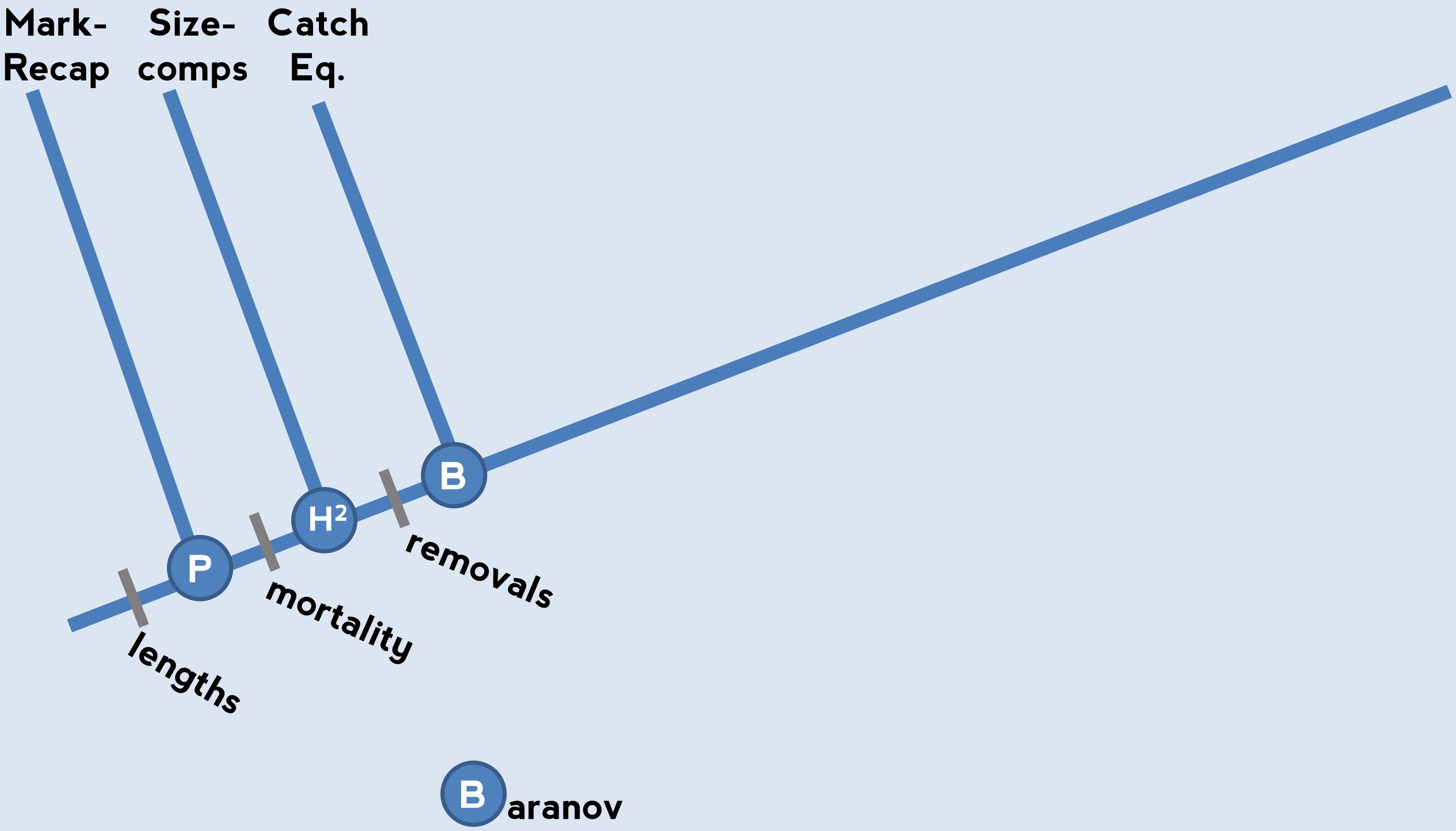
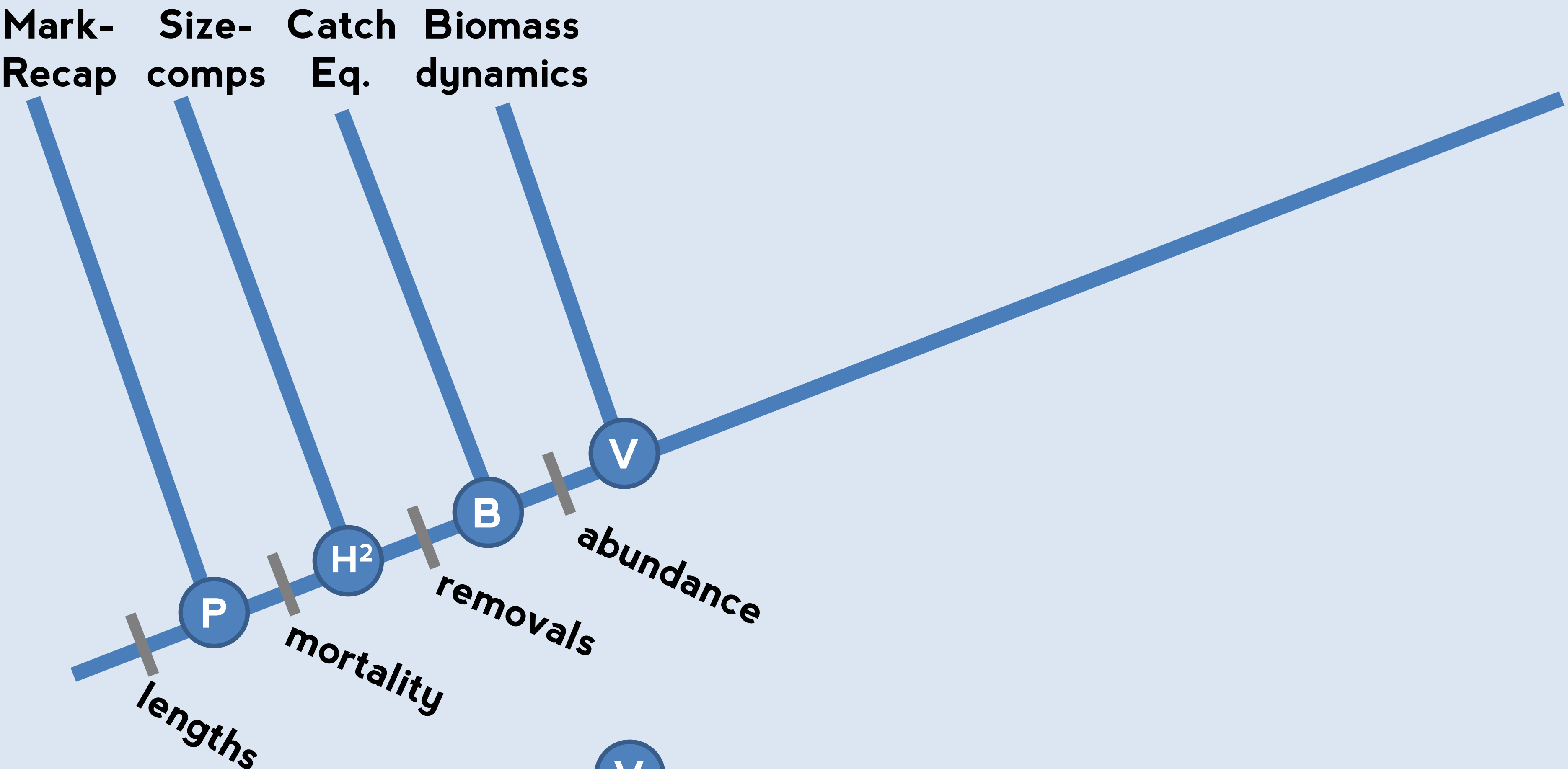
Evolution of fisheries models

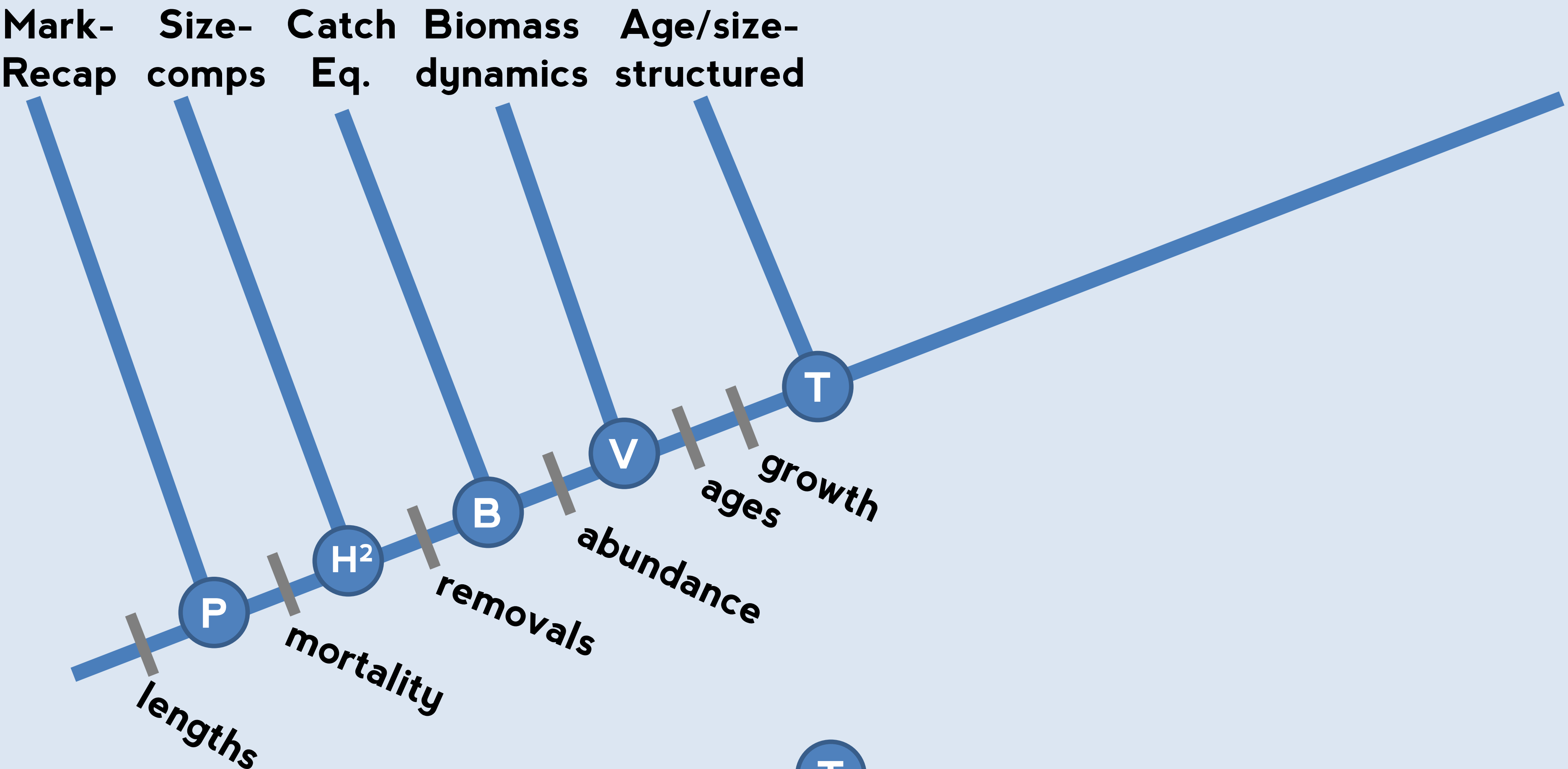


Evolution of fisheries models



Verhulst, Pearl, Lotka,
Volterra, Russell, Buckman,
Hjort, DeLury, Leslie,
Schaefer, Pella, Tomlinson

Evolution of fisheries models



Thompson, Bell, Lotka, Hjort, Leslie, Gulland, Pope

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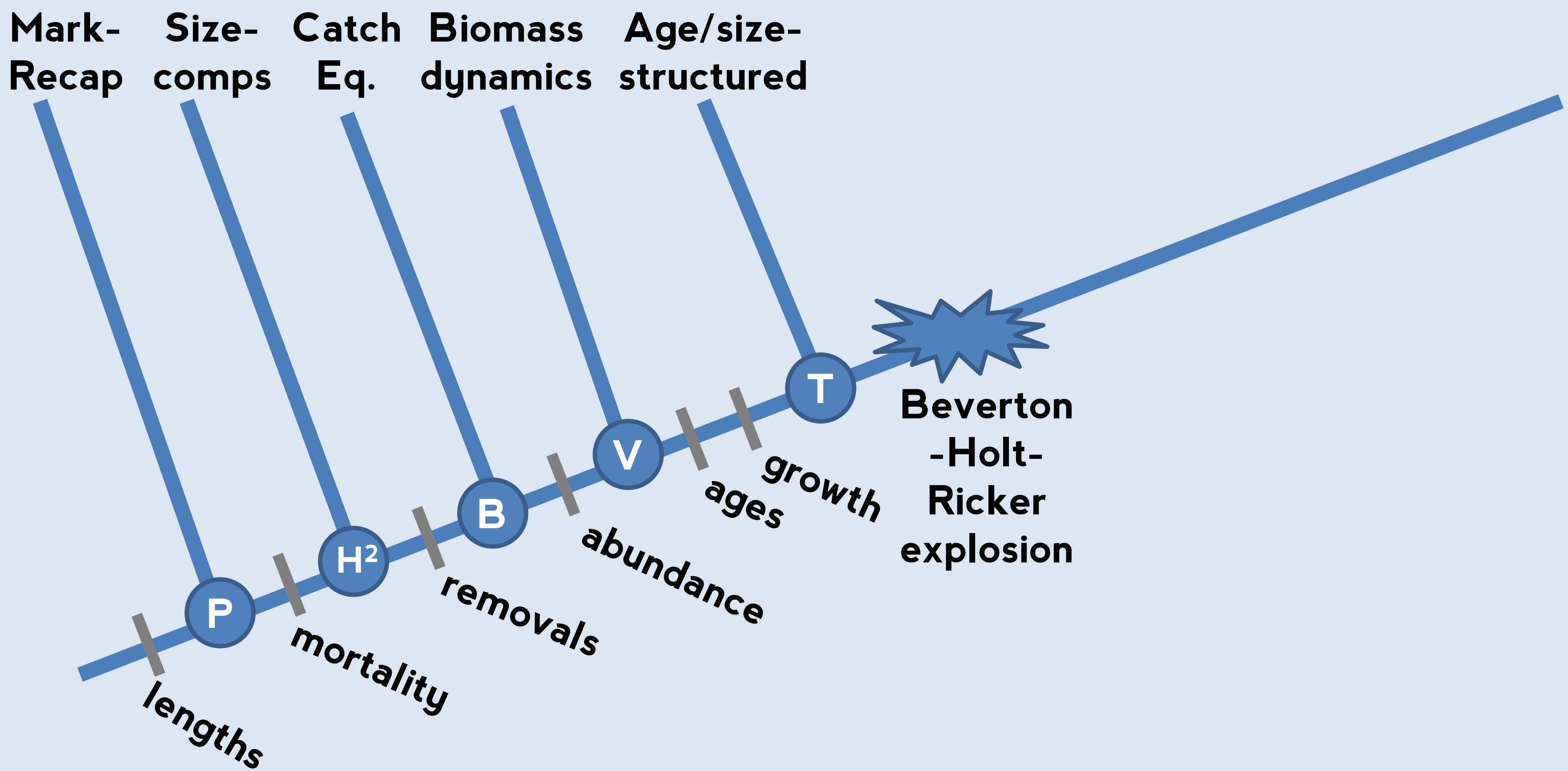
Evolution of fisheries models



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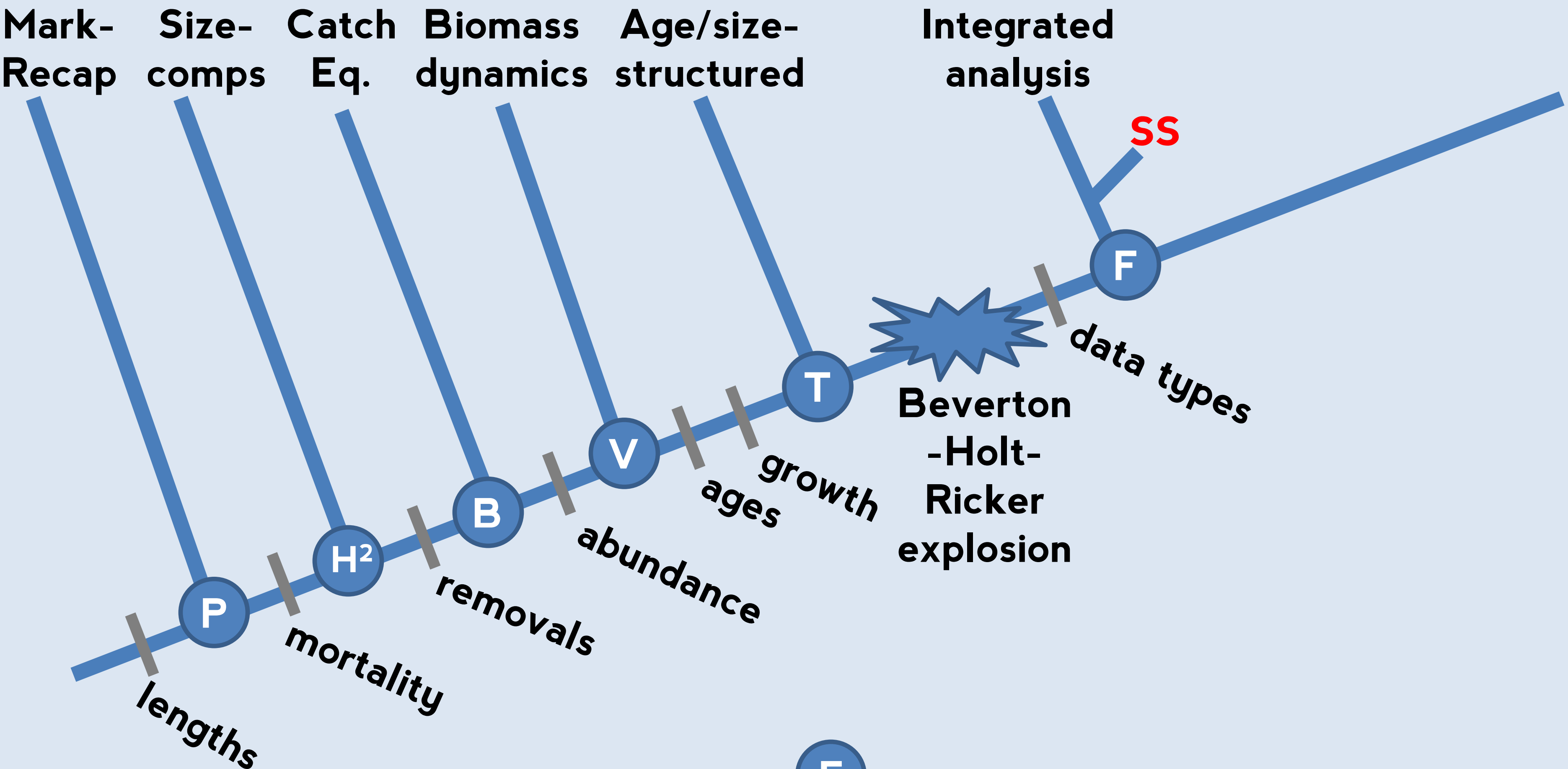
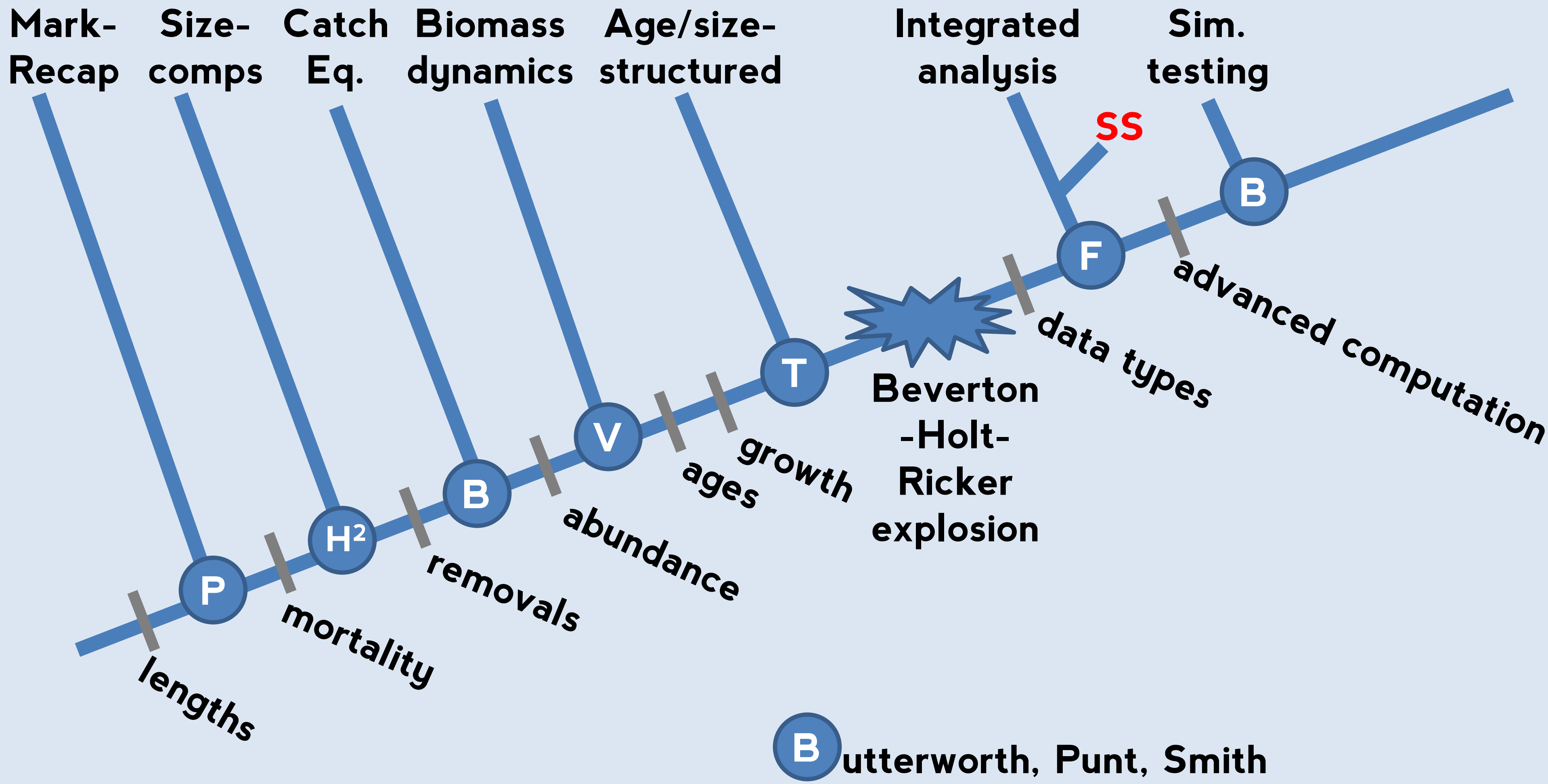


F ournier, Archibald, Methot

Evolution of fisheries models



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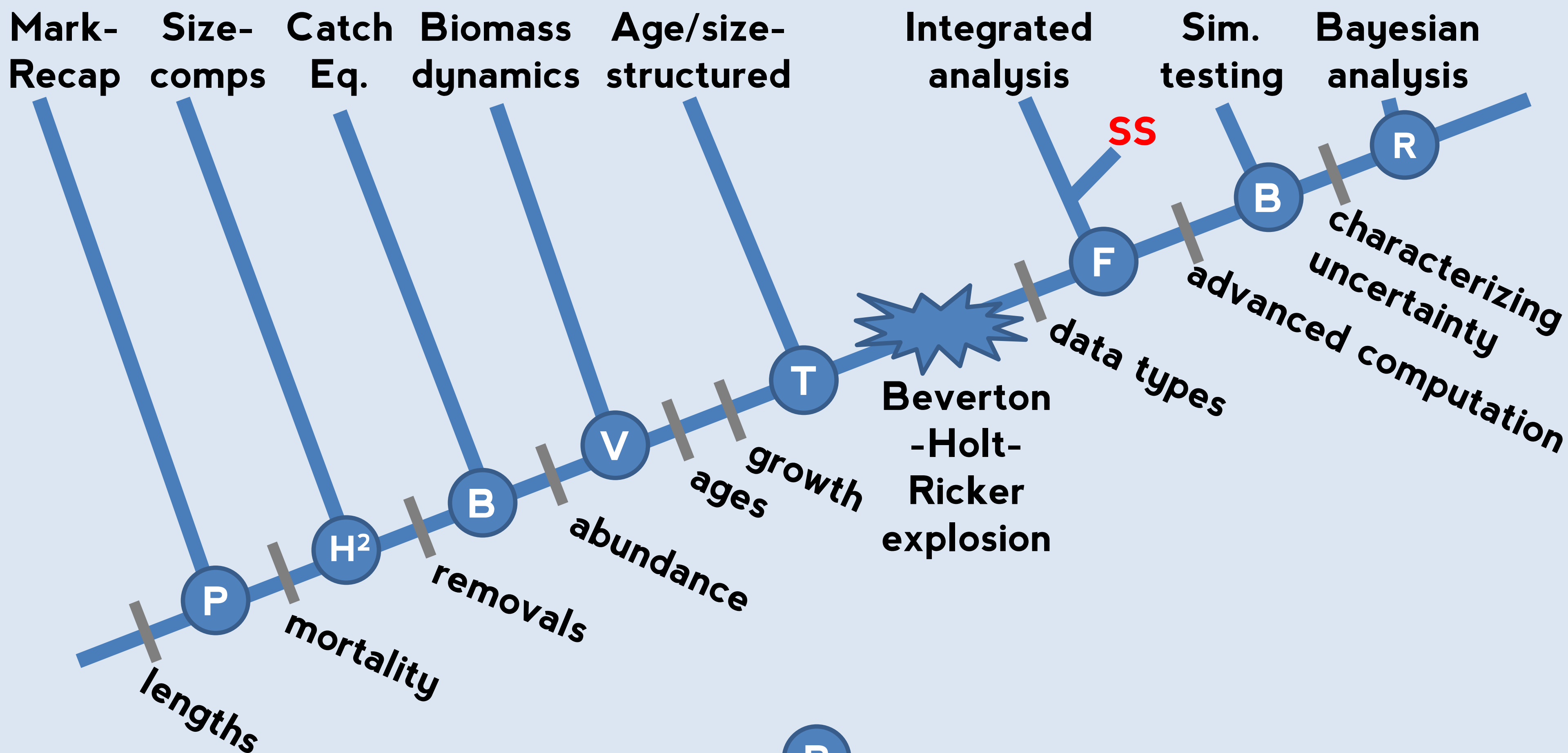
Evolution of fisheries models



R ev. Bayes, Gelman, Punt, Hilborn

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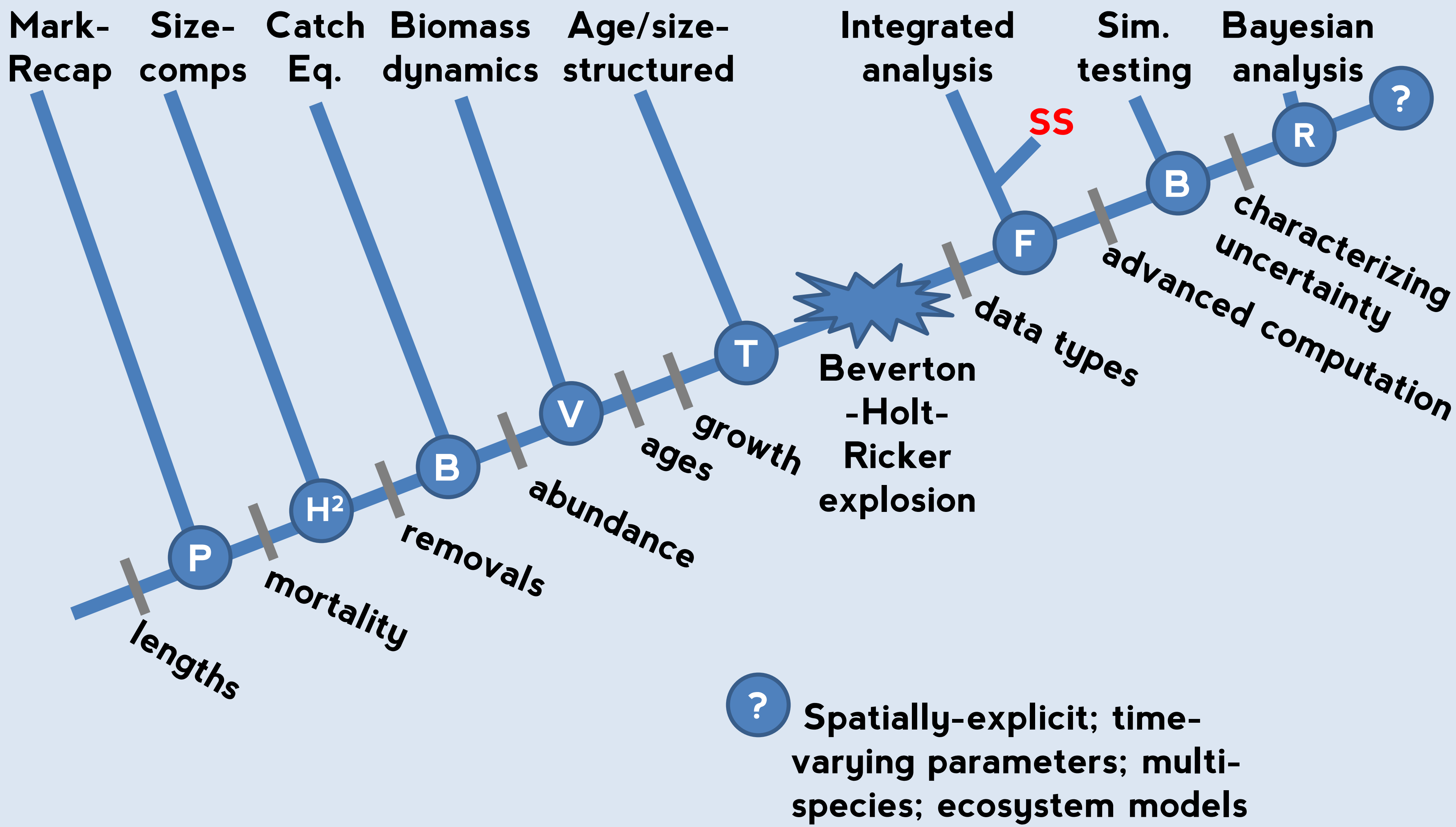
Evolution of fisheries models



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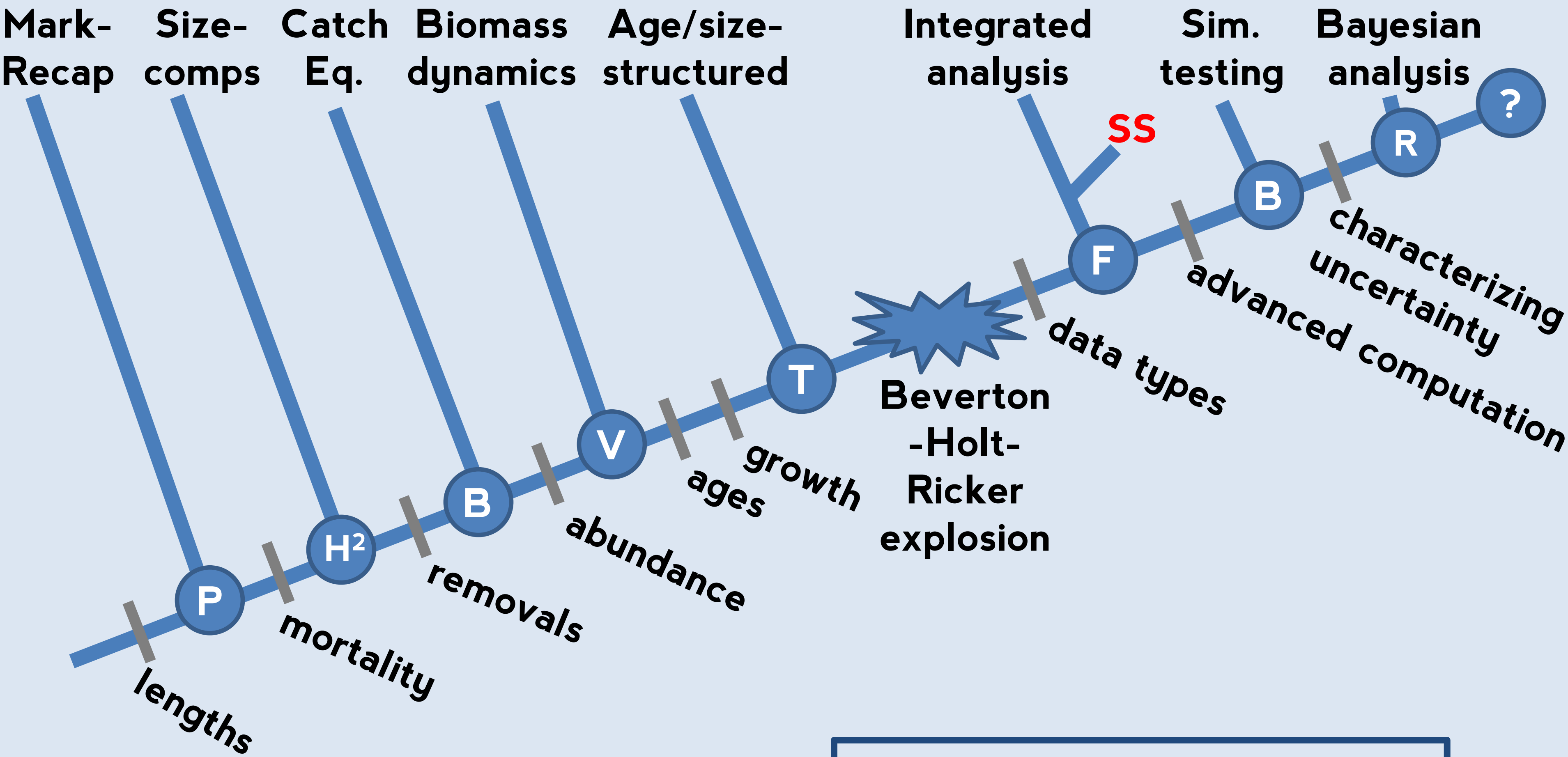
Evolution of fisheries models



Evolving towards more sophisticated, complex, & data-needy models

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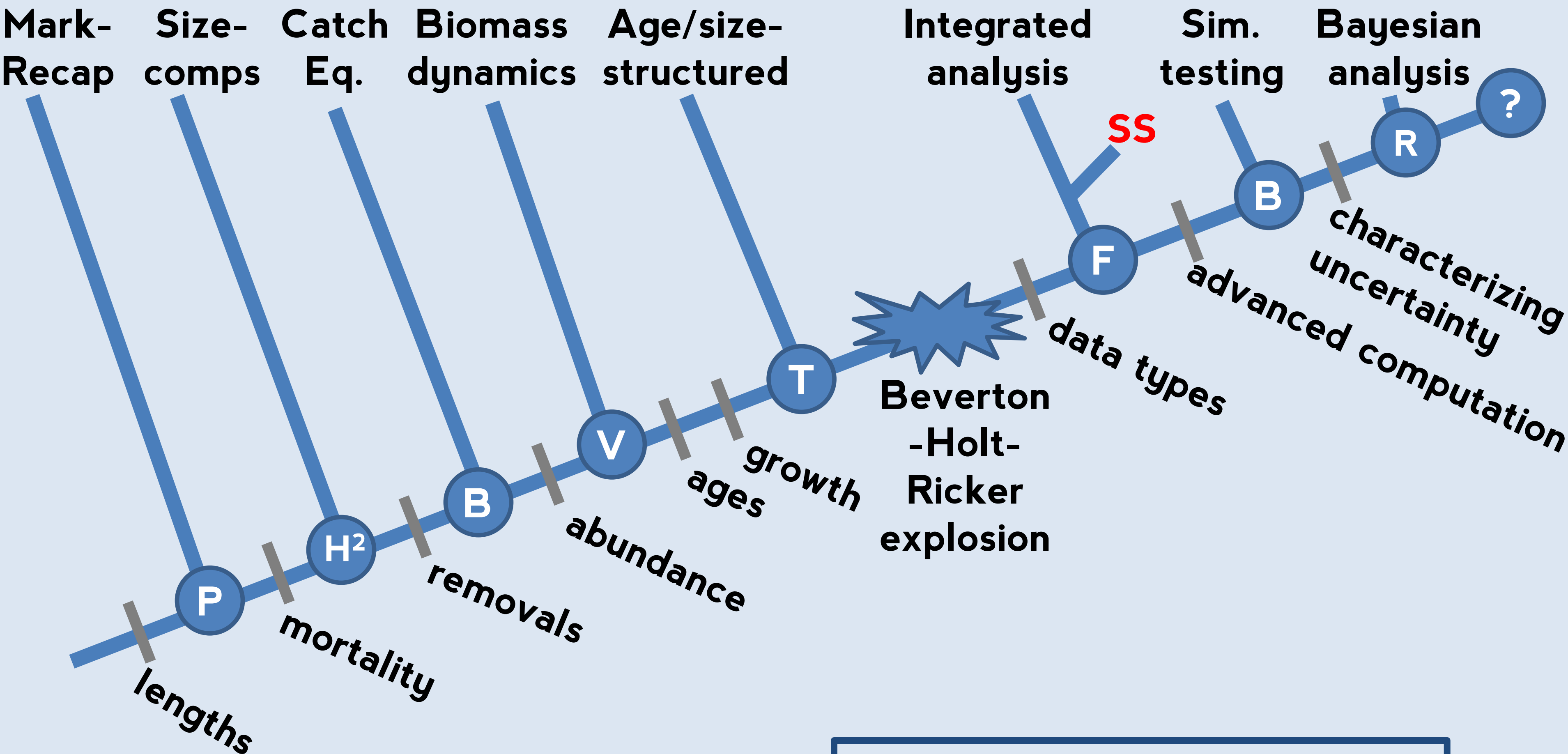
Evolution of fisheries models

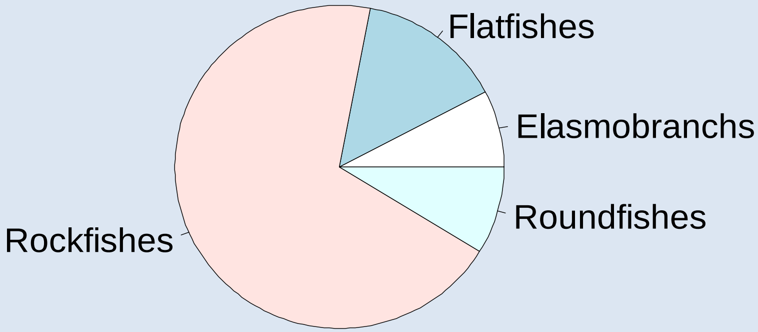


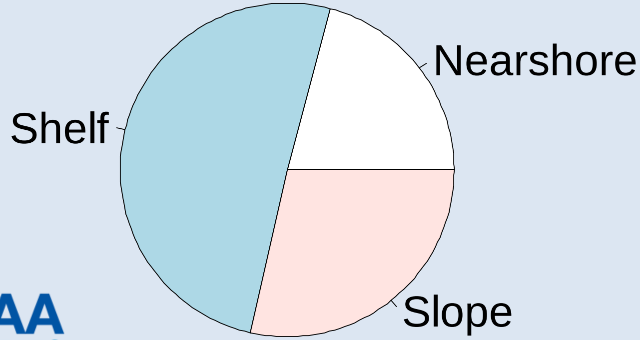
Devolution: “Back to the soup”

U.S. west coast groundfish

Groundfish FMP (est. 1982)

90+ species
Longevity: 5-200+





Fishery

- Lat. range: 32°-49° N
- Multiple factors
  - States
  - Sectors
  - Vessels
  - Gear types
- Data
  - Types
  - Quality
  - Quantity

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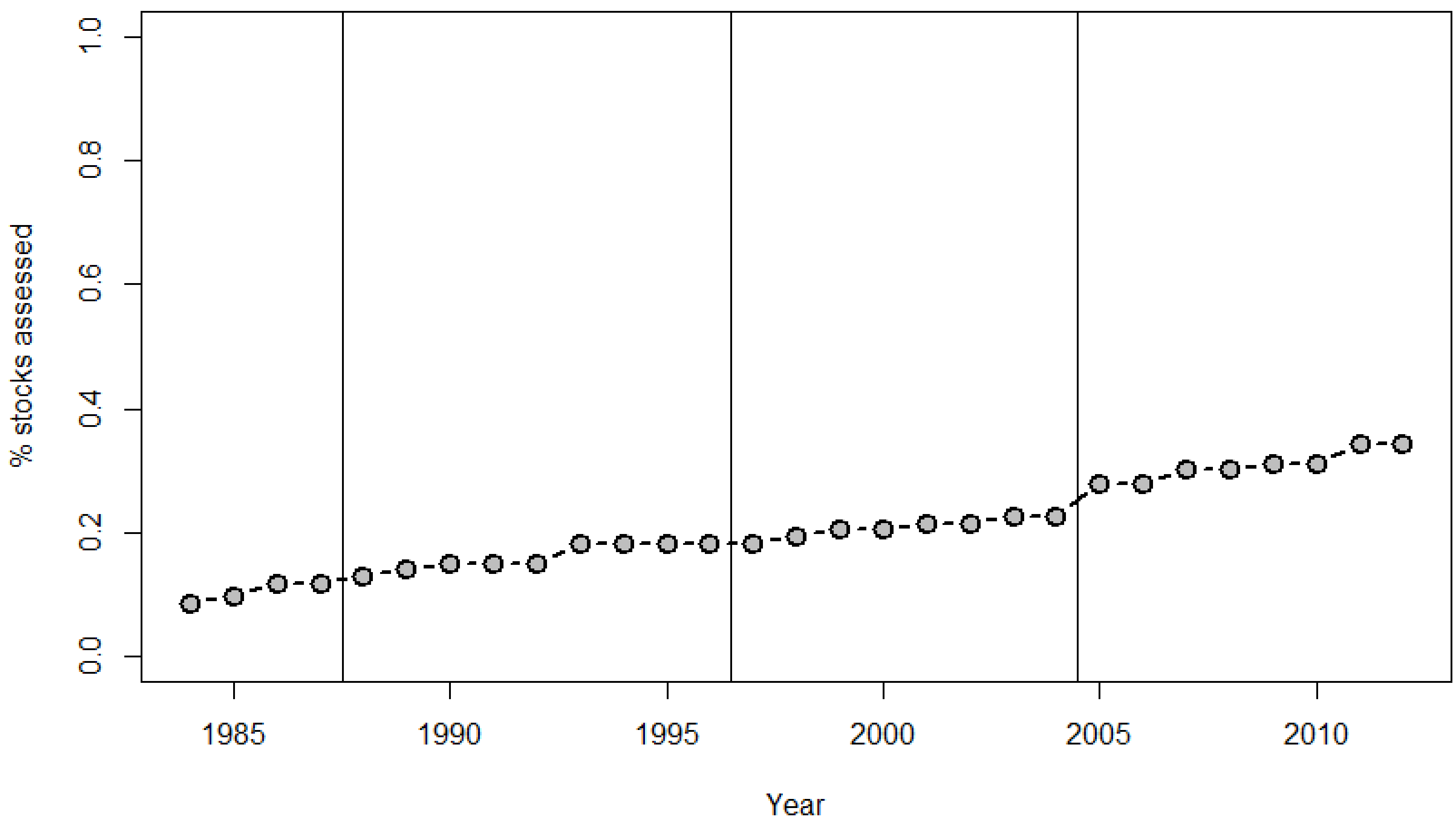
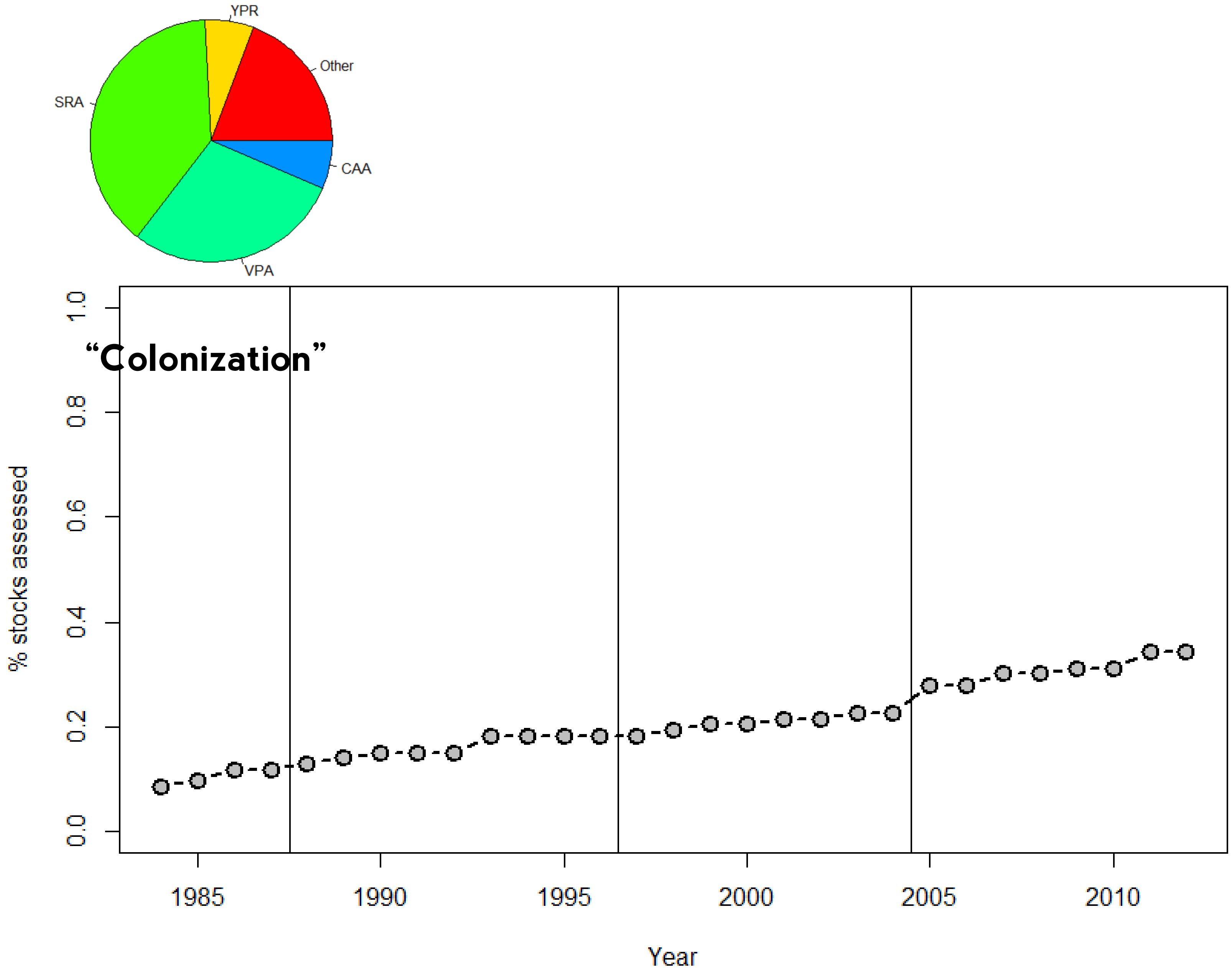
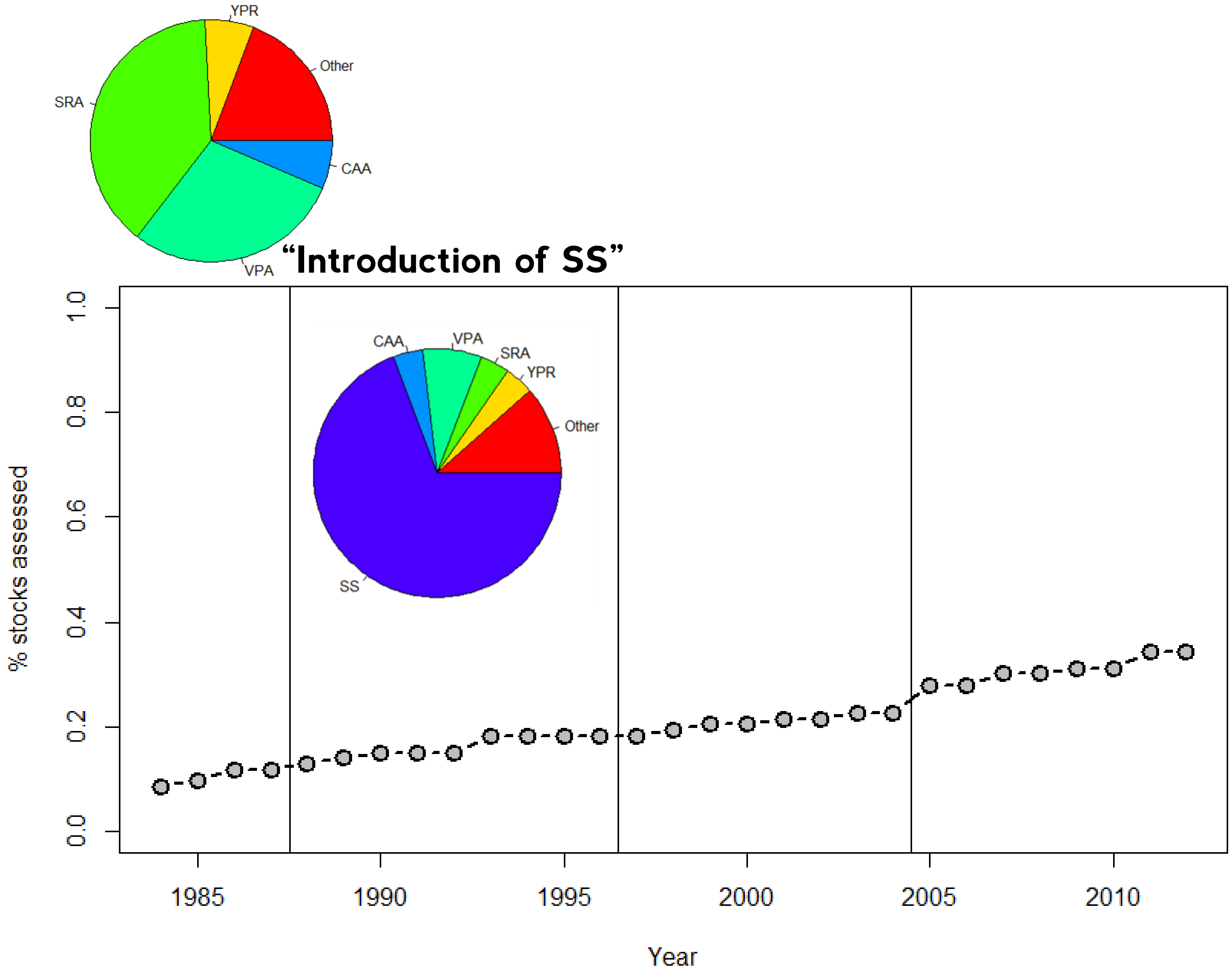
U.S. west coast assessment succession



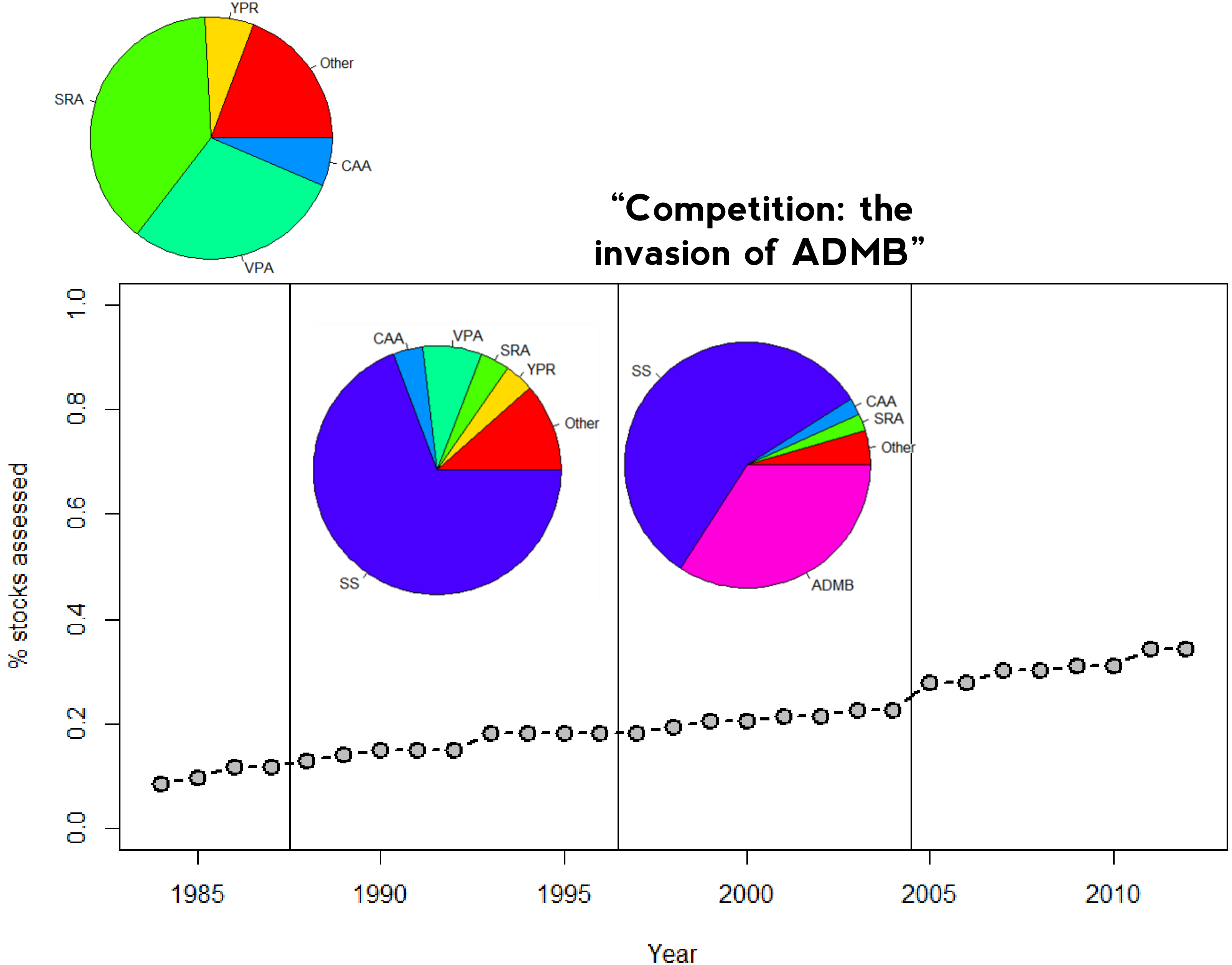
U.S. west coast assessment succession



U.S. west coast assessment succession

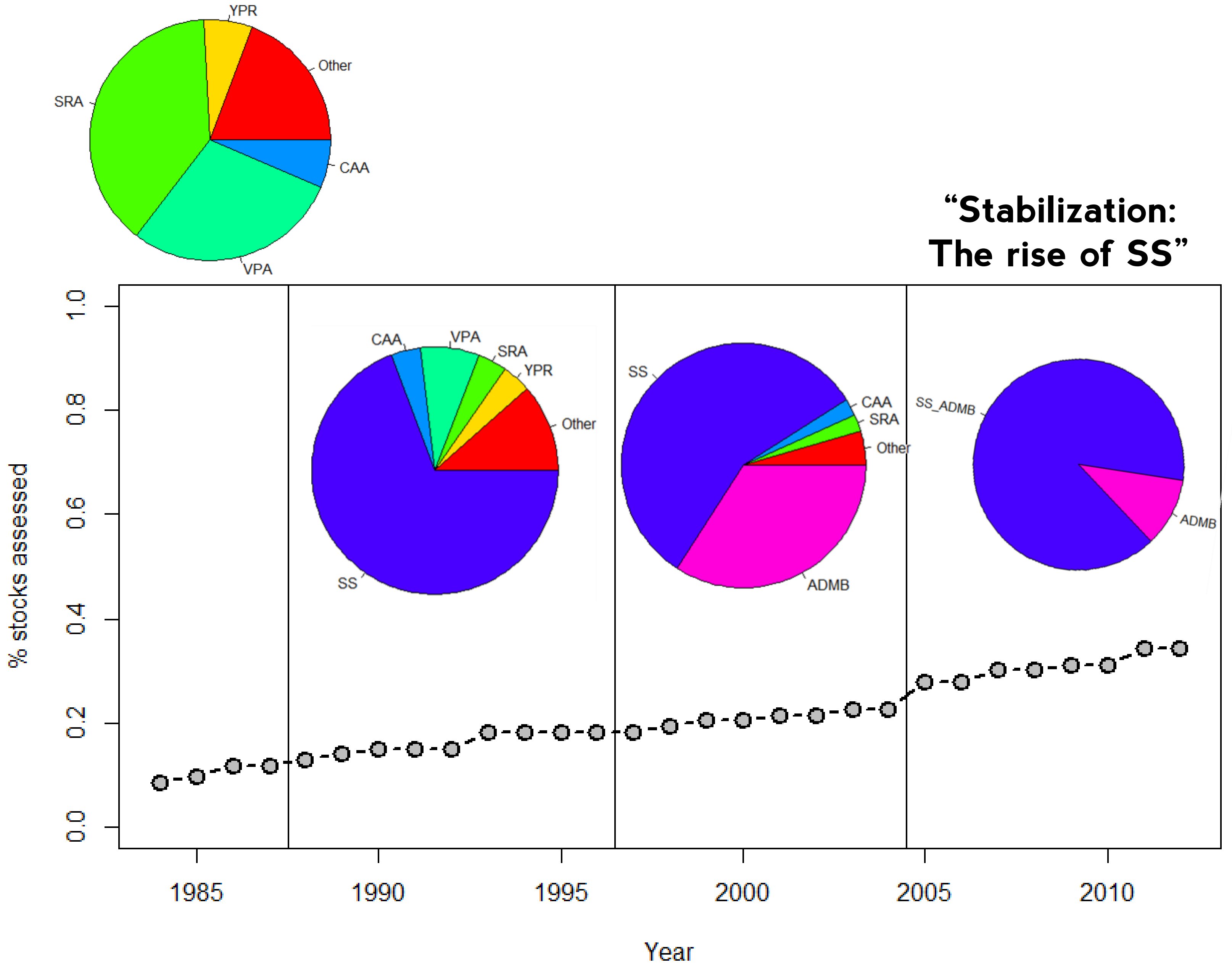


U.S. west coast assessment succession

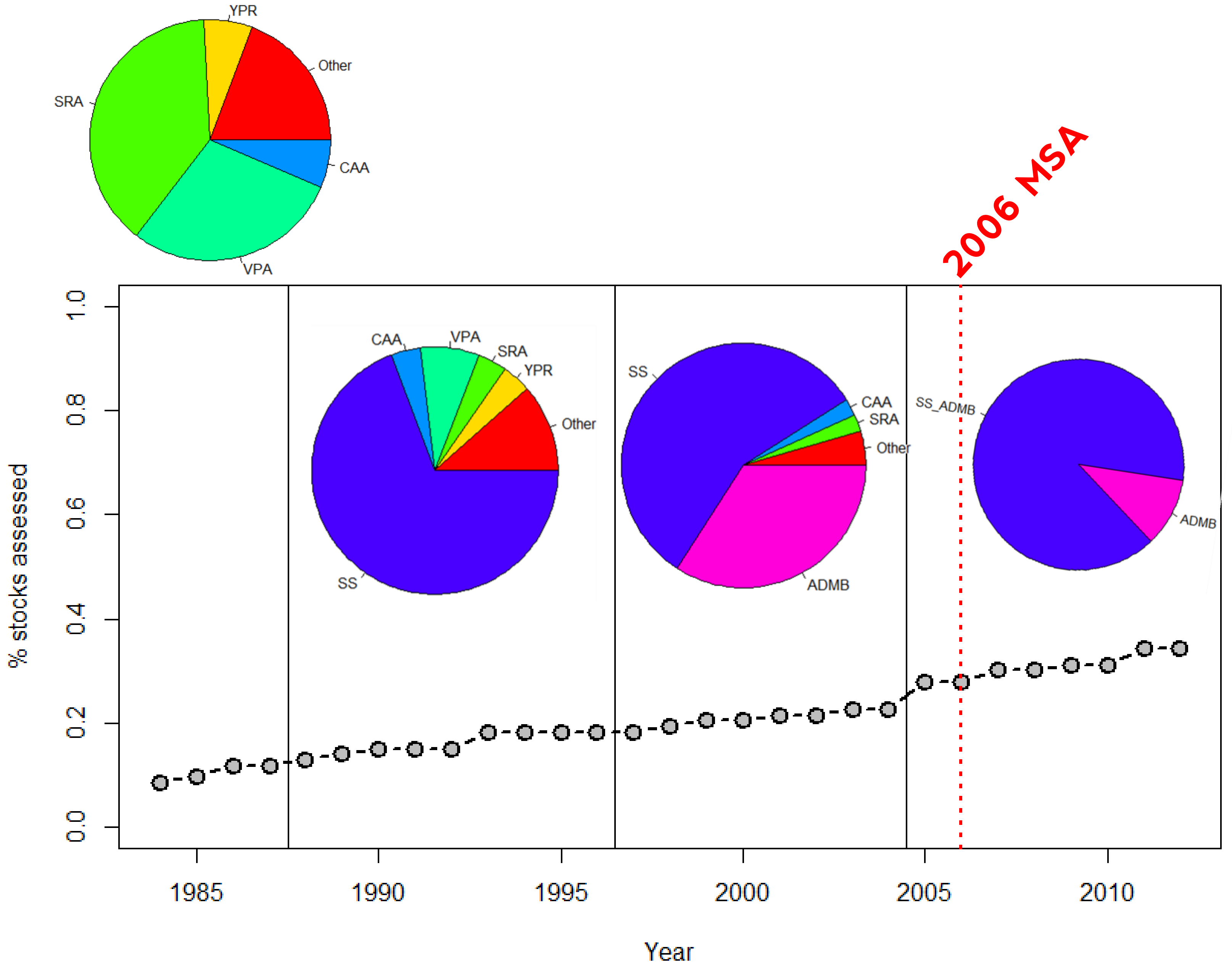


"Competition: the invasion of ADMB"

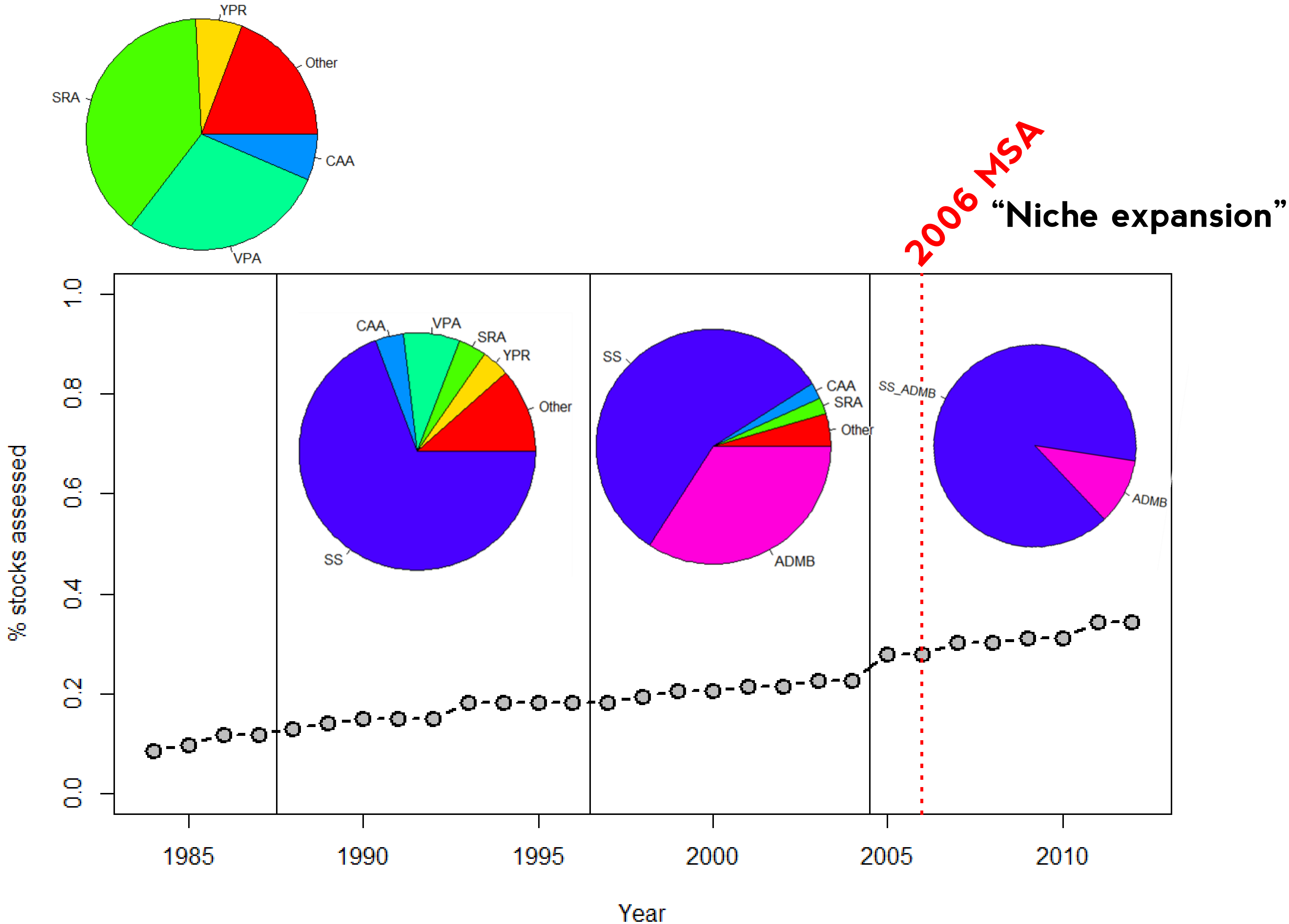
U.S. west coast assessment succession



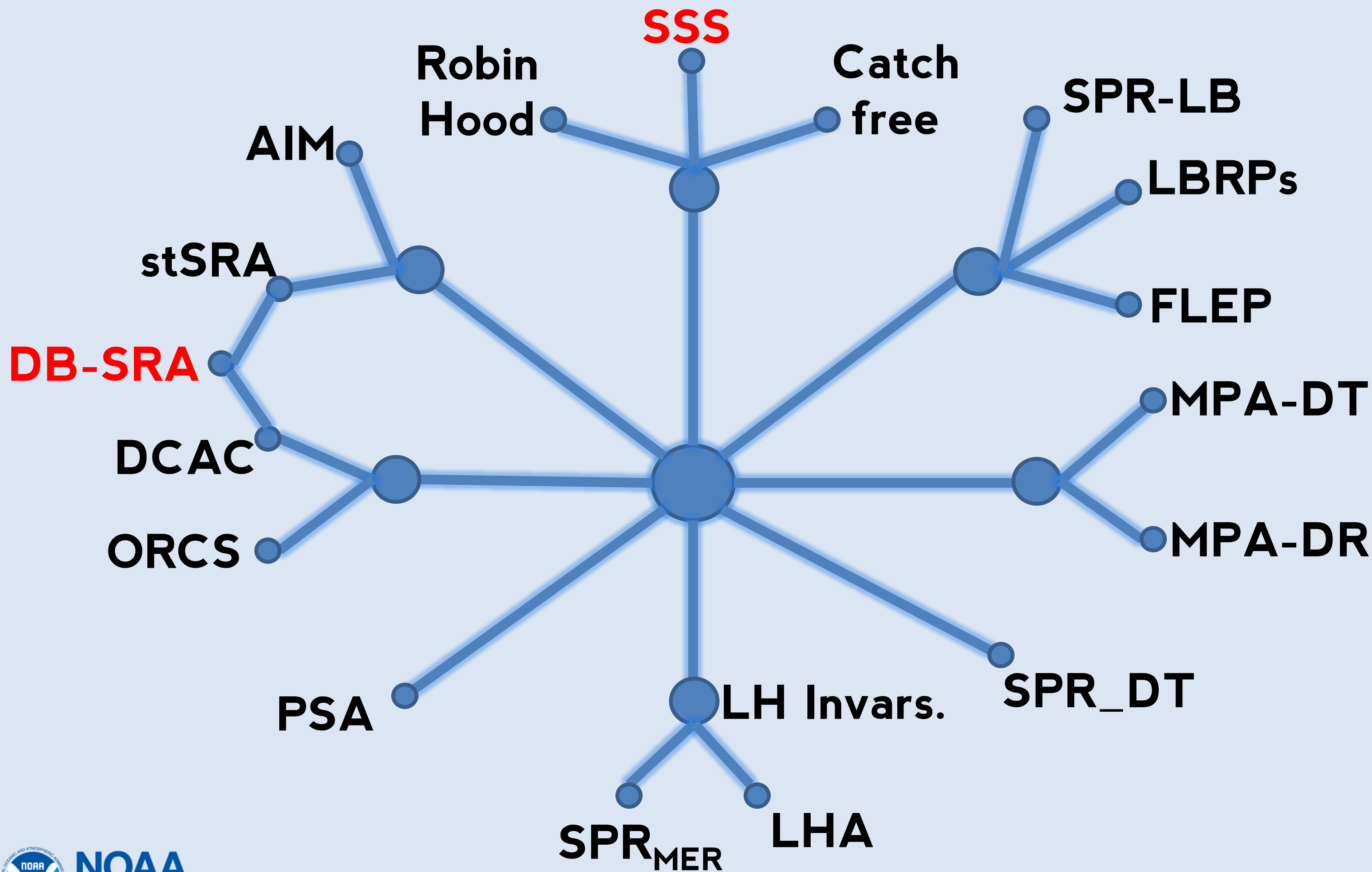
U.S. west coast assessment succession



U.S. west coast assessment succession



Radiation of data-limited approaches



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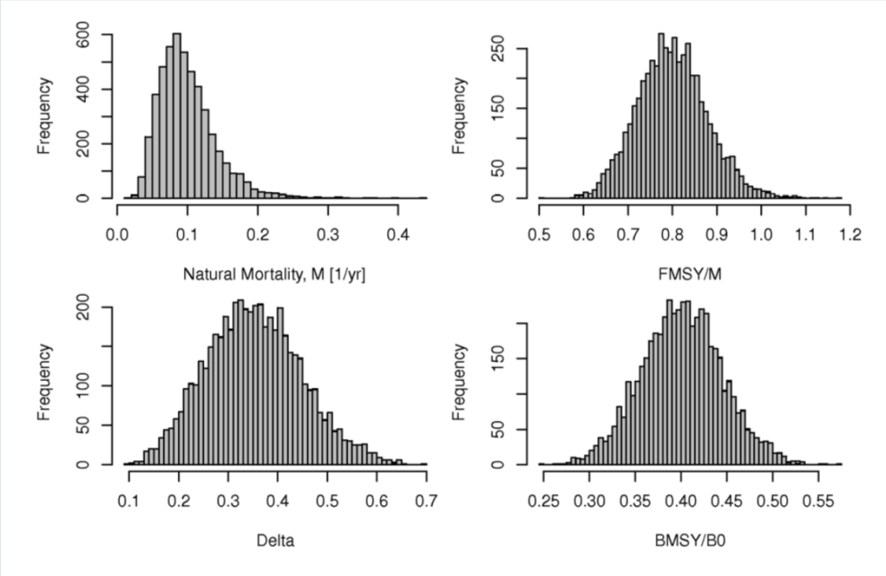
DB-SRA

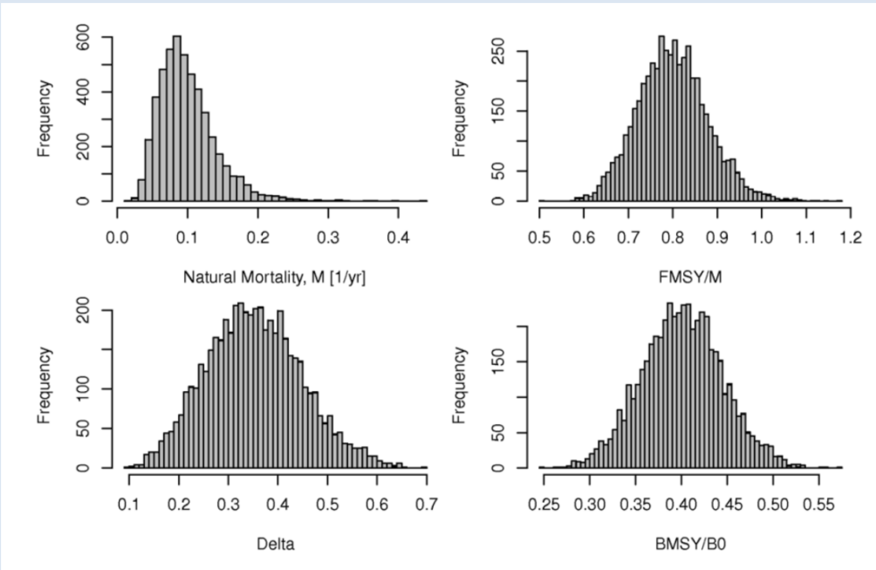
Dick and MacCall 2010,2011



2010: Applied to 45 non-assessed stocks to get Overfishing limits (OFLs)

DB-SRA

Dick and MacCall 2010,2011

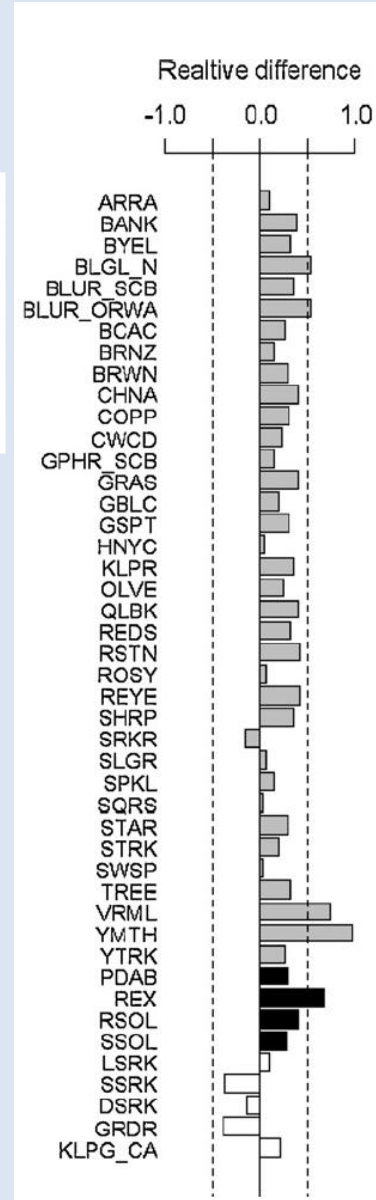


2010: Applied to 45 non-assessed stocks to get Overfishing limits (OFLs)

"Simple" SS

Cope 2013

Mimicry



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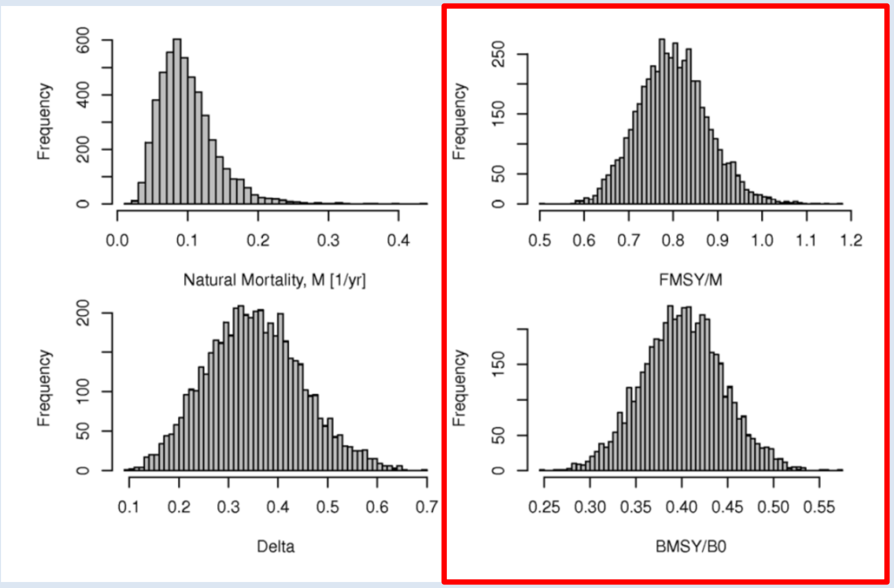
DB-SRA

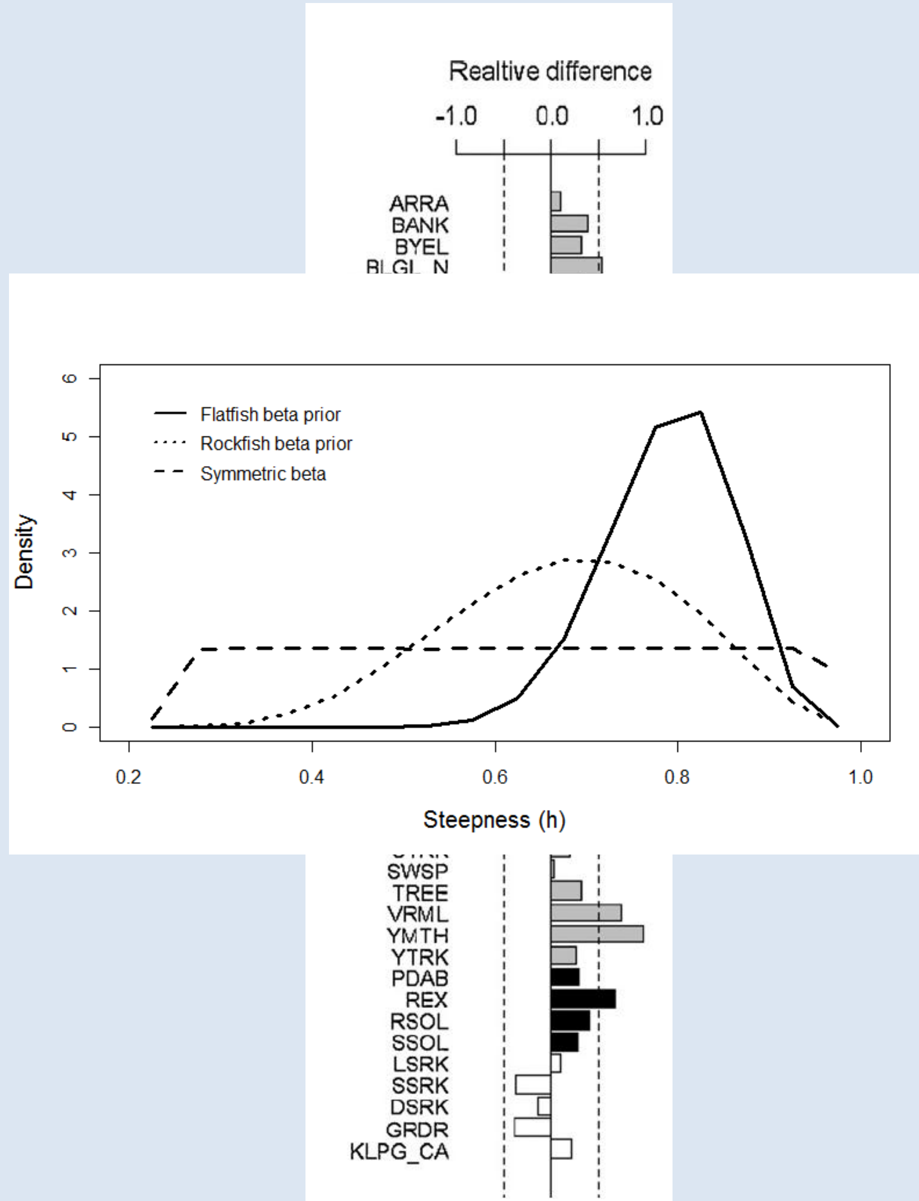
Dick and MacCall 2010,2011



2010: Applied to 45 non-assessed stocks to get Overfishing limits (OFLs)

"Simple" SS

Cope 2013



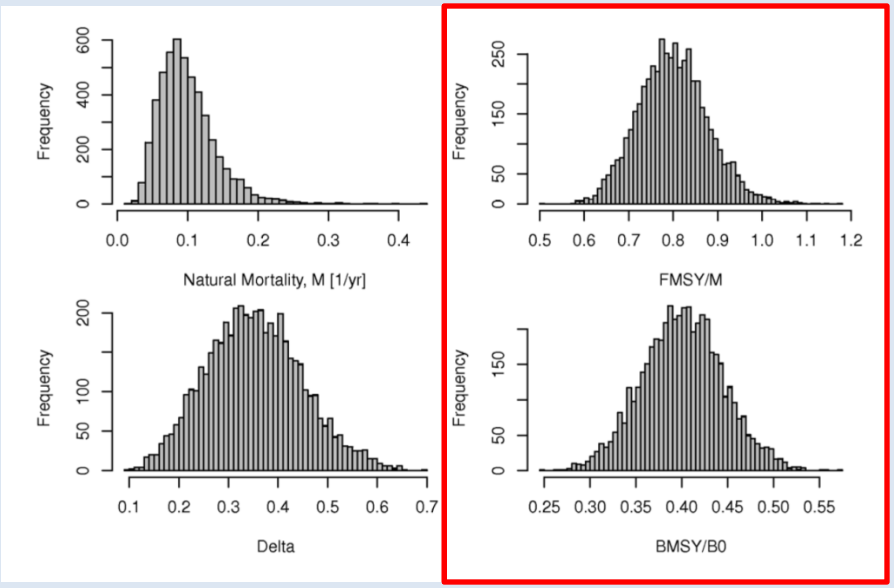
NOAA FISHERIES

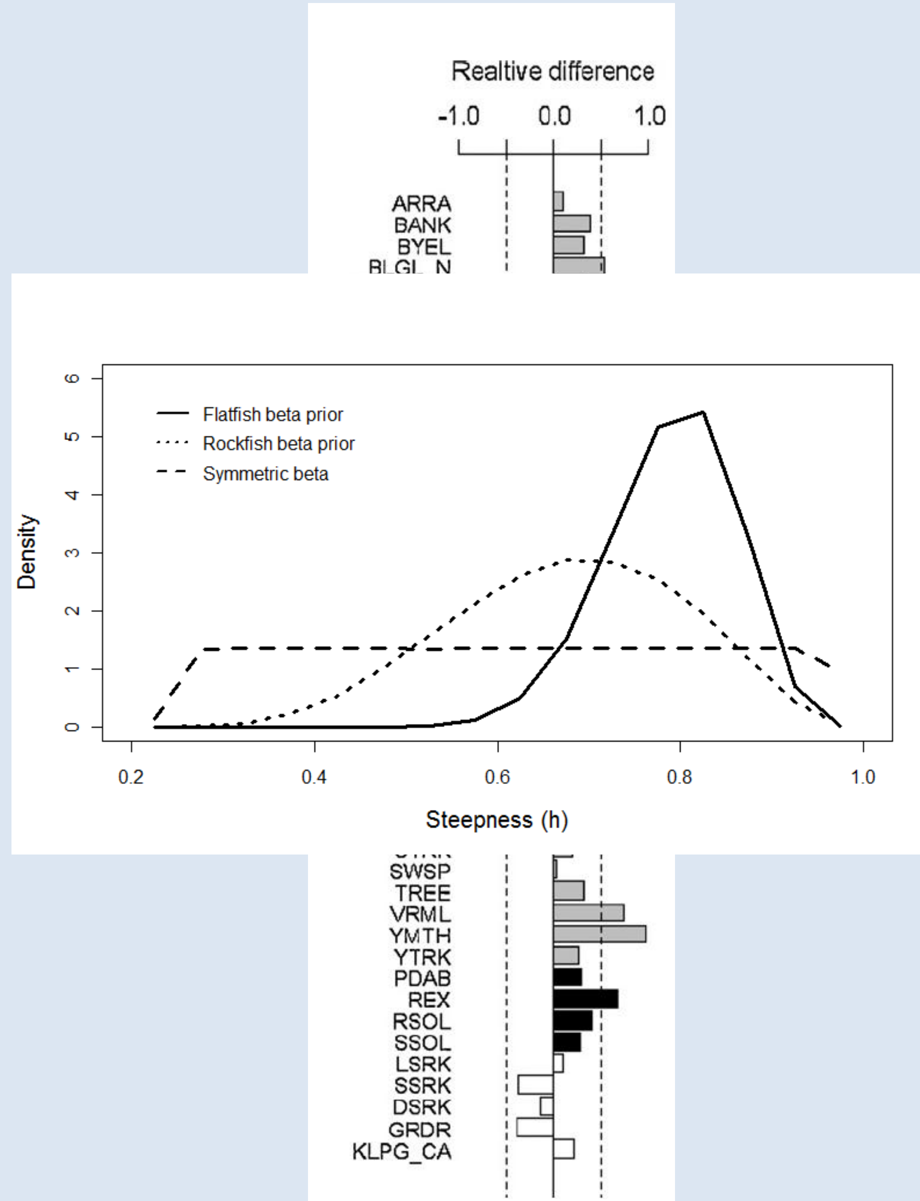
XDB-SRA

Dick and MacCall 2010,2011

exSSS

Cope 2013



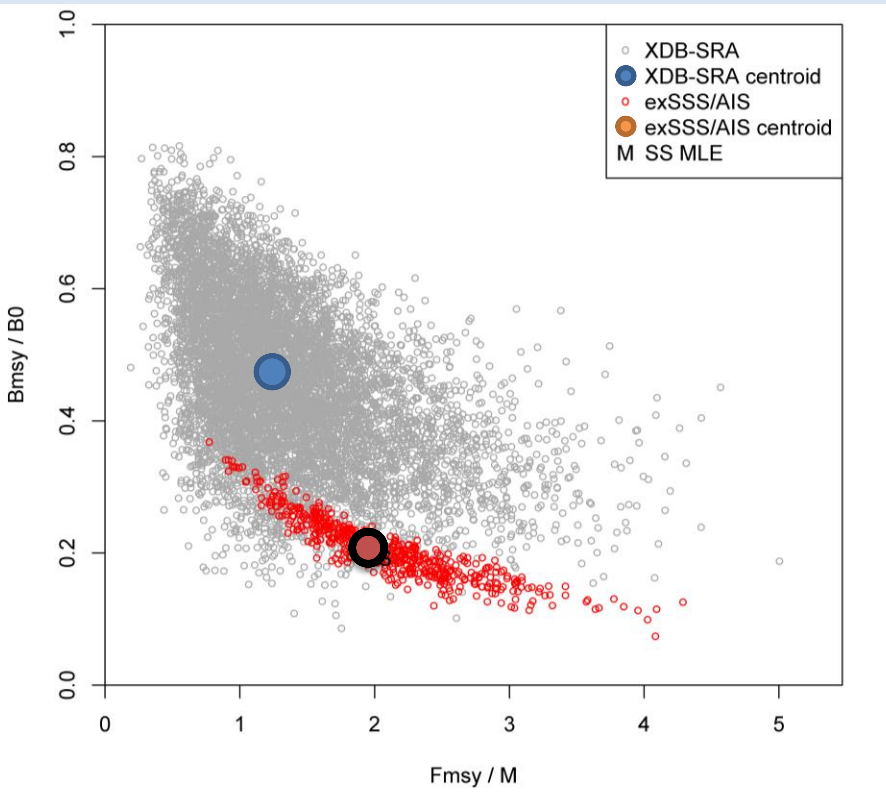


2010: Applied to 45 non-assessed stocks to get Overfishing limits (OFLs)

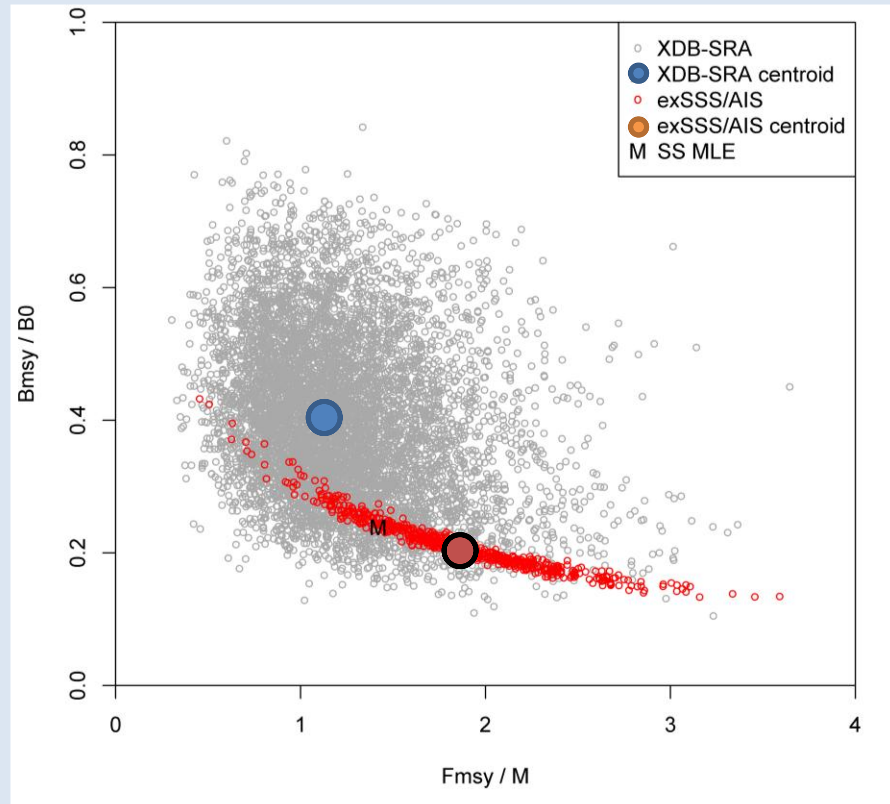
NOAA FISHERIES

Comparing parameterization: productivity

flatfish



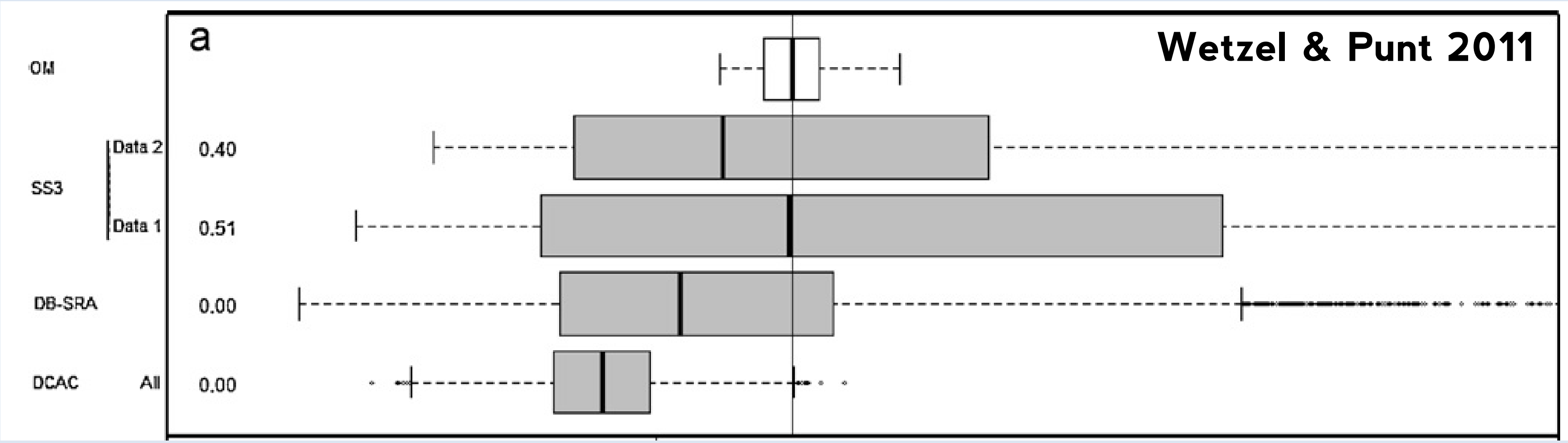
rockfish



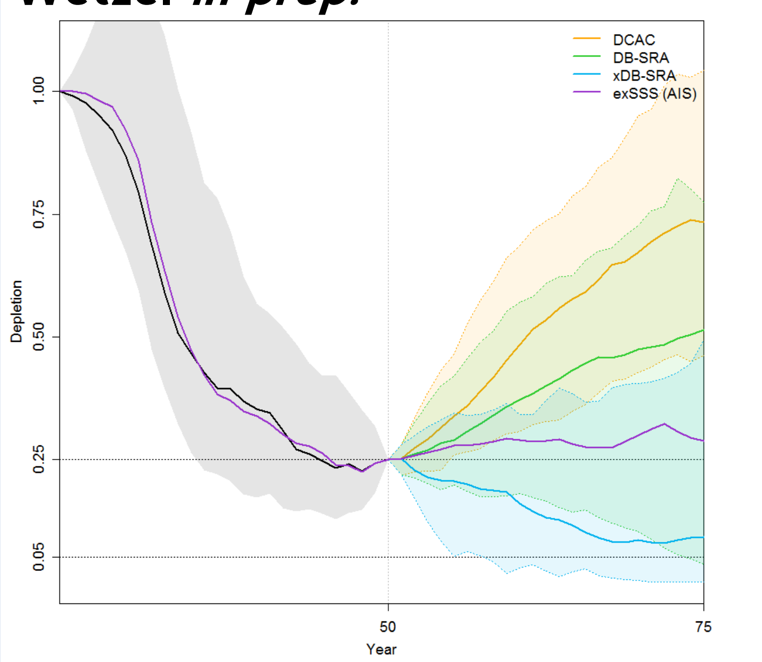
Need to understand link between parameters

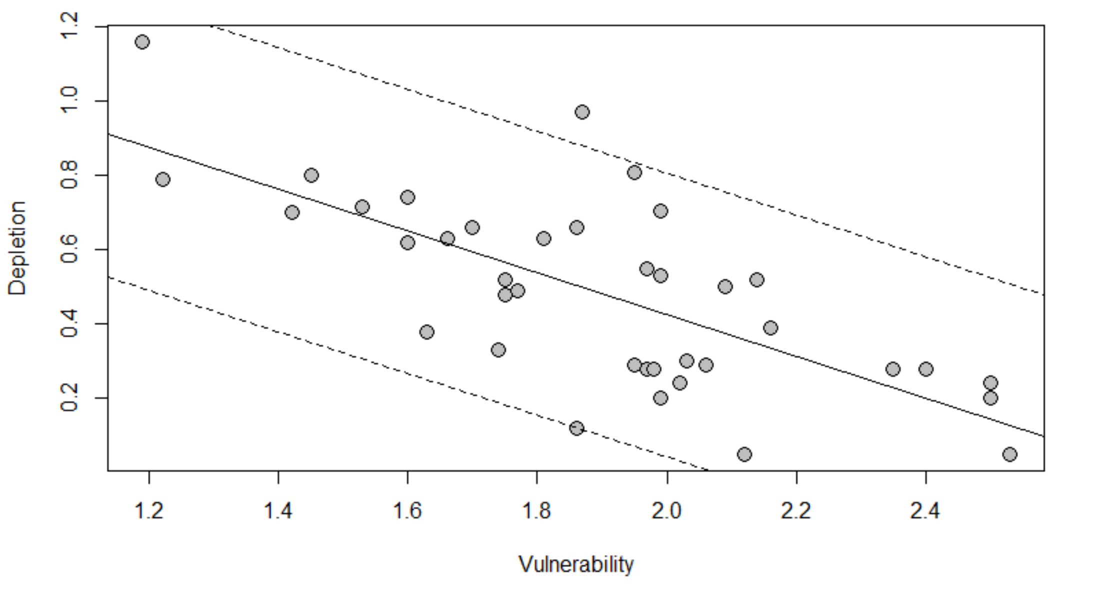
Testing & adapting

Wetzel & Punt 2011



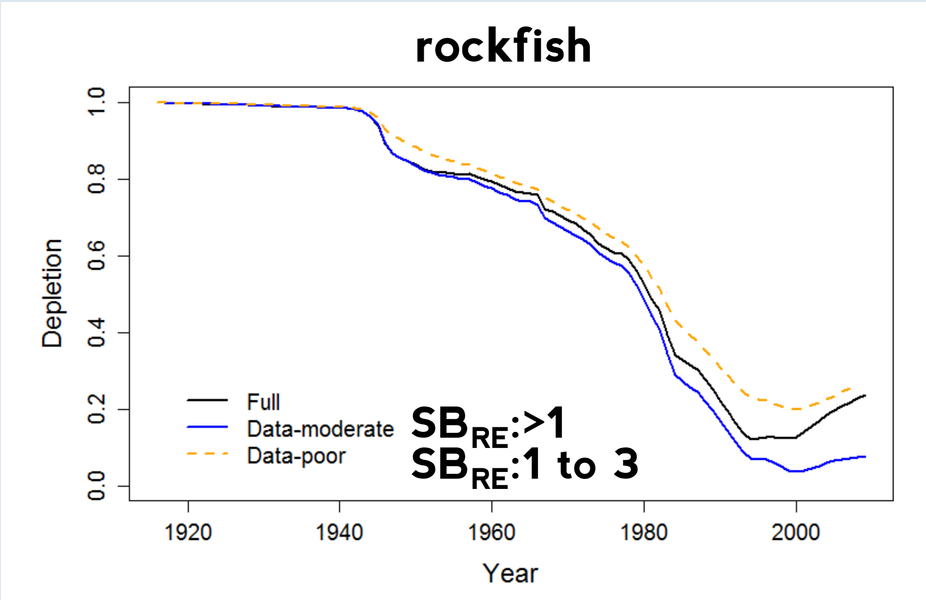
Wetzel *in prep.*

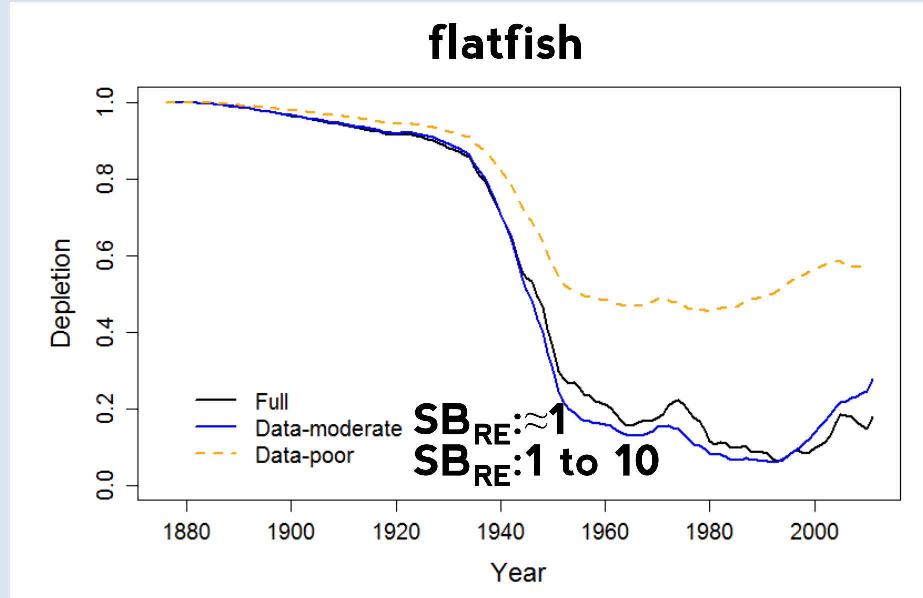


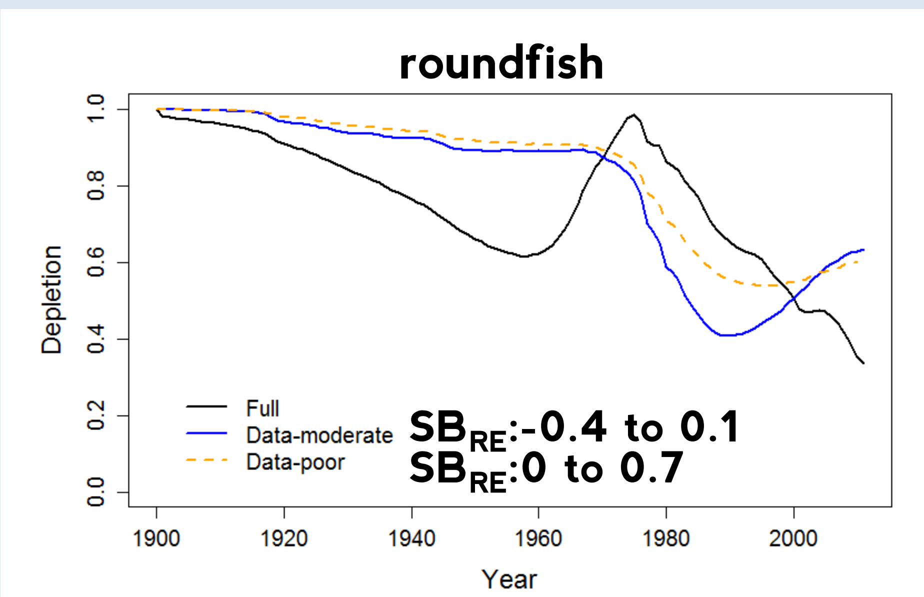


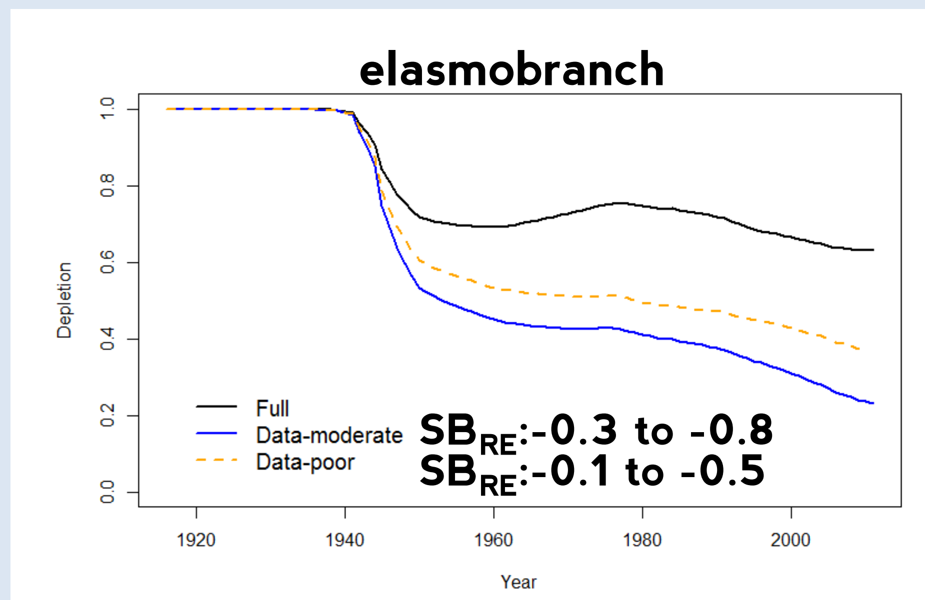
Cope et al. *in prep.*

Comparing assessment results: exSSS

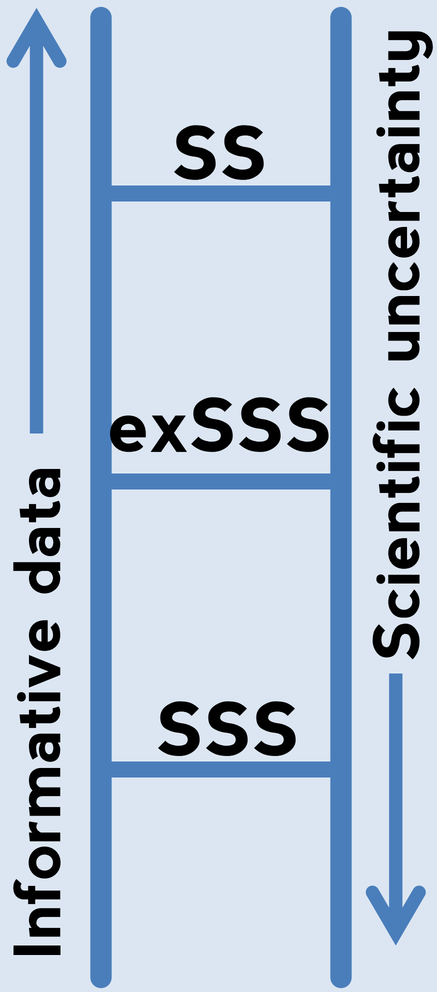




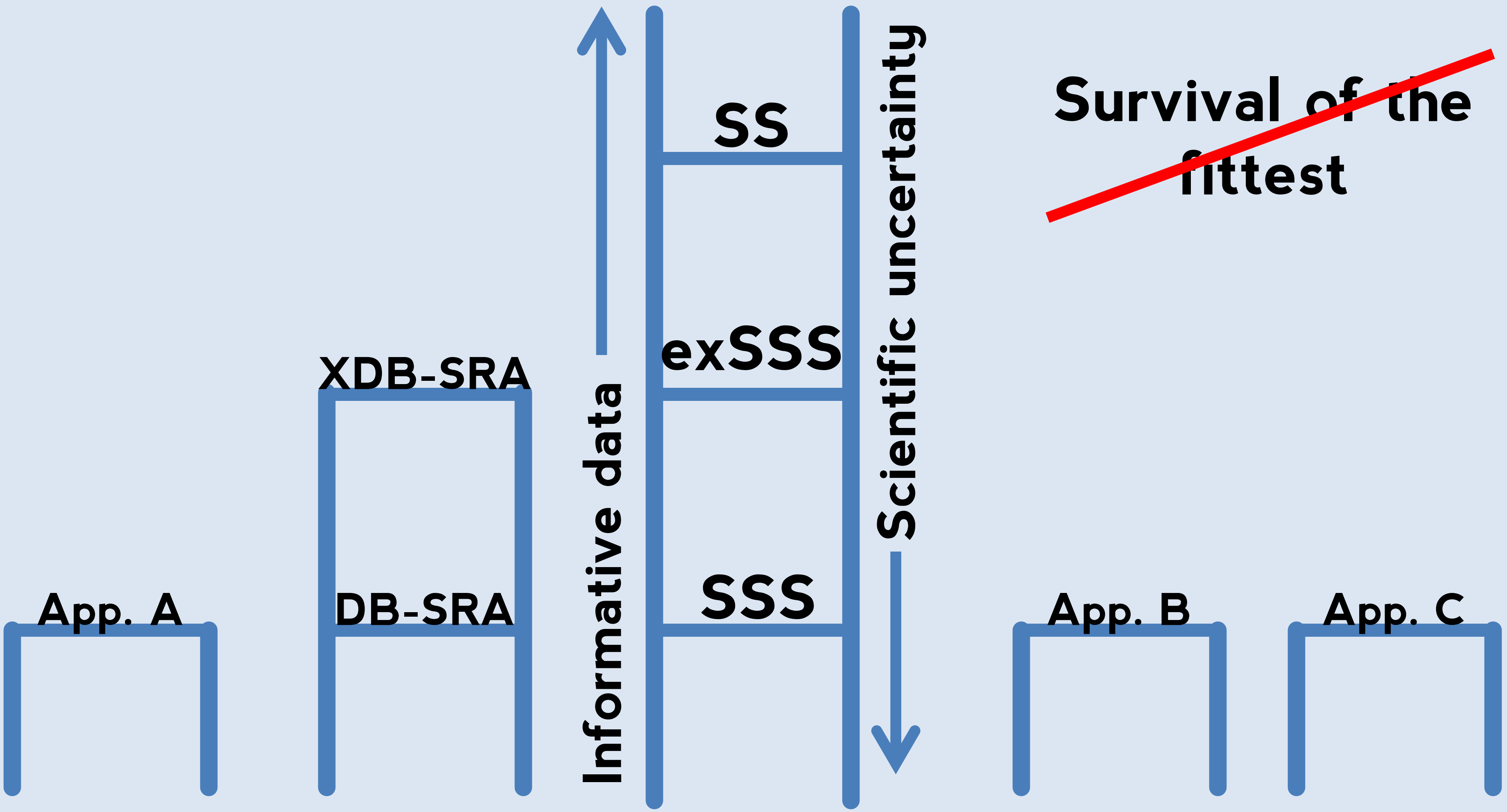




The diversity of approaches



The diversity of approaches



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Summary & recommendations

1. Advancement in data-limited approaches
    - Already being applied to management
    - Prioritize stocks for assessments
    - Adapt MSA for data-limited approaches

2. Retaining diversity of approaches
    - Different data requirements
    - Different parameterizations and linkages
    - Continued and controlled testing

3. General framework: build toward "rich" assessments

4. Devolving "rich" assessments
    - What data is telling you
    - Informative content of data-limited approaches

NOAA FISHERIES

“Nothing in Biology Makes Sense Except in the Light of Evolution”

– T. Dobzhansky

“Nothing in Biology Makes Sense Except in the Light of Evolution”

– T. Dobzhansky

“Nothing in Fisheries Science Makes Sense Except in the Light of…

“Nothing in Biology Makes Sense Except in the Light of Evolution”

– T. Dobzhansky

“Nothing in Fisheries Science Makes Sense Except in the Light of…
Life history invariants?”

“Nothing in Biology Makes Sense Except in the Light of Evolution”

– T. Dobzhansky

“Nothing in Fisheries Science Makes Sense Except in the Light of…
Life history invariants?”
Selectivity?”

“Nothing in Biology Makes Sense Except in the Light of Evolution”

– T. Dobzhansky

“Nothing in Fisheries Science Makes Sense Except in the Light of…
Life history invariants?”
Selectivity?”
Catchability?”

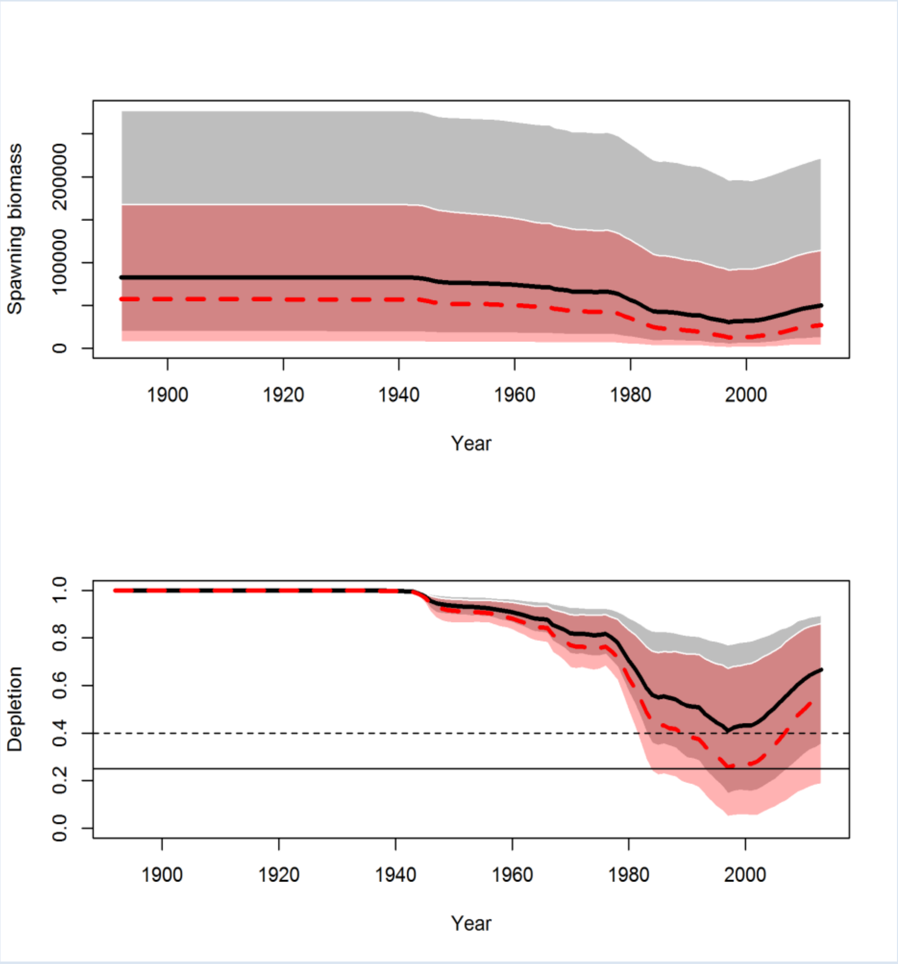
“Nothing in Biology Makes Sense Except in the Light of Evolution”

– T. Dobzhansky

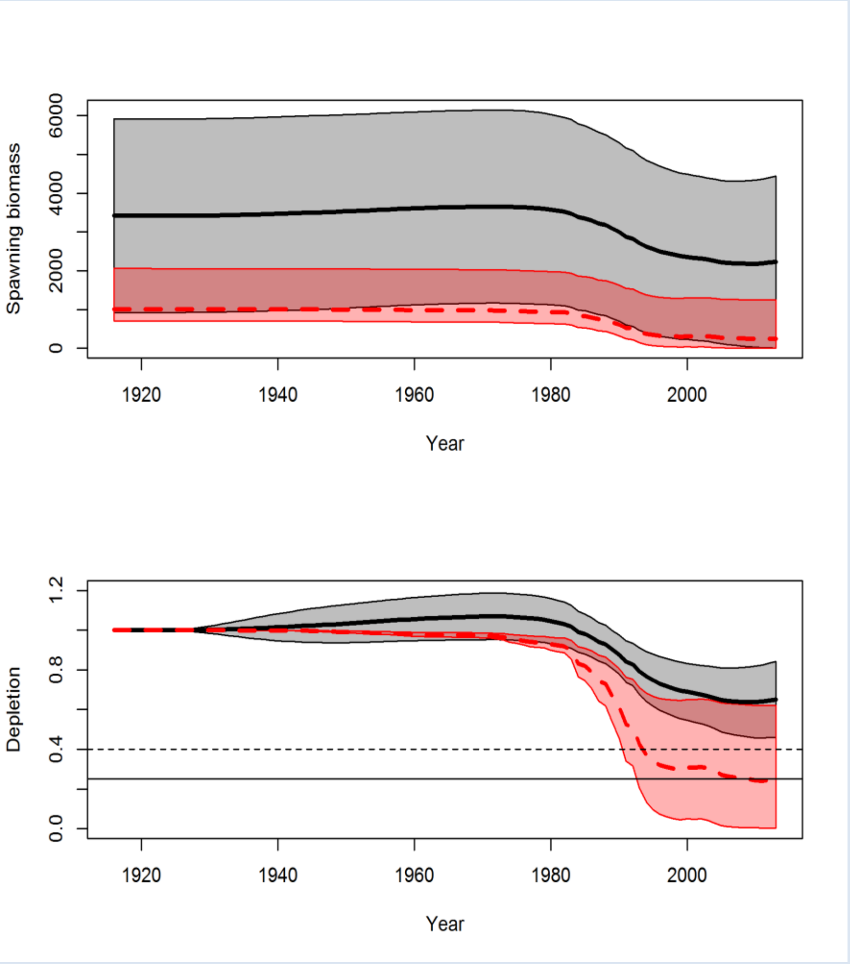
“Nothing in Fisheries Science Makes Sense Except in the Light of… *we are still looking*”

Scale and status

flatfish



rockfish



The Effect of Selectivity and Spatial Scale on DB-SRA

Brandon Owashi
David Sampson

Sea Grant
Oregon

Important DB-SRA Assumptions

- Selectivity curve matches the maturity curve
- Generally aggregates large portions of data together despite potentially distinct regions

Spatial Scale

1 Region
2 Fisheries

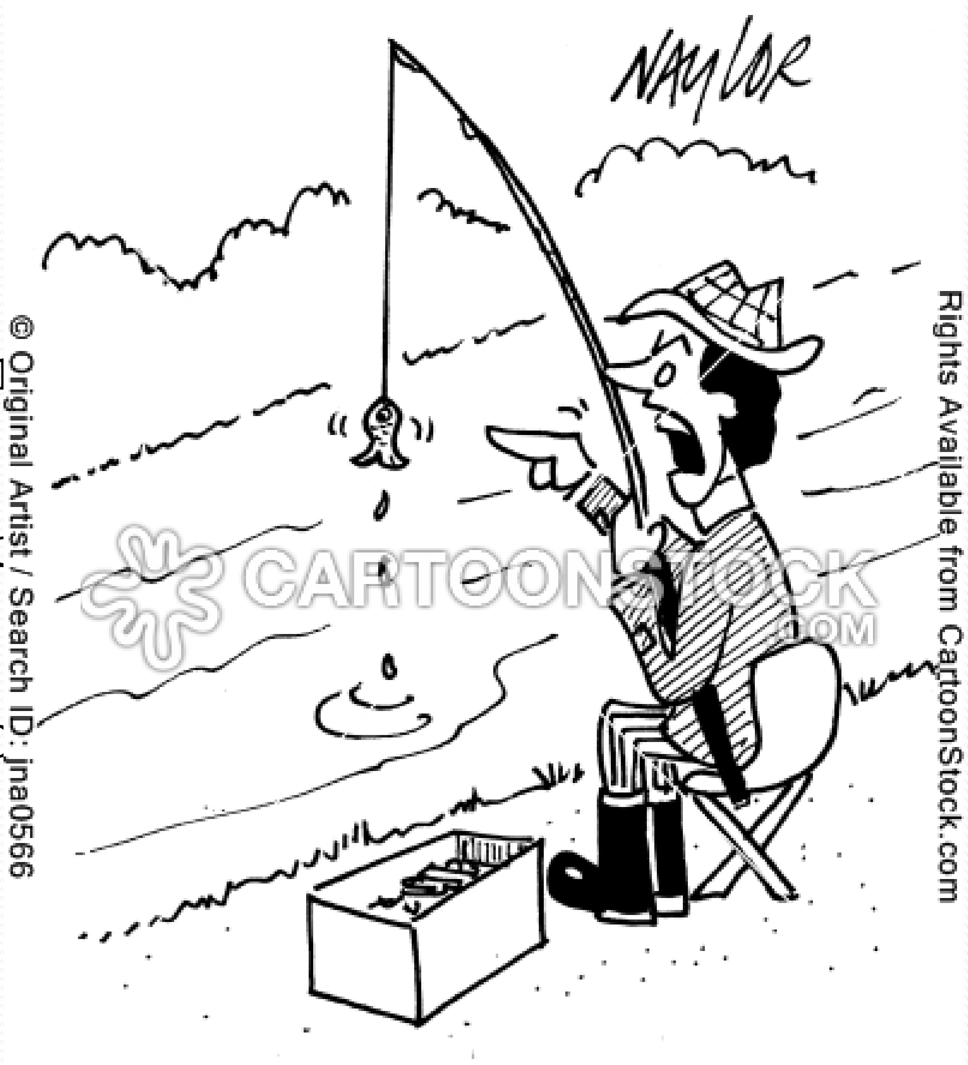
2 Regions
2 Fisheries

Justification

- Unlikely selectivity curve is always equal to maturity curve
  - Immature fish often caught in recreational fisheries
- Help determine the potential benefits (or consequences) from local or regional management

Justification

- Unlikely selectivity cu
curve
  - Immature fish often c
- Help determine the pc
regional management



"Not you again. Go and get your big brothers and sisters."

Justification

- Unlikely selectivity curve is always equal to maturity curve
  - Immature fish often caught in recreational fisheries
- Help determine the potential benefits (or consequences) from local or regional management

Objectives

- Determine how the performance of DB-SRA is affected when:
  - Selectivity assumptions are violated
  - There are two distinct regions that are treated as one

Methods

- Generate data – generic rockfish (no movement)
  - Two regions (A and B): only F history and selectivity differ
  - Total (data summed from region A and B)
  - Calculate “true OFL”
- Run data in DB-SRA
- Calculate relative error (RE) between estimated OFL and “true OFL”
- Compare RE (through paired T test) for:
  - Violations of selectivity assumptions
  - Sum of estimated OFL from region A & region B and total estimated OFL

Default vs. True Ratio Values

- Default values if the true values are not known

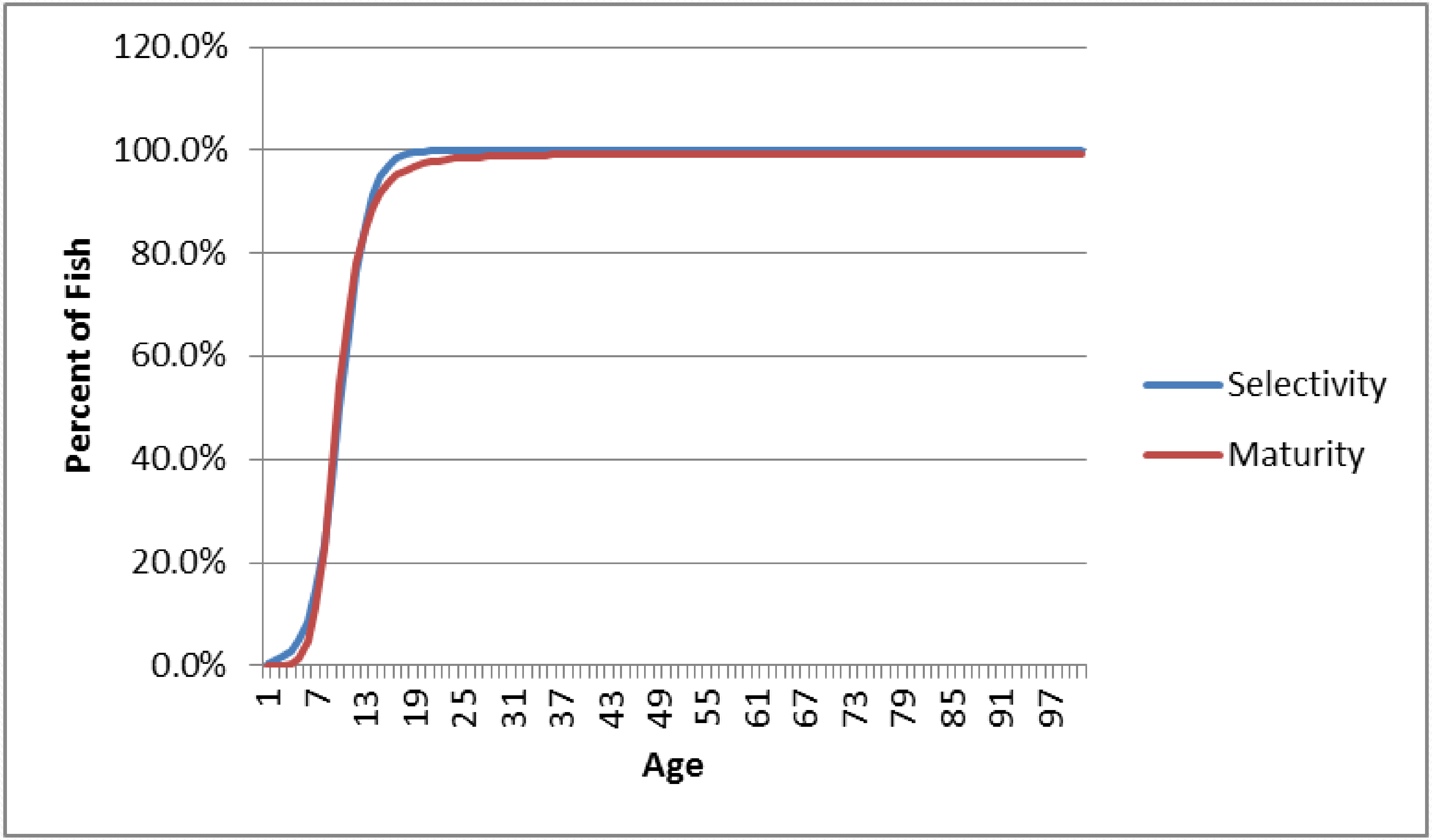
Default (Dick & MacCall 2011):

	F_{MSY}/M	B_{MSY}/K	Delta
Rockfish	0.8	0.4	0.6

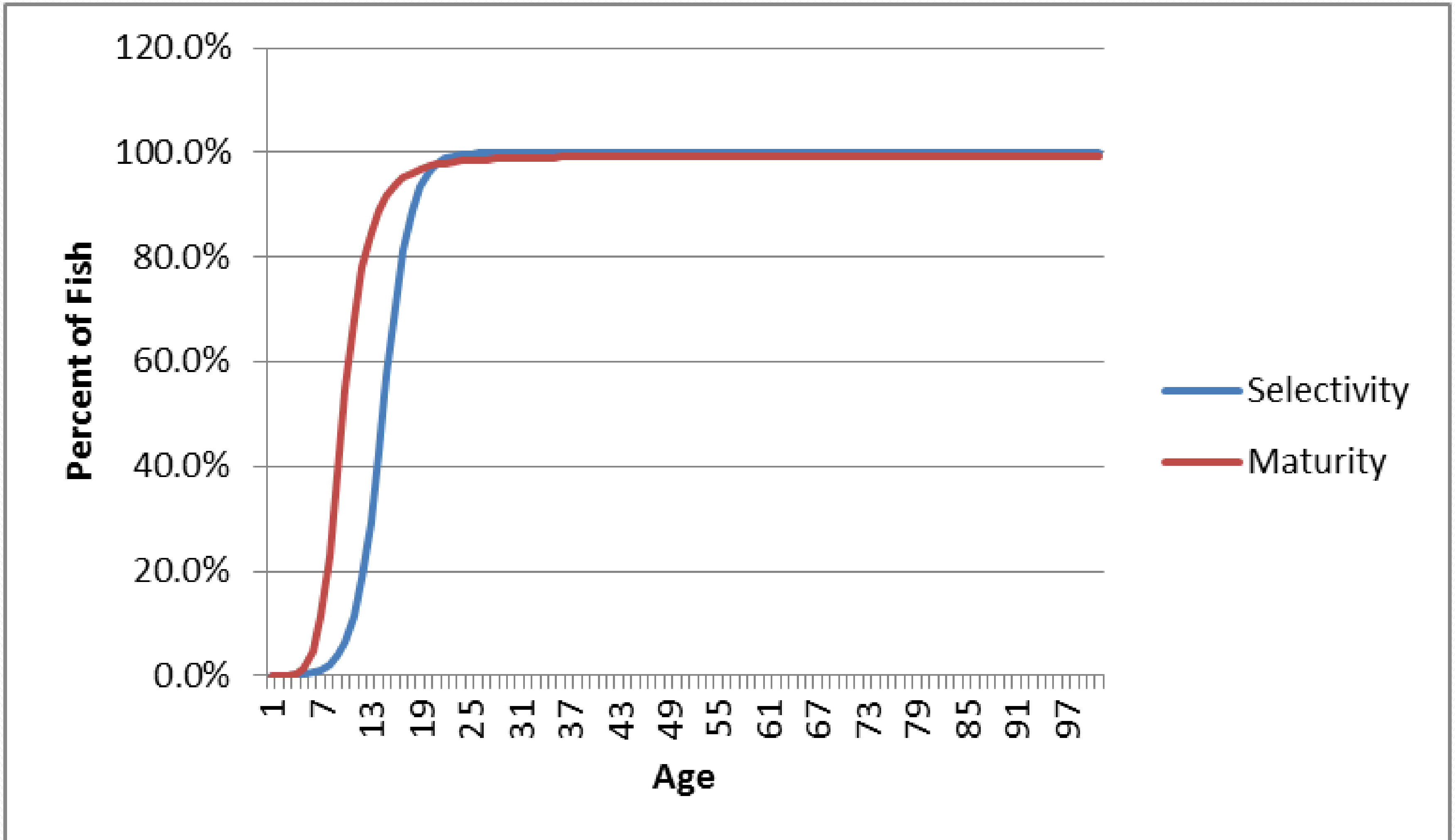
Experimental Design

- Position of selectivity curve compared to maturity curve
  - Ahead
  - Same
  - Behind
- F history
  - Constant
  - Increasing
  - Domed

Experimental Design



Experimental Design



Experimental Design

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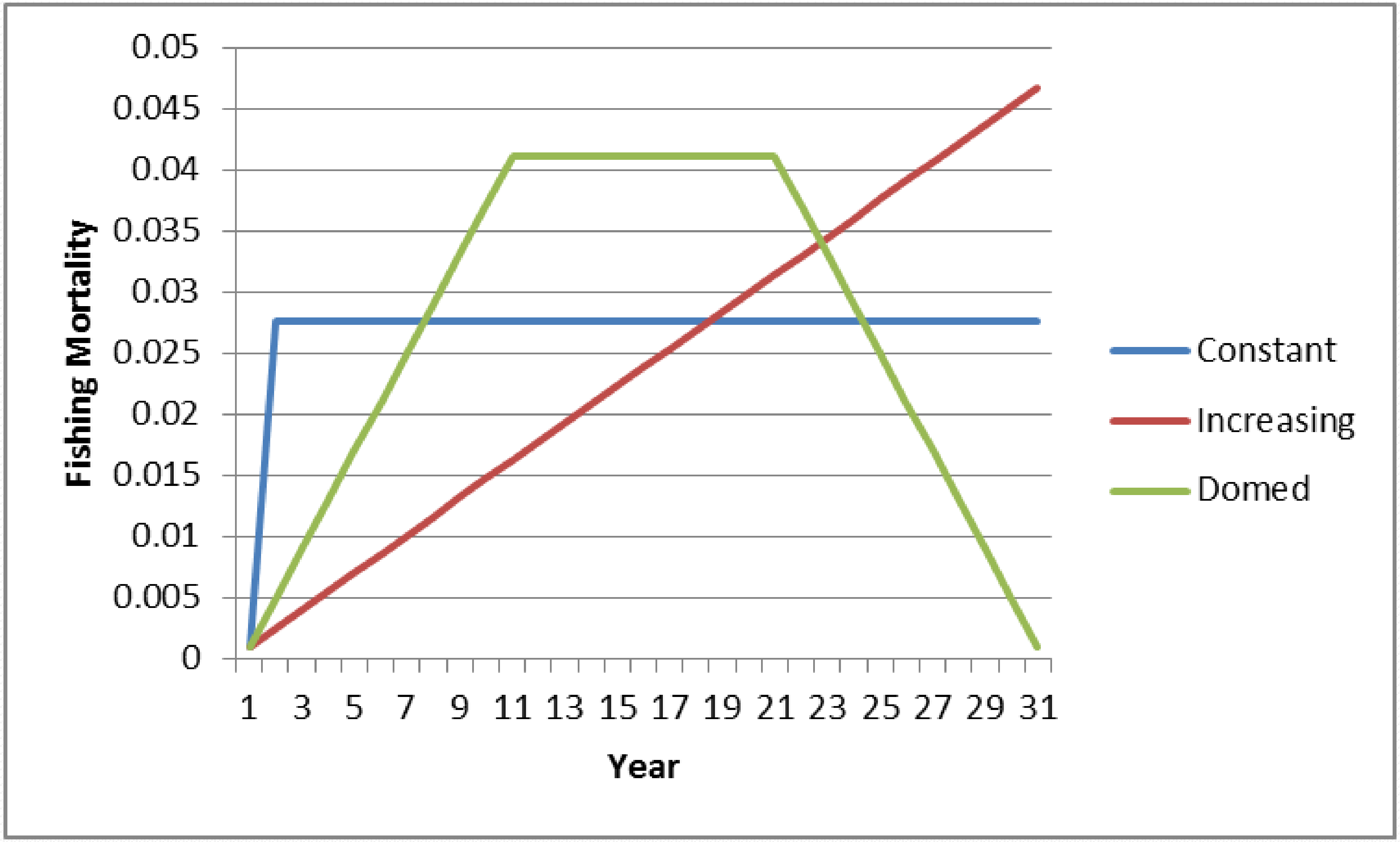
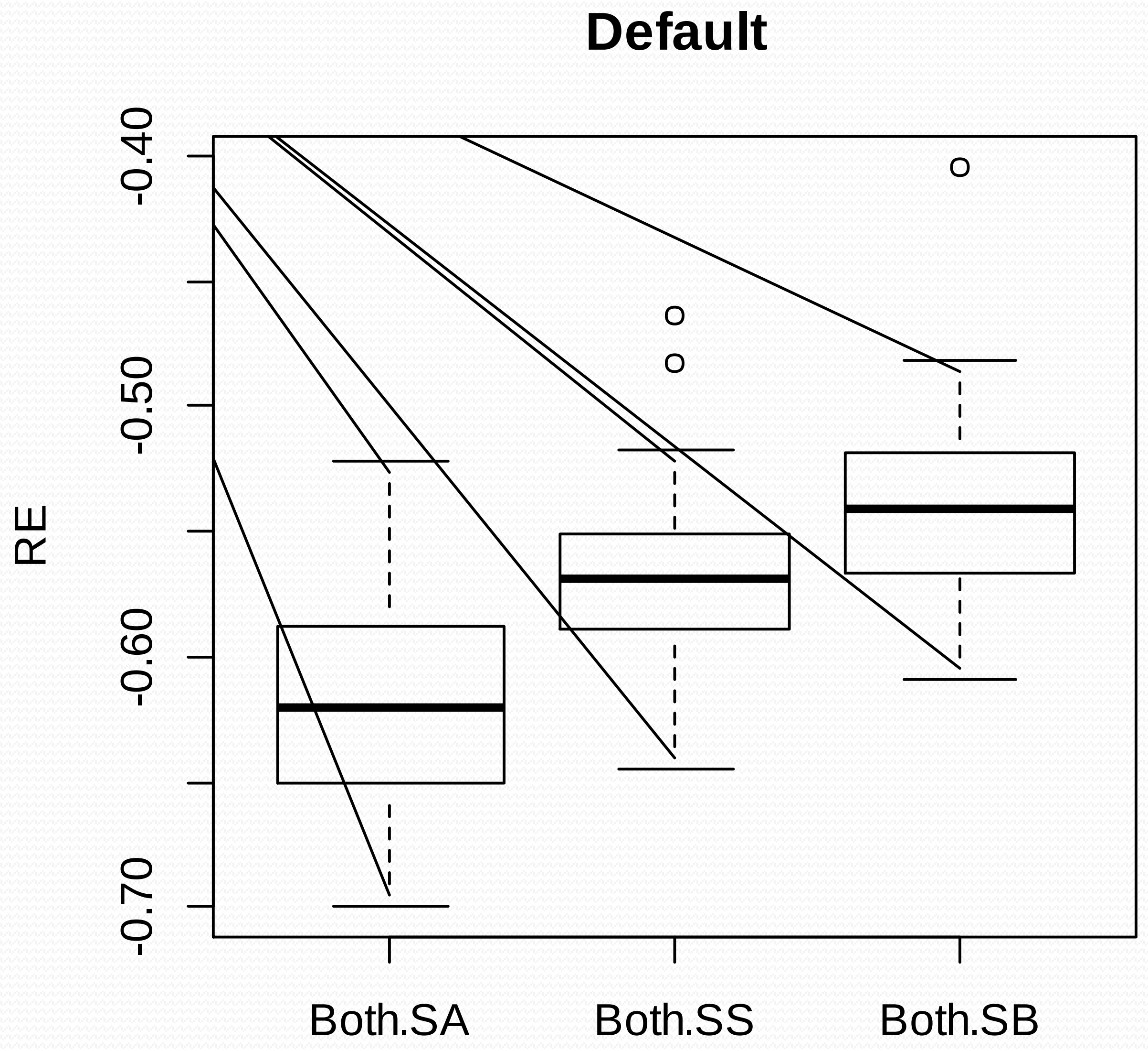
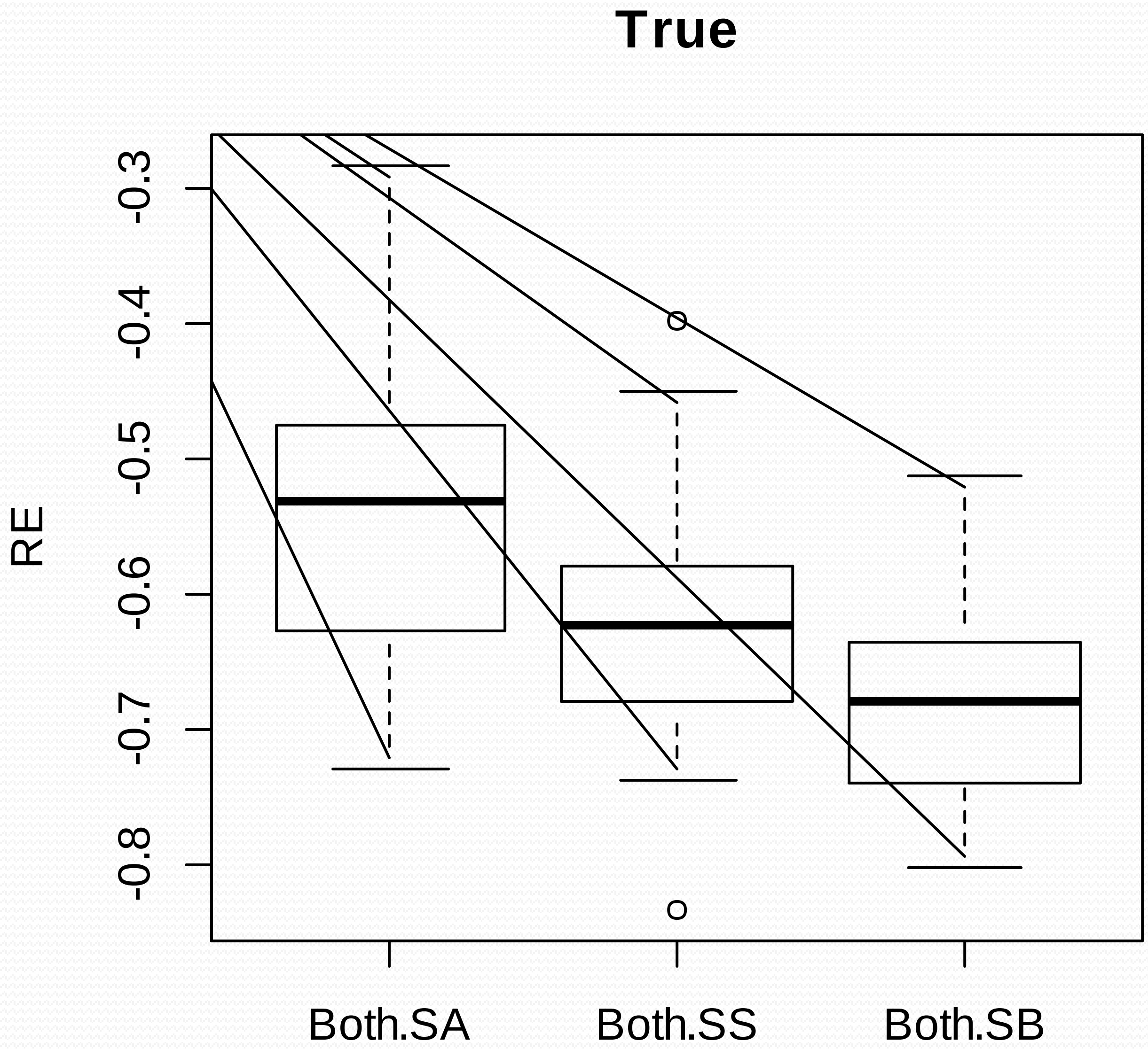
Experimental Design



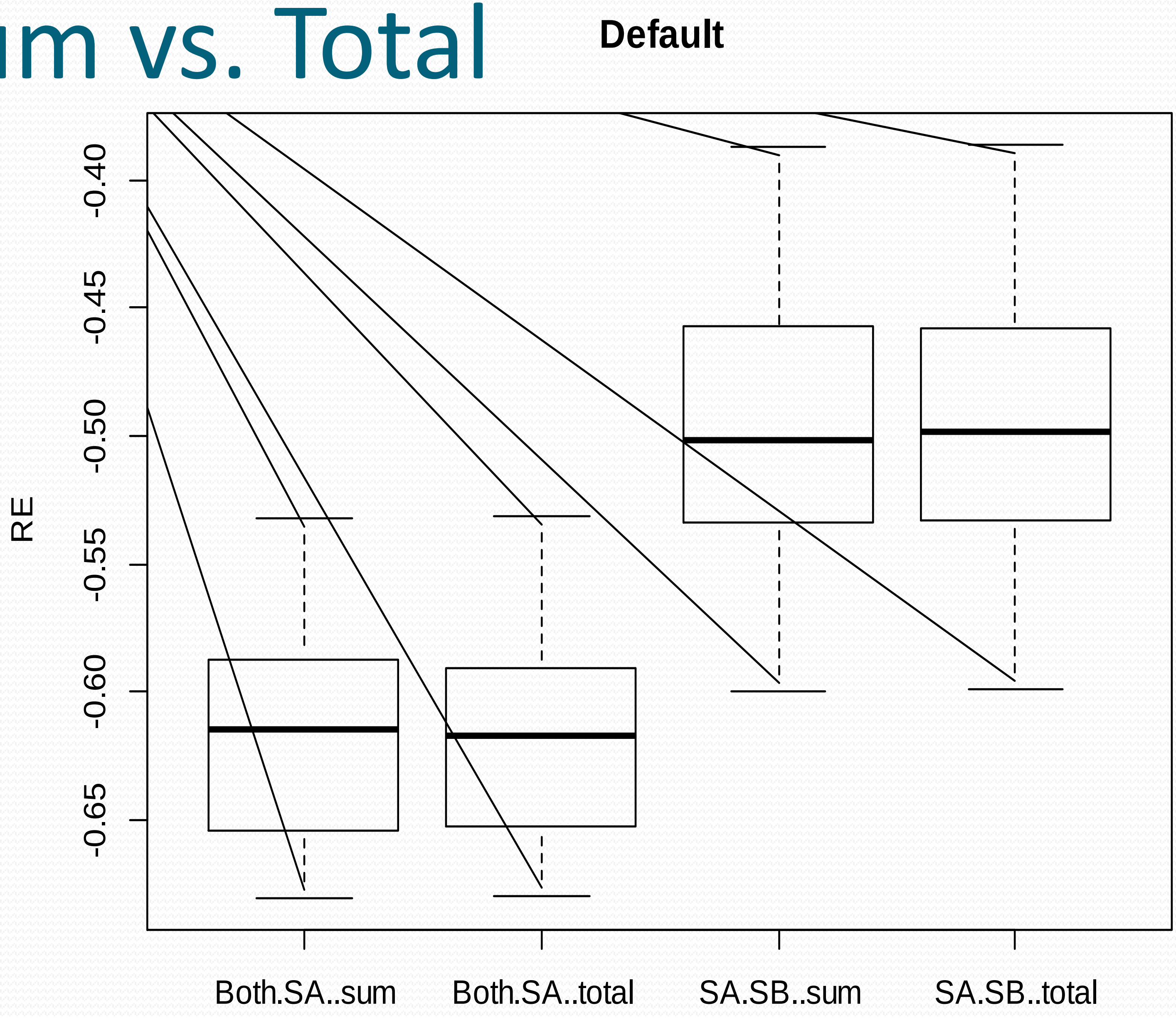
Selectivity Position



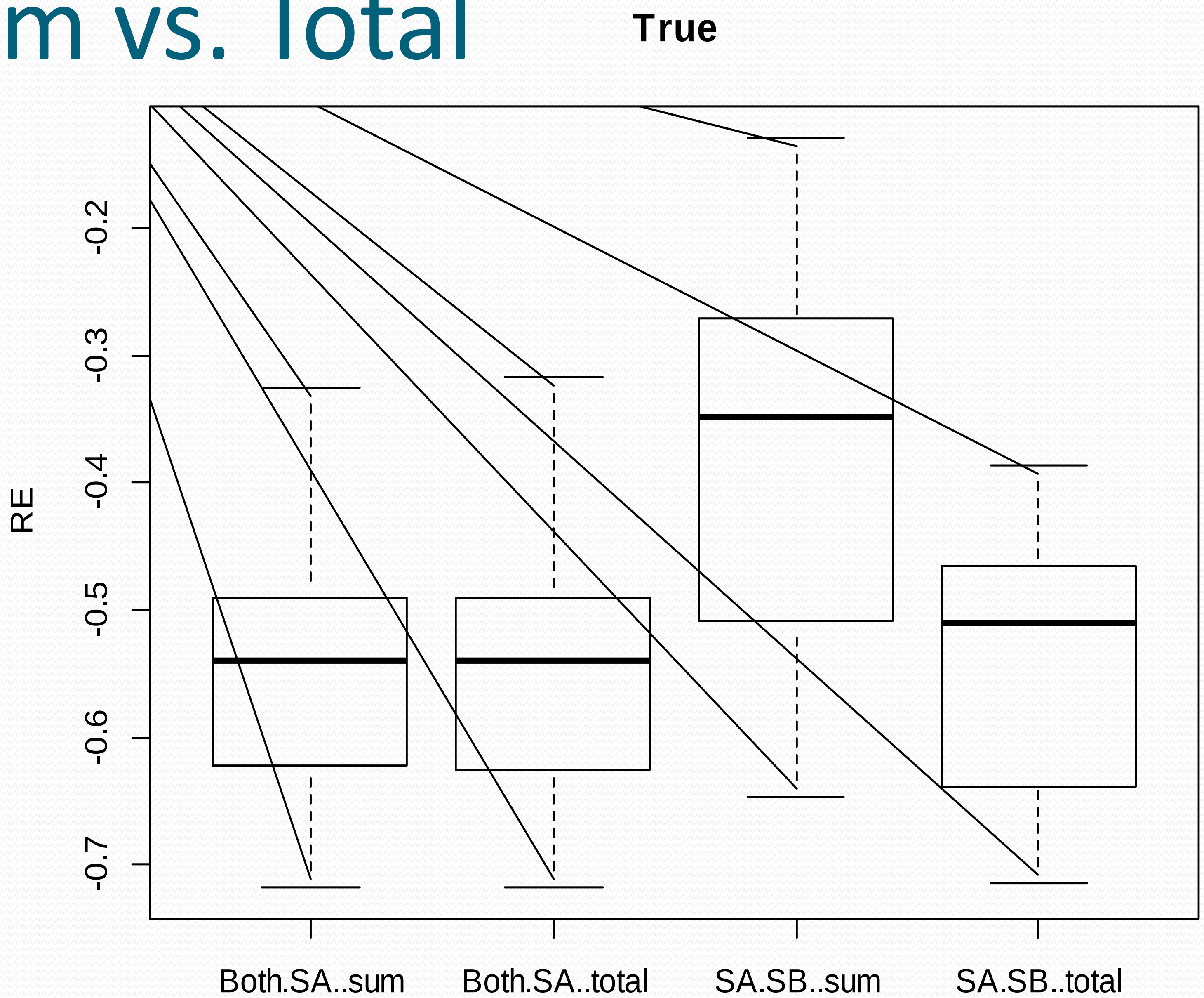
Selectivity Position



Sum vs. Total


Default
RE
-0.40
-0.45
-0.50
-0.55
-0.60
-0.65
Both.SA..sum
Both.SA..total
SA.SB..sum
SA.SB..total

Sum vs. Total


True
RE
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
Both.SA..sum
Both.SA..total
SA.SB..sum
SA.SB..total

Conclusions

- Differences when data has selectivity curve that is not equal to the maturity curve
  - Potentially develop mechanism that could allow for the $a_{50\%}$ selection to change

- Under certain circumstances, the sum of the estimated OFLs from two regions produced a higher estimated OFL than aggregating the data together before running DB-SRA

4.07 - Extending the principal of Beverton-Holt Life History Invariants for length based assessment of SPR

Adrian Hordyk & Jeremy Prince*

Centre for Fish, Fisheries and Aquatic Ecosystems Research

MURDOCH UNIVERSITY
PERTH, WESTERN AUSTRALIA

Meta-analysis

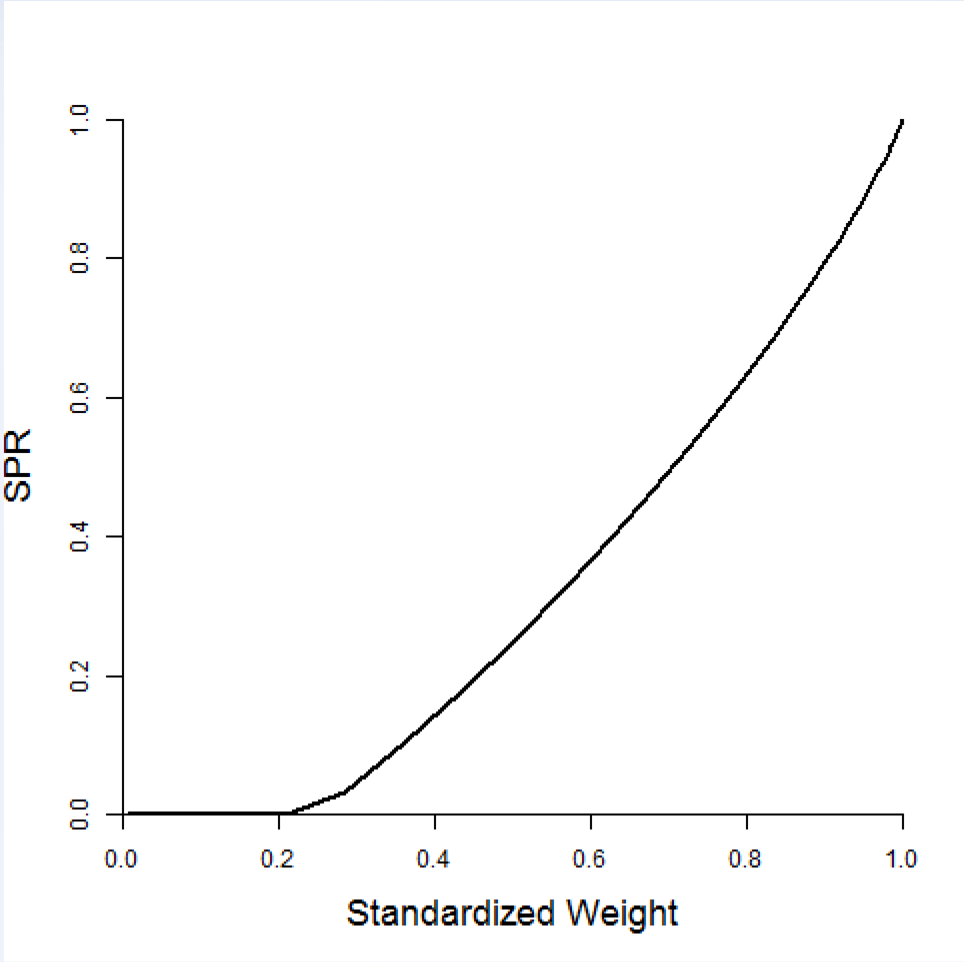
Collected high quality biological parameters for range of marine species (Gislason et al. 2010 – Criteria used).

For each species:

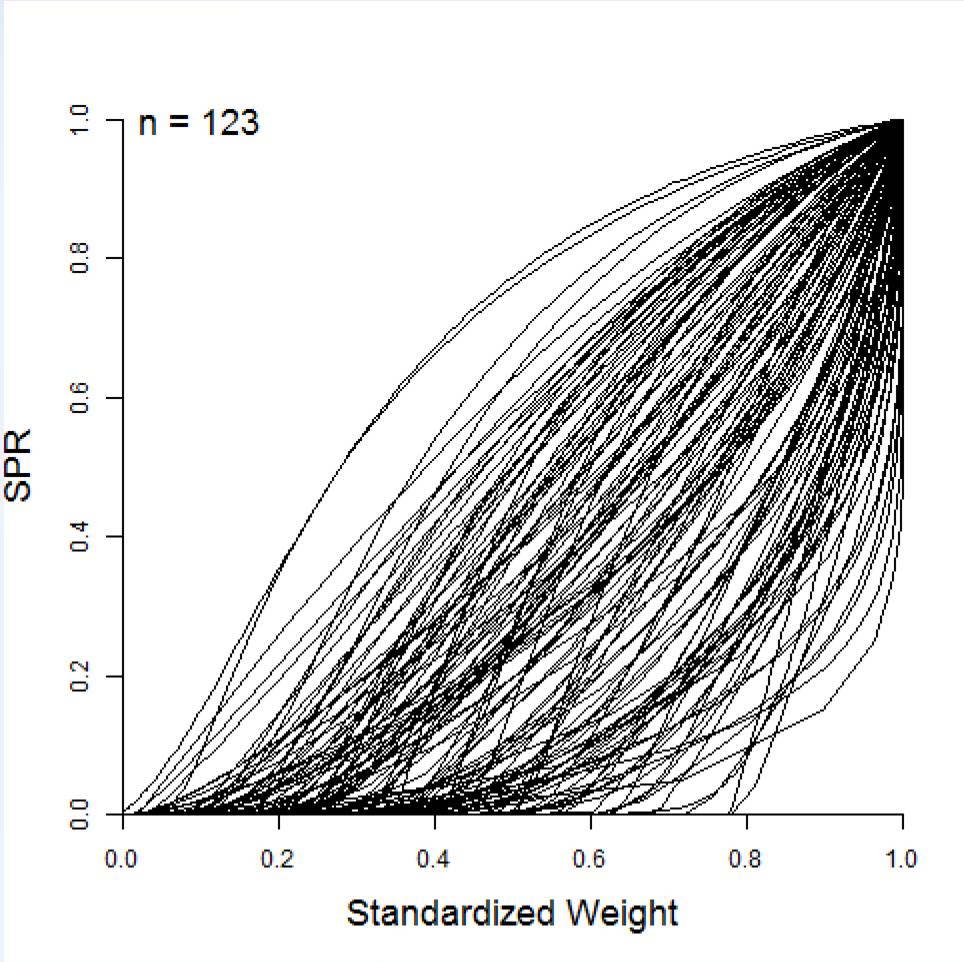
- **Growth model**
- **Natural mortality (*M*)**
- **Size-fecundity model or maturity ogive**
- **Length – weight model**

Examined patterns life history strategies

SPR at Size

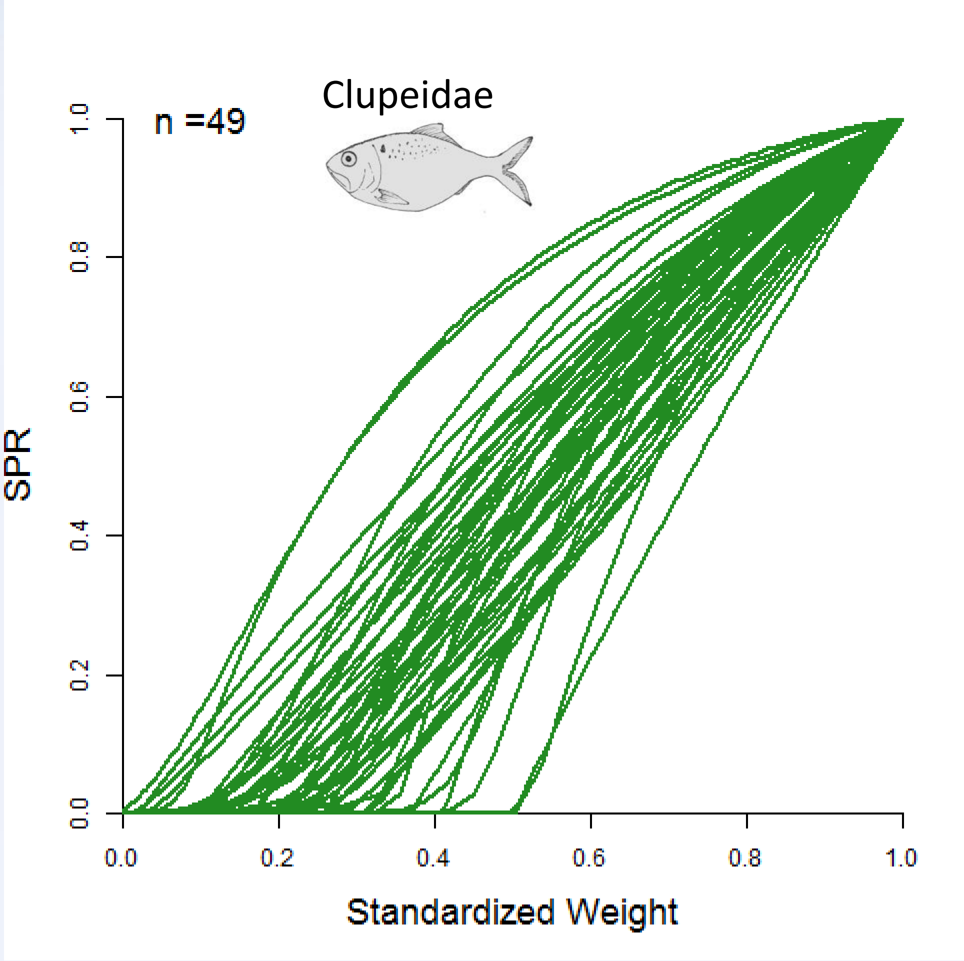


SPR at Size



SPR at Size: r- vs. K- strategists

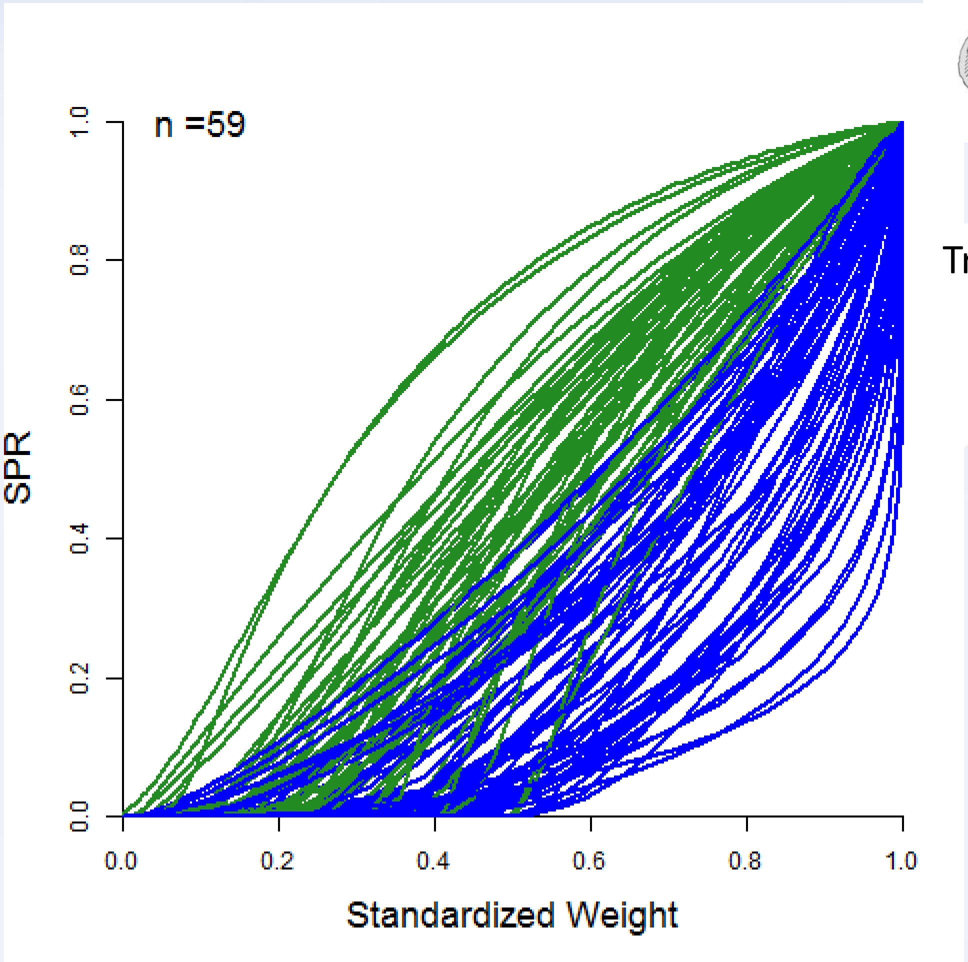
Type I $\frac{M}{k} > 1$



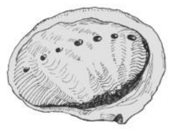
SPR at Size: r- vs. K- strategists

Type I $\frac{M}{k} > 1$

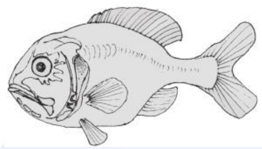
Type II $\frac{M}{k} < 1$



Haliotidae



Trachichthyidae



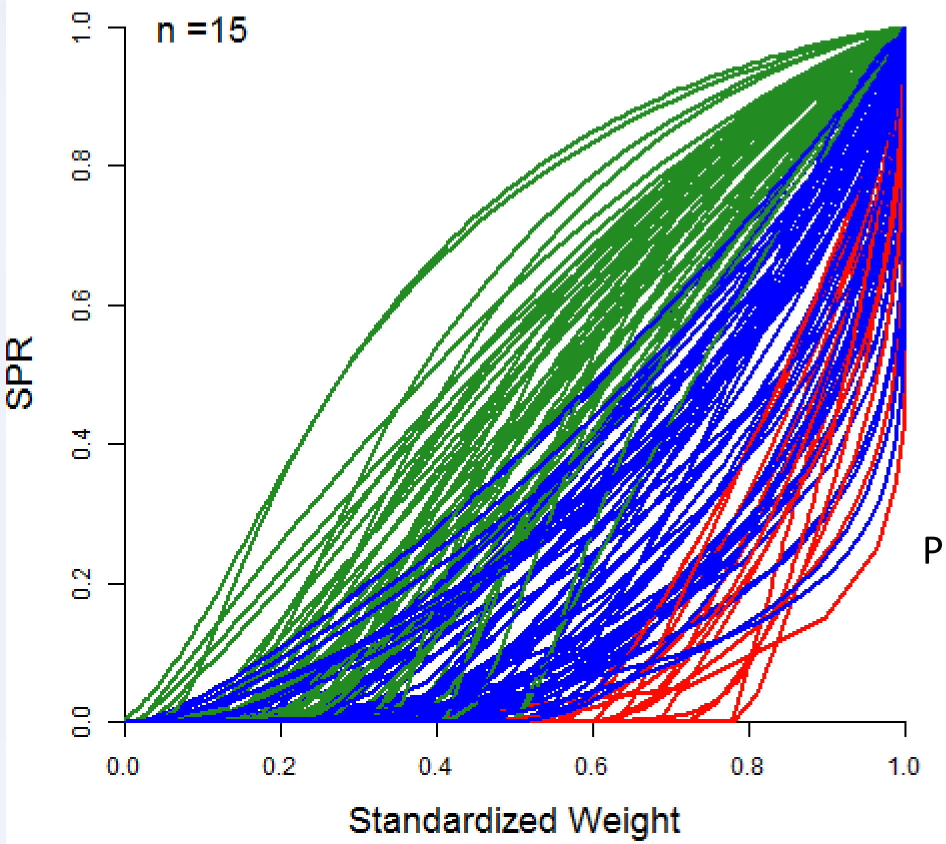
SPR at Size: r- vs. K- strategists

Type I $\frac{M}{k} > 1$

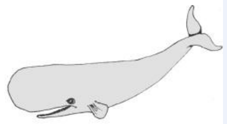
Type II $\frac{M}{k} < 1$

Type III $\frac{M}{k} < 1$

& $\frac{L_m}{L_\infty} > 0.85$



Physeteridae



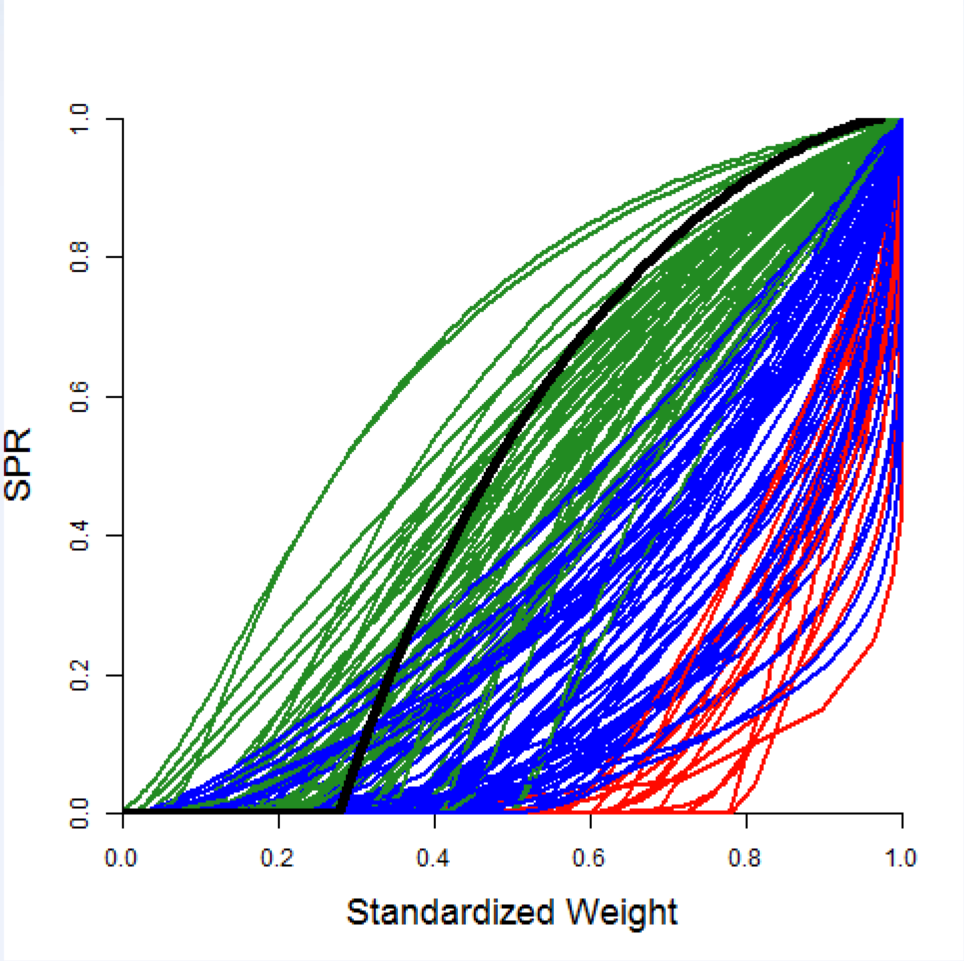
Beverton-Holt Life History Invariants

$M/k = 1.5$

$L_m/L_\infty = 0.66$

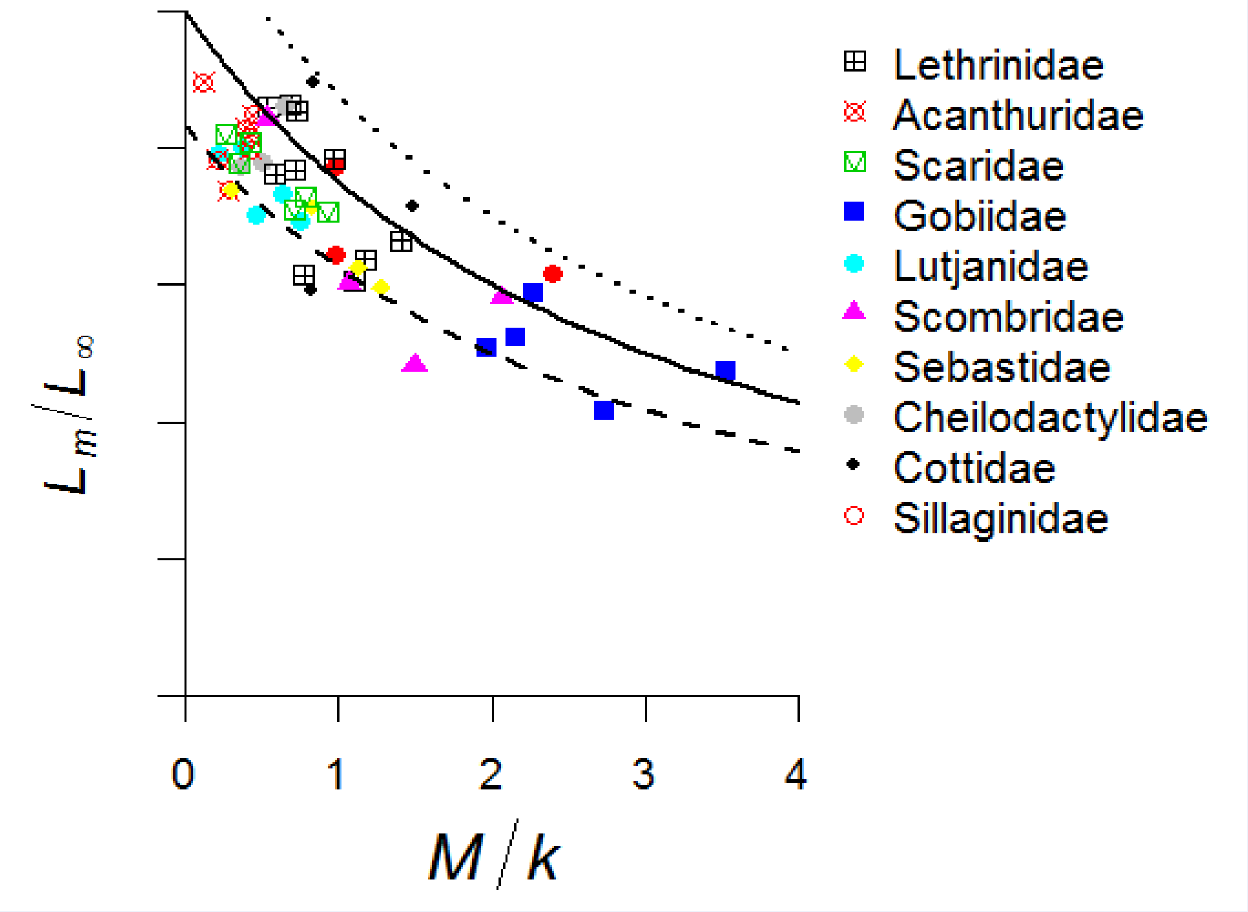
$M \times Age_m = 1.65$

Fec. ~ Adult Wt.

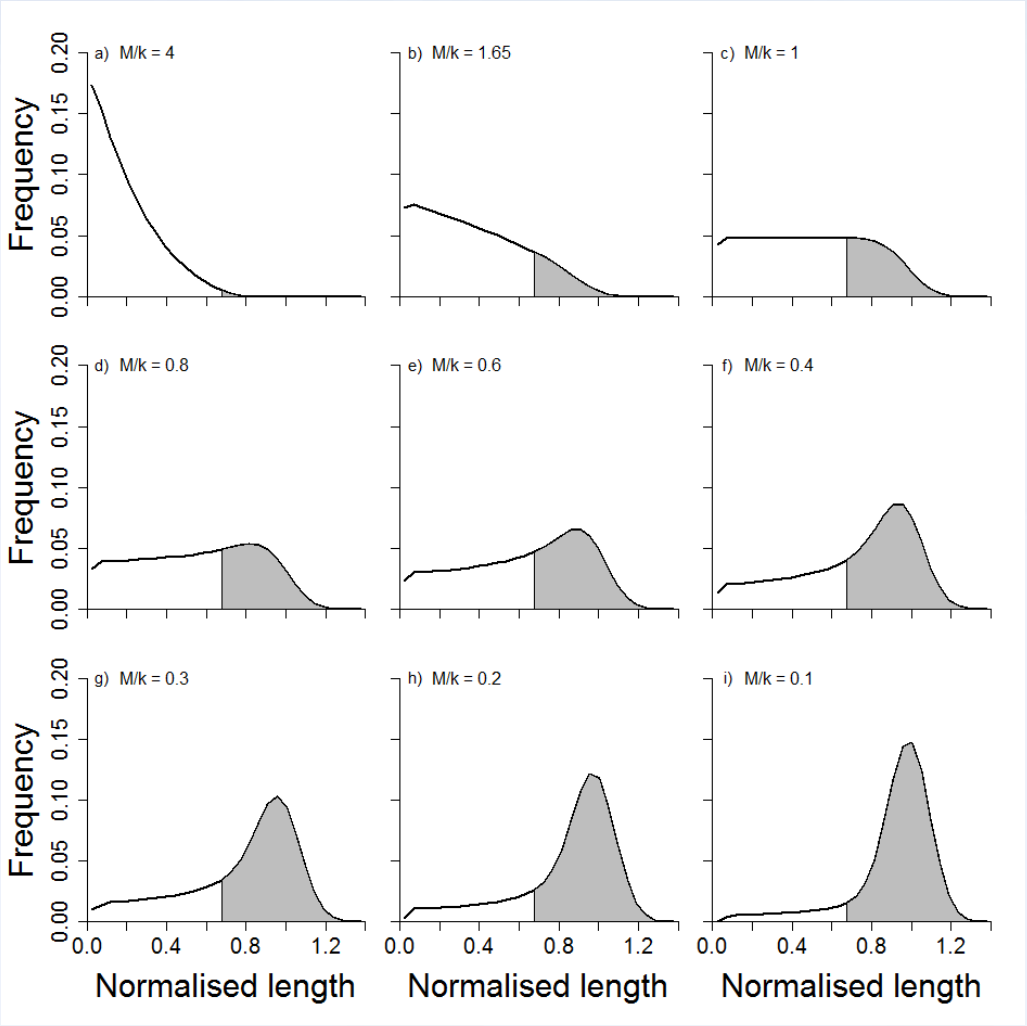


Meta-analysis & Beverton (1992)

$$L_m/L_\infty = 3/(3 + M/k).$$

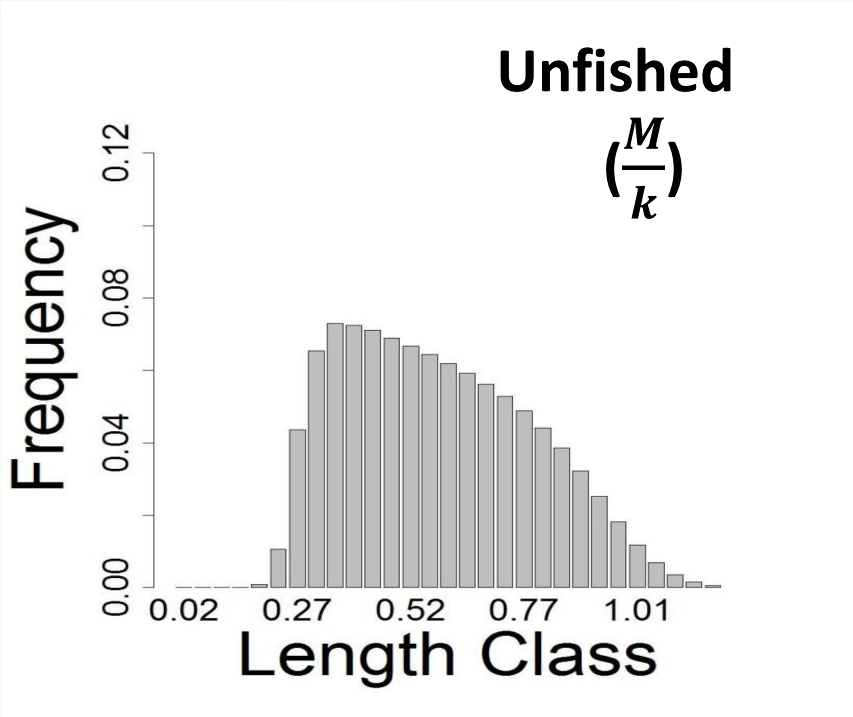


Unfished Length Composition



Length Based SPR Estimation Method

: expected unfished length distribution



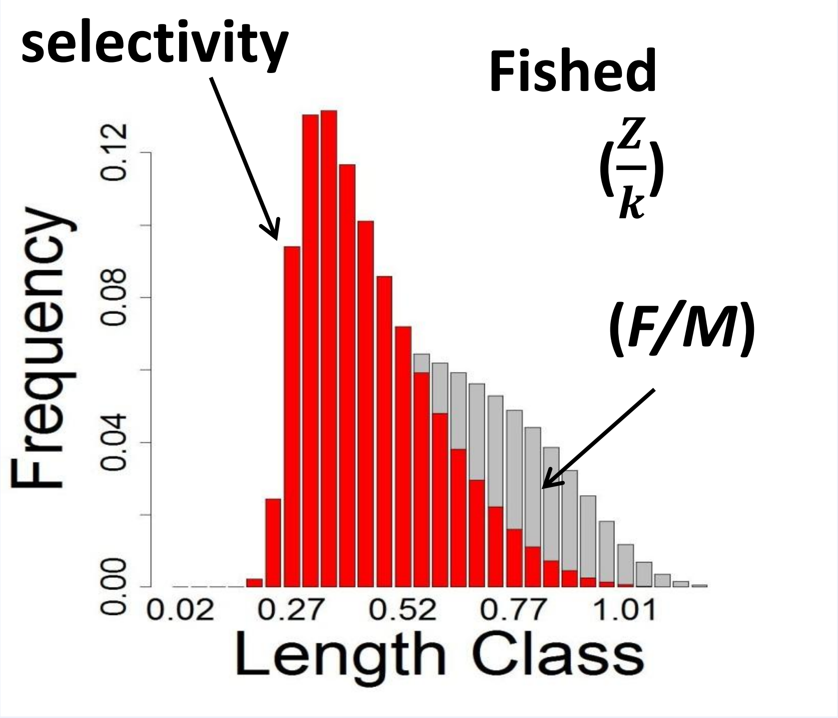
Standardised to L_∞

Length Based SPR Estimation Method

: expected unfished length distribution

: length frequency of catch ($Z = F + M$)

SPR & F/M:
Calculated from M/k & L_m/L_∞



Standardised to L_∞

Important Assumptions

Length frequency of catch representative of exploited stock

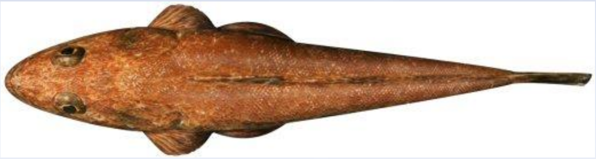
Asymptotic selectivity

Same growth curve or female length data

Knowledge of maturity at size

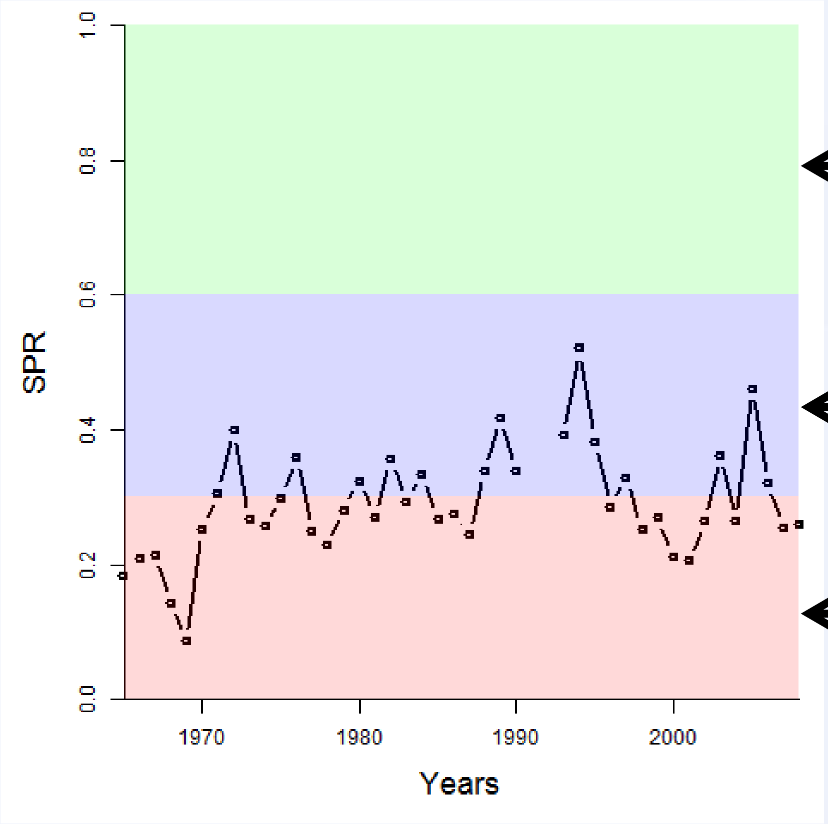
Equilibrium method

Calibration against Stock Assessments



Tiger Flathead

Neoplatycephalus richardsoni



← **High**

← **Ok**

← **Low**

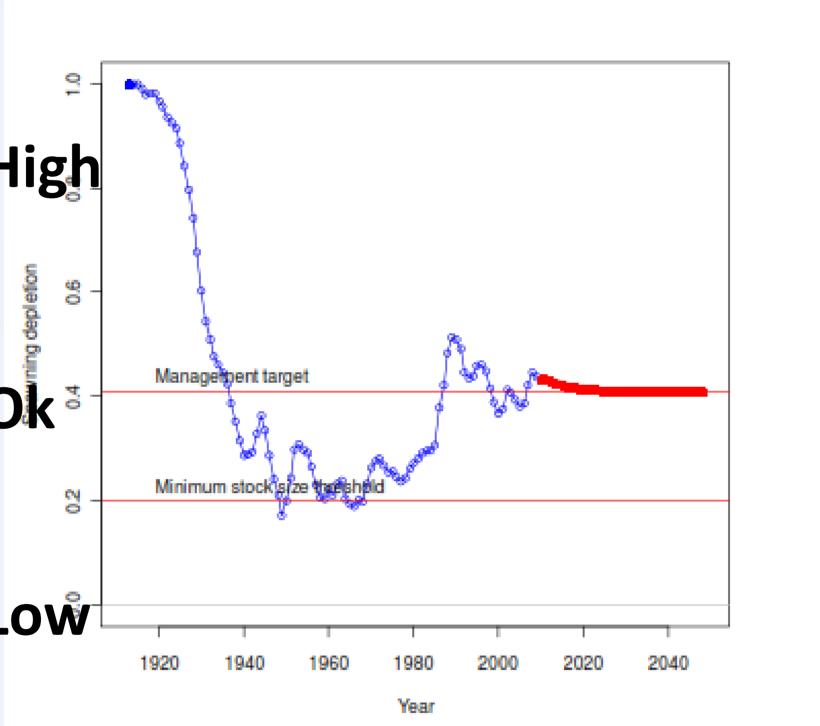
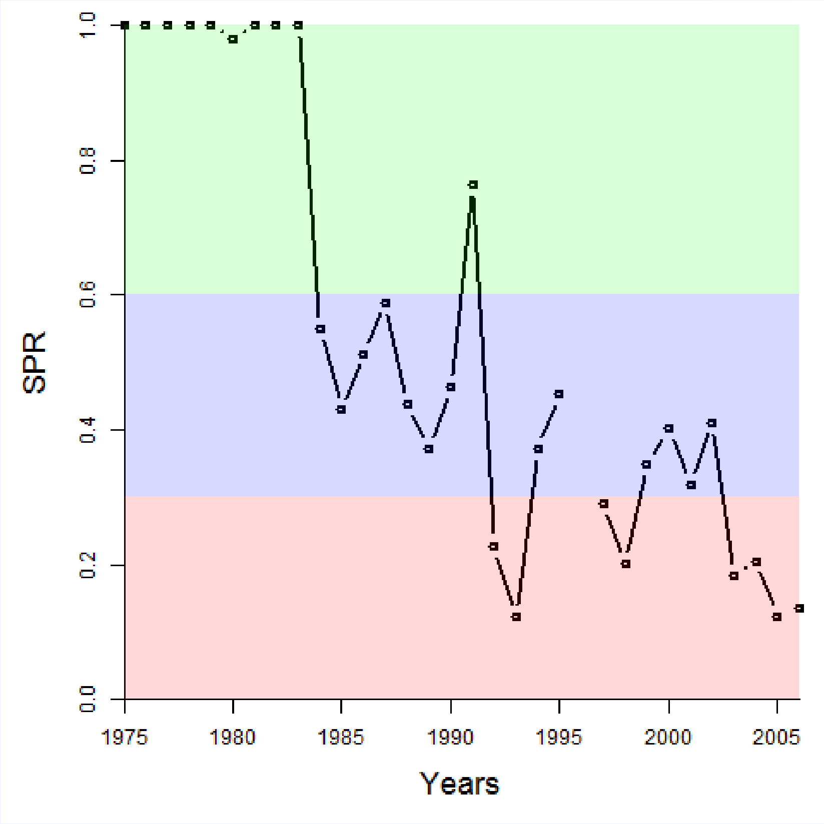


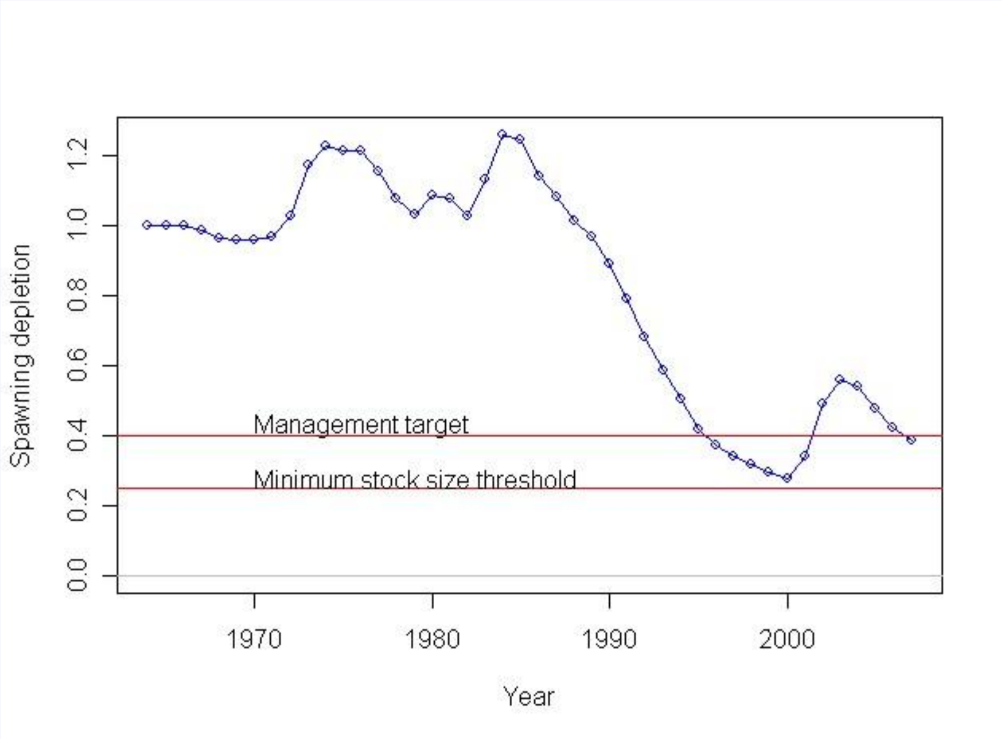
Figure 16. Spawning biomass depletion level per year for the base case.

Calibration against Stock Assessments

Pacific Hake

Merluccius productus



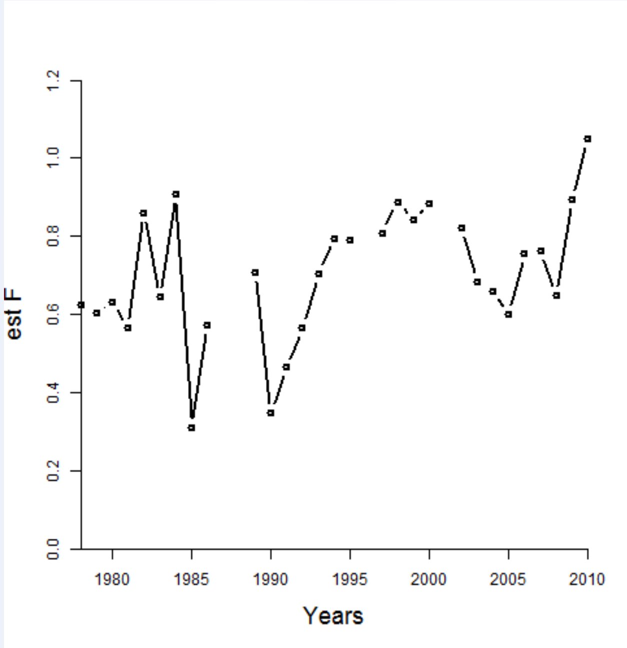


Calibration against Stock Assessments

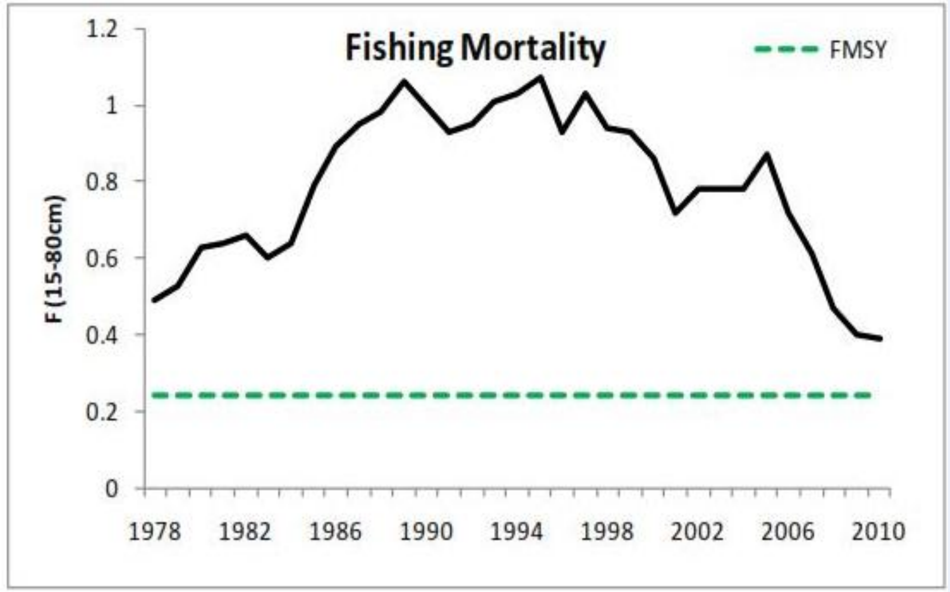
Northern Hake – ICES dataset

Merluccius merluccius

LB-SPR



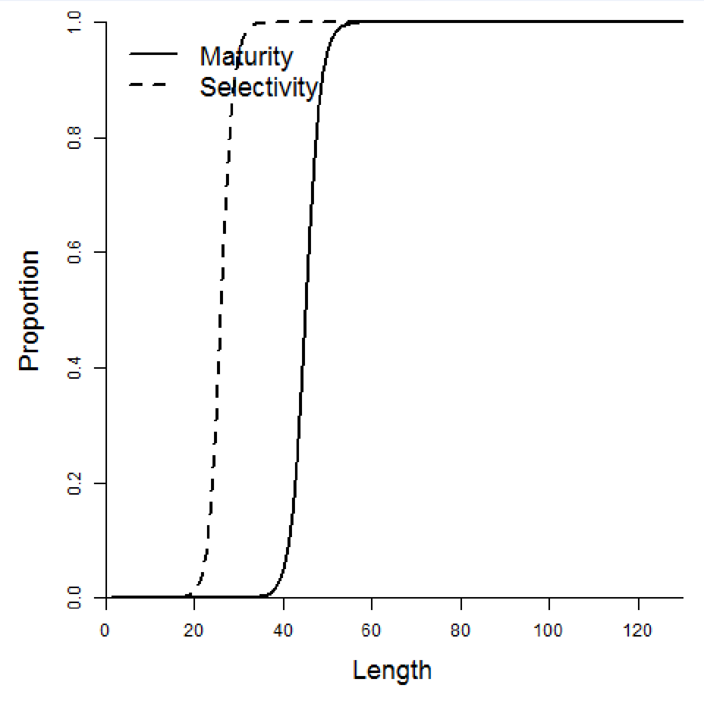
Assessment

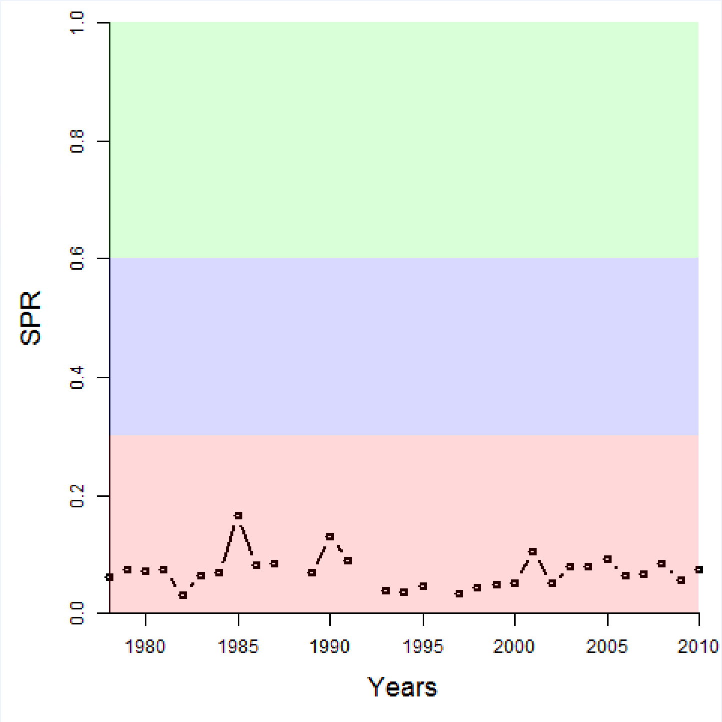


Calibration against Stock Assessments

Merluccius merluccius

Northern Hake – ICES dataset





Conclusion

Meta-analysis *M/k* ratio defines life-history strategy & Size composition e.g. tuna are just scaled up anchovy. Conceptual framework for borrowing information from data-rich species.

BH-LHI Only covers a small subset of the species in the meta-analysis.
Productivity of K-strategists parameterised by BH-LHI have been over-estimated.

Application Cost-effective estimation of SPR & *F/M* from length-data, L_m & meta-analysis for Data-poor and small scale fisheries.

Acknowledgements

Thank you

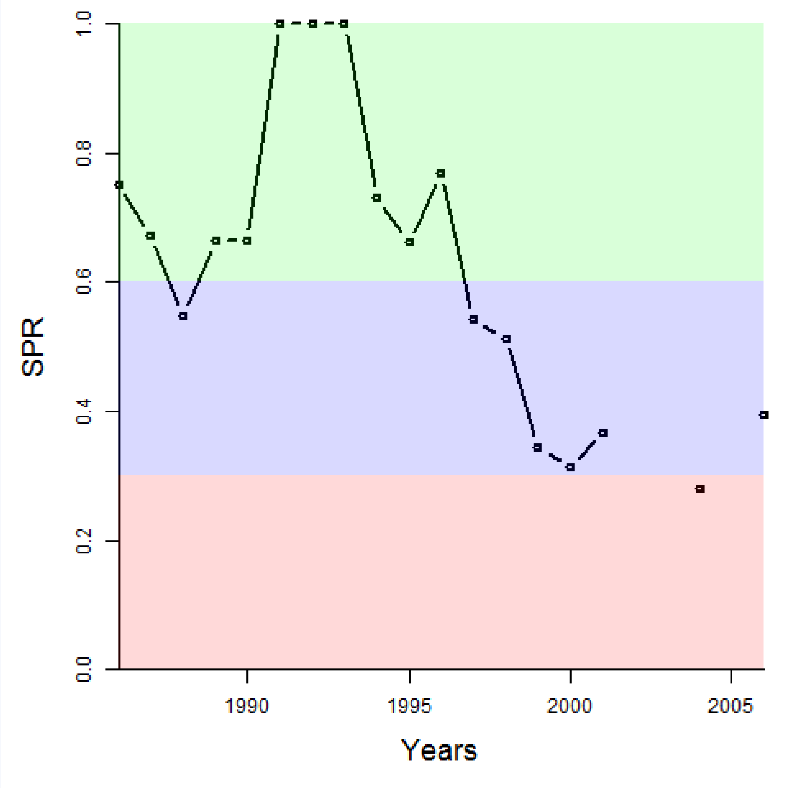
Funding
David and Lucile Packard Foundation
Marine Stewardship Council
The Nature Conservancy
Murdoch University

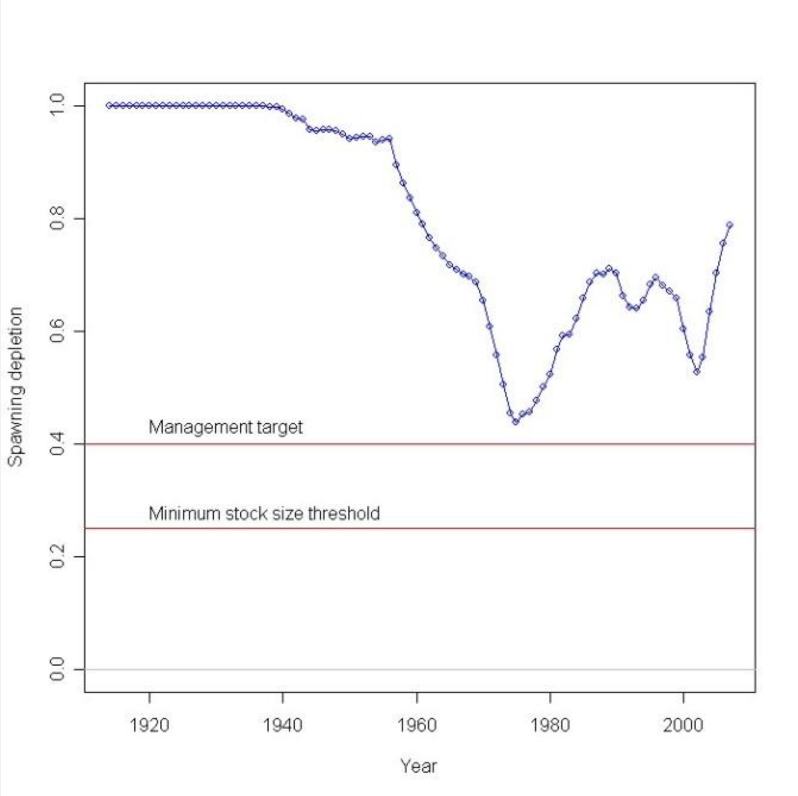
Data & Assistance
Kotaro Ono, Sarah Valencia, Keith Sainsbury, Neil Loneragan

Calibration against Stock Assessments

Atheresthes stomias

Arrowtooth Flounder





Estimation Model

Model input parameters:

M/k

L_∞

$CV_{L\infty}$

L_{50} & L_{95}

$\Big\}$ Female parameters

Estimated parameters:

F/M

S_{L50} & S_{L95}

SPR

$$\boldsymbol{MLE\left(\widehat{S_{L50}}, \widehat{S_{L95}}, \widehat{F/M}\right) = \underset{(S_{L50}, S_{L95}, F/M)}{arg\,min} \left[\sum_{L=L_{min}}^{L=L_{max}} O_L \log \frac{P_{PL}}{O_{PL}}\right]}$$

Exploring data-limited methods to assess global fisheries: conceptual framework, applications and limitations

World Conference on Stock Assessment Methods
July 19, 2013

Kristin M. Kleisner (presenter), Trevor Branch, Andrew Cooper, Mark Dickey-Collas, Nicolas L. Gutiérrez, Ray Hilborn, Catherine Longo, Carolina V. Minte-Vera, Cóilín Minto, Iago Mosqueira, Giacomo Chato Osio, Dan Ovando, Andrew A. Rosenberg, Elizabeth R. Selig, James Thorson, Yimin Ye*

*In alphabetical order

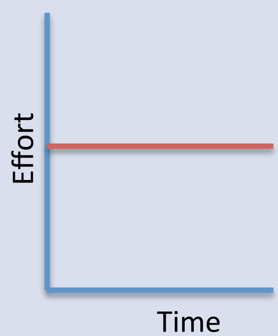
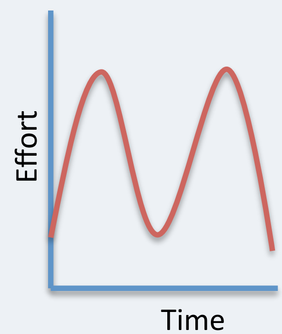
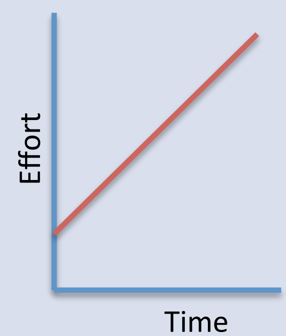
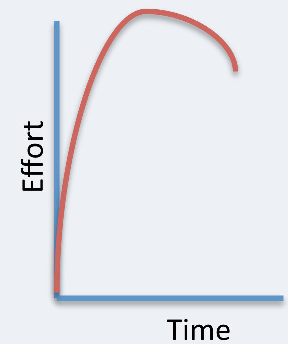
Goals and motivation

- Ability to recover stock status for unassessed stocks
- Test the performance of 4 simple methods
- Range of deterministic and stochastic scenarios
- Critically evaluate performance relative to a limited set of performance measures
- Distill high-dimensional information

Method comparison

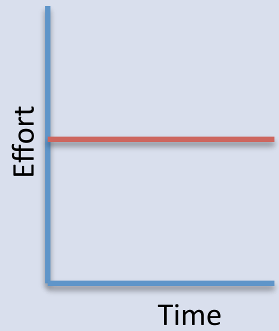
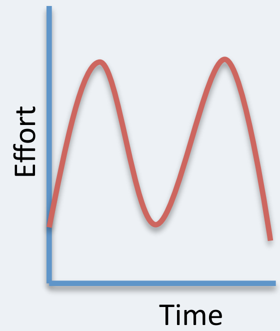
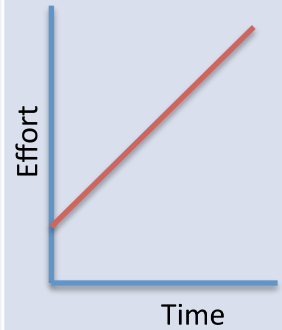
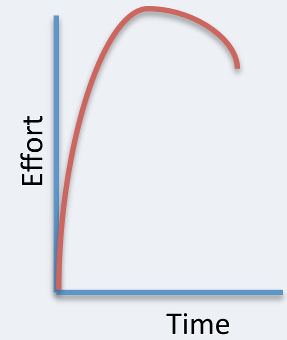
	Empirical	Mechanistic		
Model	**Modified panel regression**	**Modified Catch-MSY**	**COM-SIR**	**SSCOM**
Method	•Log-linear regression •Reference: RAM Legacy	•Schaefer model with estimated r+K •Reference: FishBase (r +K) + catch (depletion)	•Schaefer + effort dynamics •Bayesian model	•Schaefer + effort dynamics •State-space Bayesian model
Input	Catch; life-history, fishing history	Catch; priors for r+K; depletion (from peak-catch)	Catch; depletion; priors for r+K; rate of effort	Catch, depletion priors (life-history, others)
Reference	Costello et al. (2012) *Science*	Martell and Froese (2012) *Fish and Fisheries*	Vasconcellos and Cochrane (2005) *Alaska Sea Grant*	Thorson *et al.* (In review) *CJFAS*

Full Factorial Deterministic Design

Factor	Level 1	Level 2	Level 3	Level 4
Initial depletion (ID)	0%	30%	60%	
Effort dynamics (ED)	Constant effort (ED0): 	ED model with a=1 (Bmsy) and x=0.6 (ED 0.6): 	One-way trip (OW): 	Roller Coaster (RC): 
Time-series length (TS)	20	60		
Life-history (LH) *Gislason et al 2008	'Clupeoid' (SP)	'Gadoid' (D)	'Tuna' (LP)	

3*4*2*3 = 72 simulated stocks in full factorial design

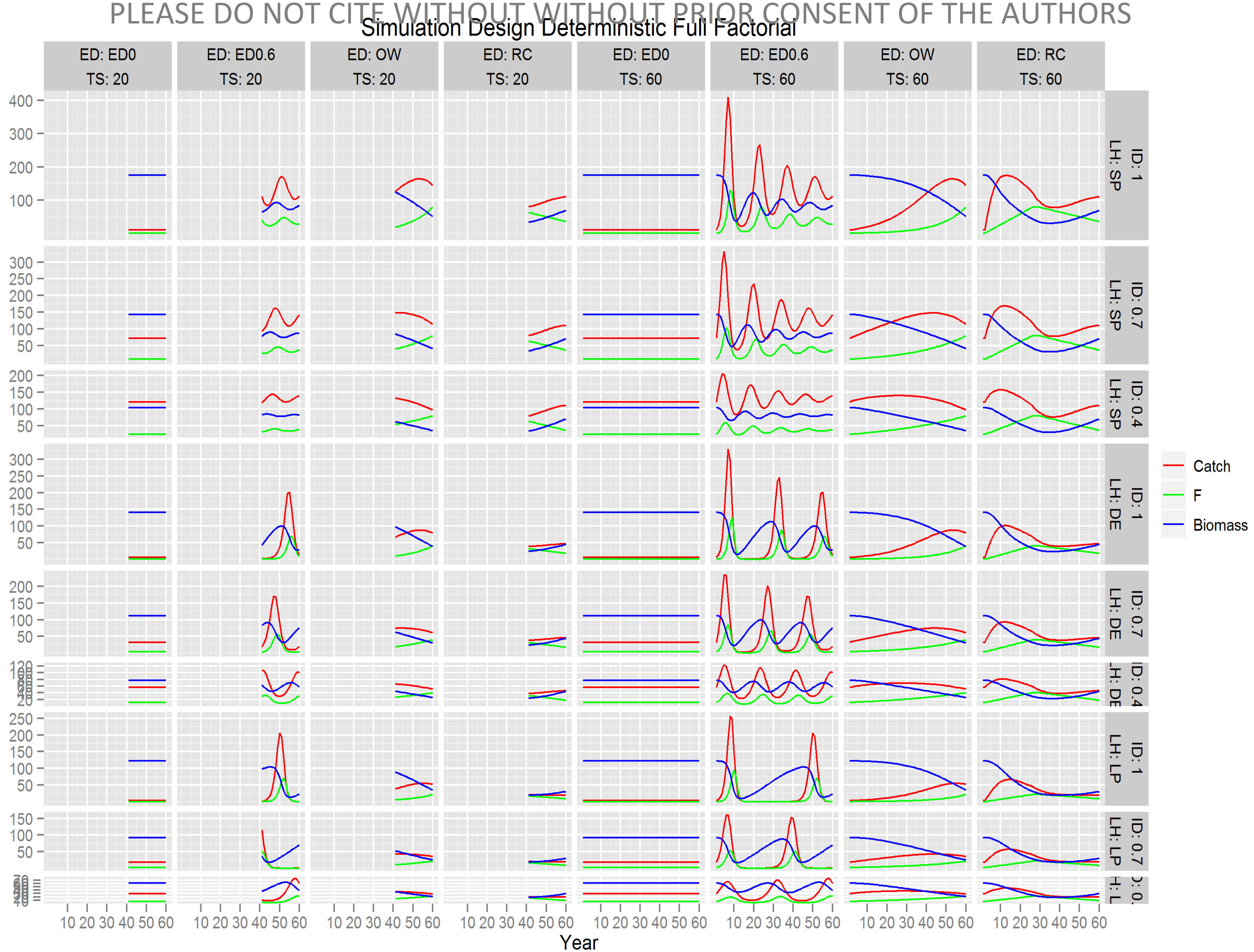
Full Factorial Stochastic Design

Factor	Level 1	Level 2	Level 3	Level 4
Initial depletion (ID)	0%	30%	60%	
Effort dynamics (ED)				
Time-series length (TS)	20	60		
Life-history (LH)	'Clupeoid' (SP)	'Gadoid' (D)	'Tuna' (LP)	
Autoregressive process error on recruitment variability AR(1)	0	0.6		
Recruitment variability (sigmaR)	0.2	0.6		
Catch error (sigmaC)	0	0.2		

576 simulated stocks with 10 replications

Hexagon supercomputing for full factorial analysis

- Double blind:
  - Simulation set-up independent from methods 'developers':
    - True biomass, F and LH not disclosed
    - Only Catch timeseries, Linf, tmax and tmat were provided
- 576 (scenarios) x 10 (iterations) x 4 (methods) = 23,040 data poor assessments
- For agreed convergence level (MCMC,SIR) requires 19.5 CPU years on single processor
- Completed work in walltime of 7.5 days on Hexagon cluster


Simulation Design Deterministic Full Factorial
ED: ED0 TS: 20
ED: ED0.6 TS: 20
ED: OW TS: 20
ED: RC TS: 20
ED: ED0 TS: 60
ED: ED0.6 TS: 60
ED: OW TS: 60
ED: RC TS: 60
ID: 1 LH: SP
ID: 0.7 LH: SP
ID: 0.4 LH: SP
ID: 1 LH: DE
ID: 0.7 LH: DE
ID: 1 LH: LP
ID: 0.7 LH: LP
Catch
F
Biomass
10 20 30 40 50 60
Year

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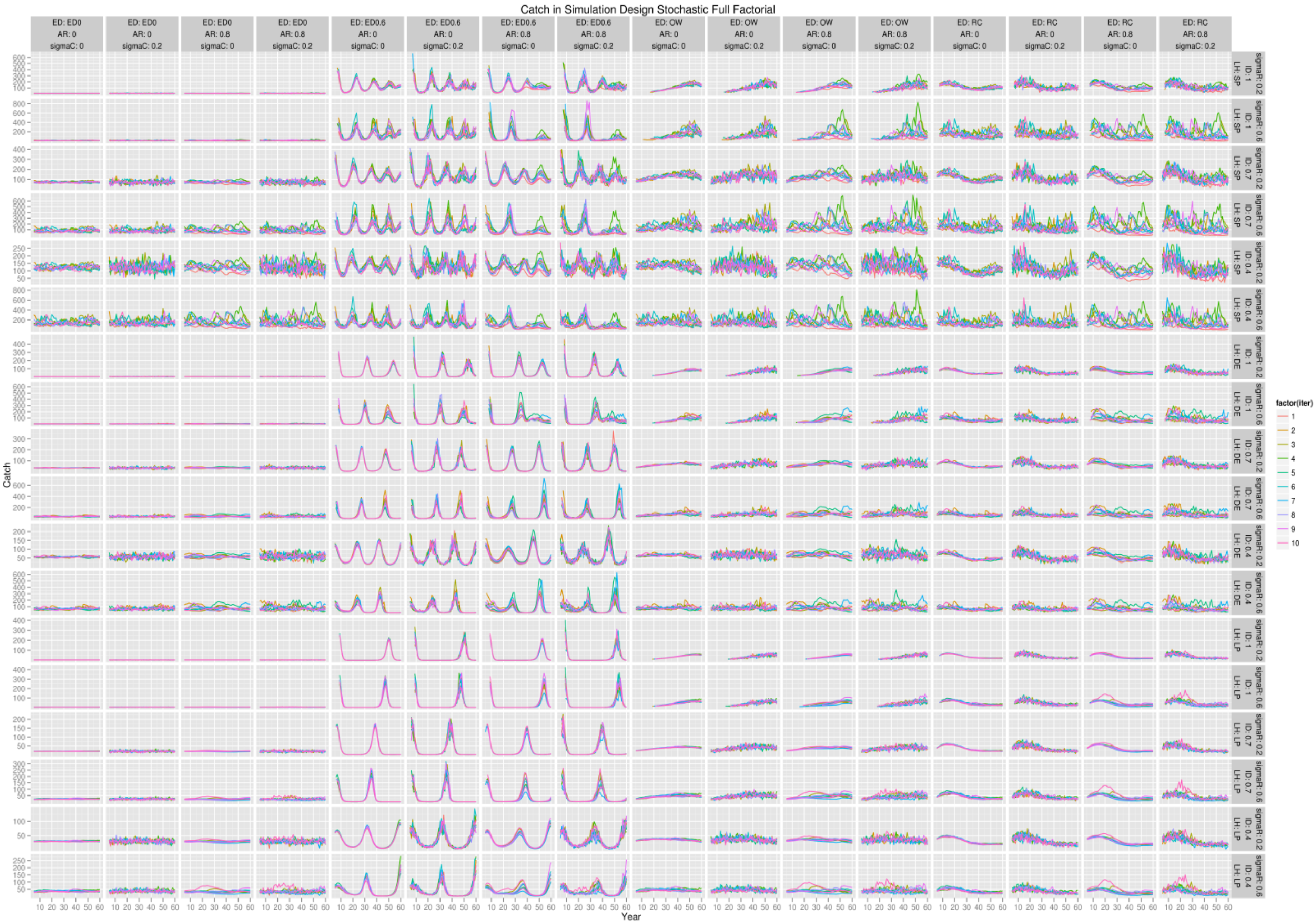

Determining model performance

- Proportional Error: measure of bias

$$PE = \frac{(estimated - true)}{true}$$

- Absolute Proportional Error (APE): measure of error (bias + precision)

$APE =$

$$APE = \left| \frac{estimated - true}{true} \right|$$

  - We used Mean APE (MAPE) or MPE
- Other diagnostics examples (not shown here):
  - Posterior Predictive Score (PPS)
  - Coverage (of estimated vs. true biomass)

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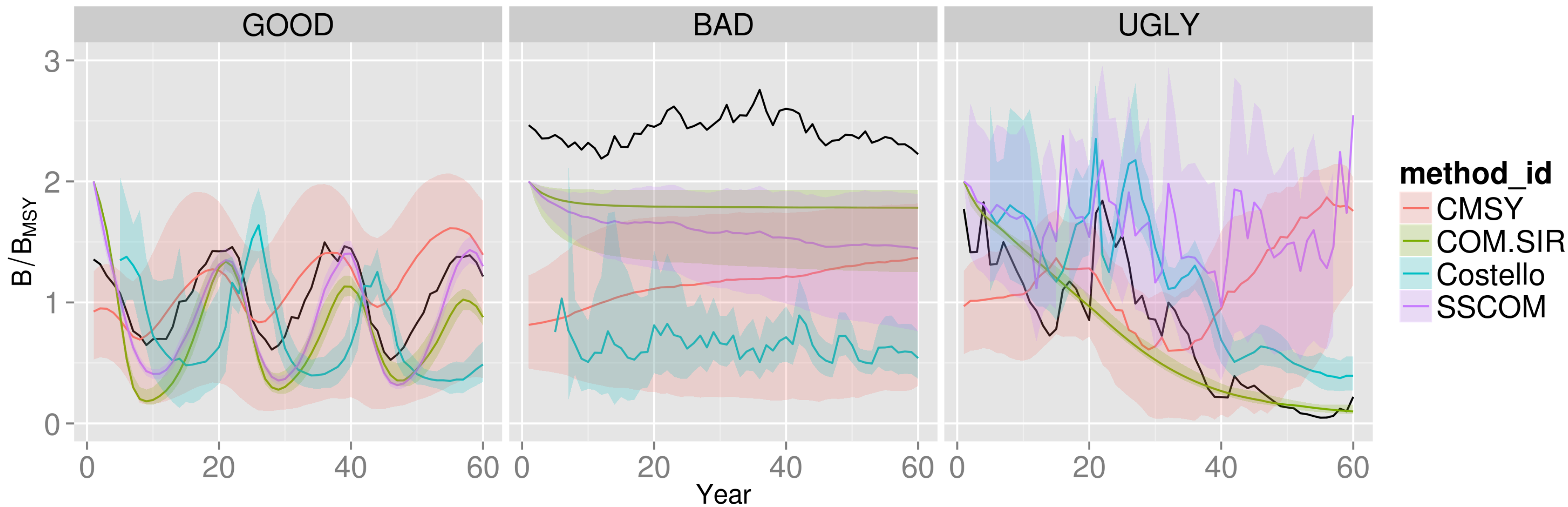
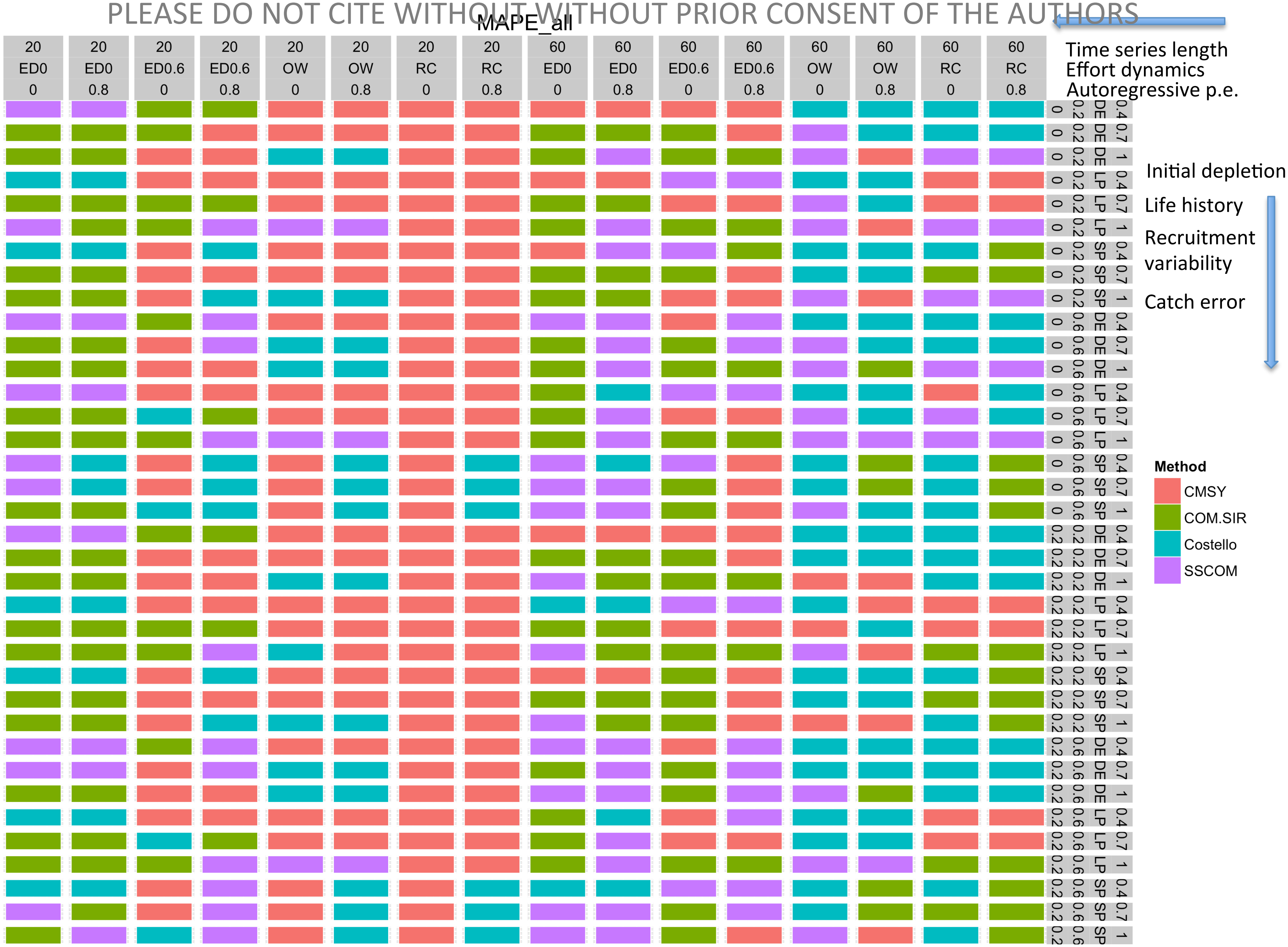
Example Fits of B/B_{MSY}

- **Black line is 'true'**

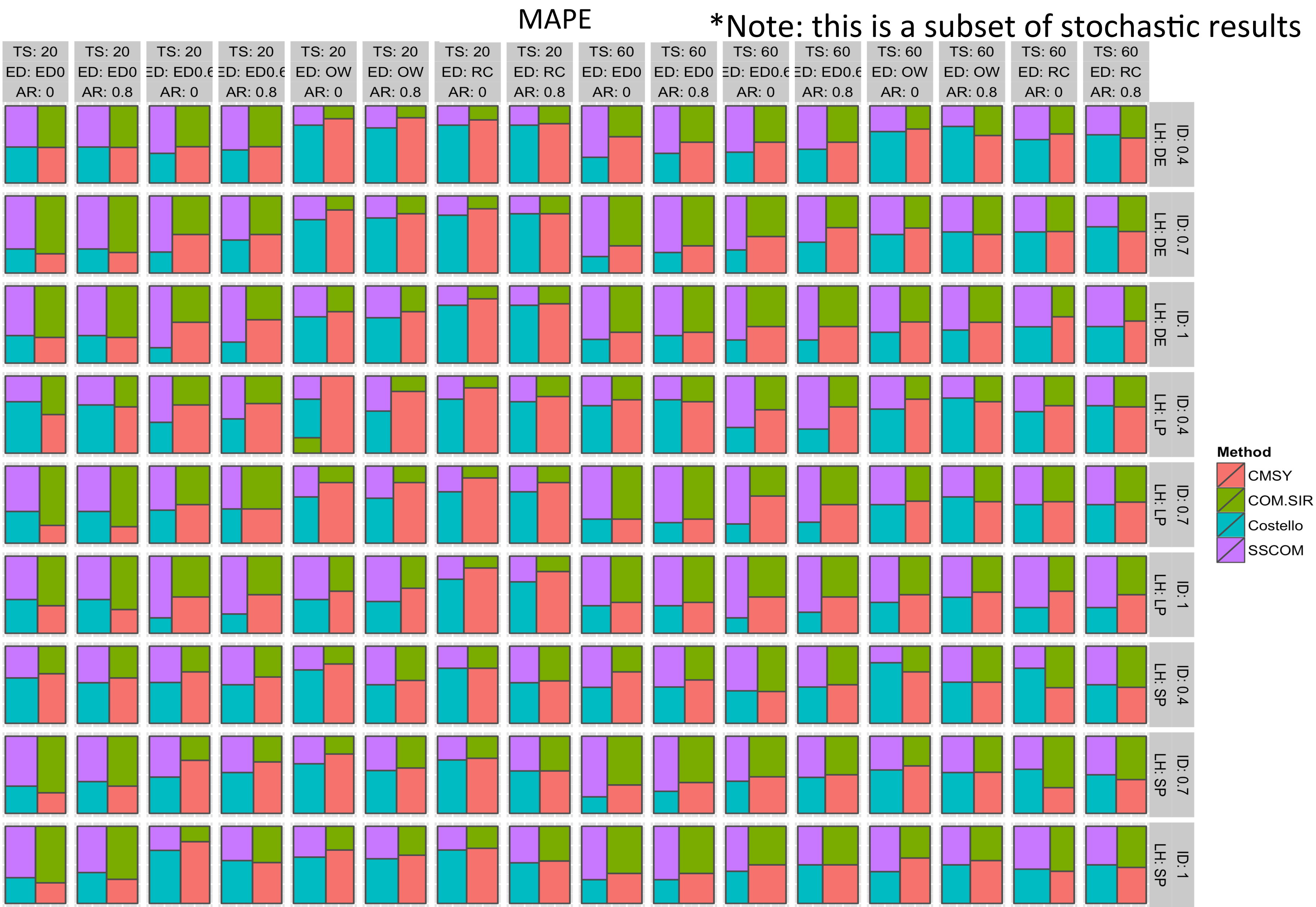


Demersal, ED = 0.6	Demersal, ED = 0	Small pelagic, ED = OW
ID = 60%	ID = 0%	ID = 30%
AR = 0	AR = 0	AR = 0.6
Recruitment var = 0.2	Recruitment var = 0.2	Recruitment var = 0.6
Catch error = 0	Catch error = 0	Catch error = 0.2

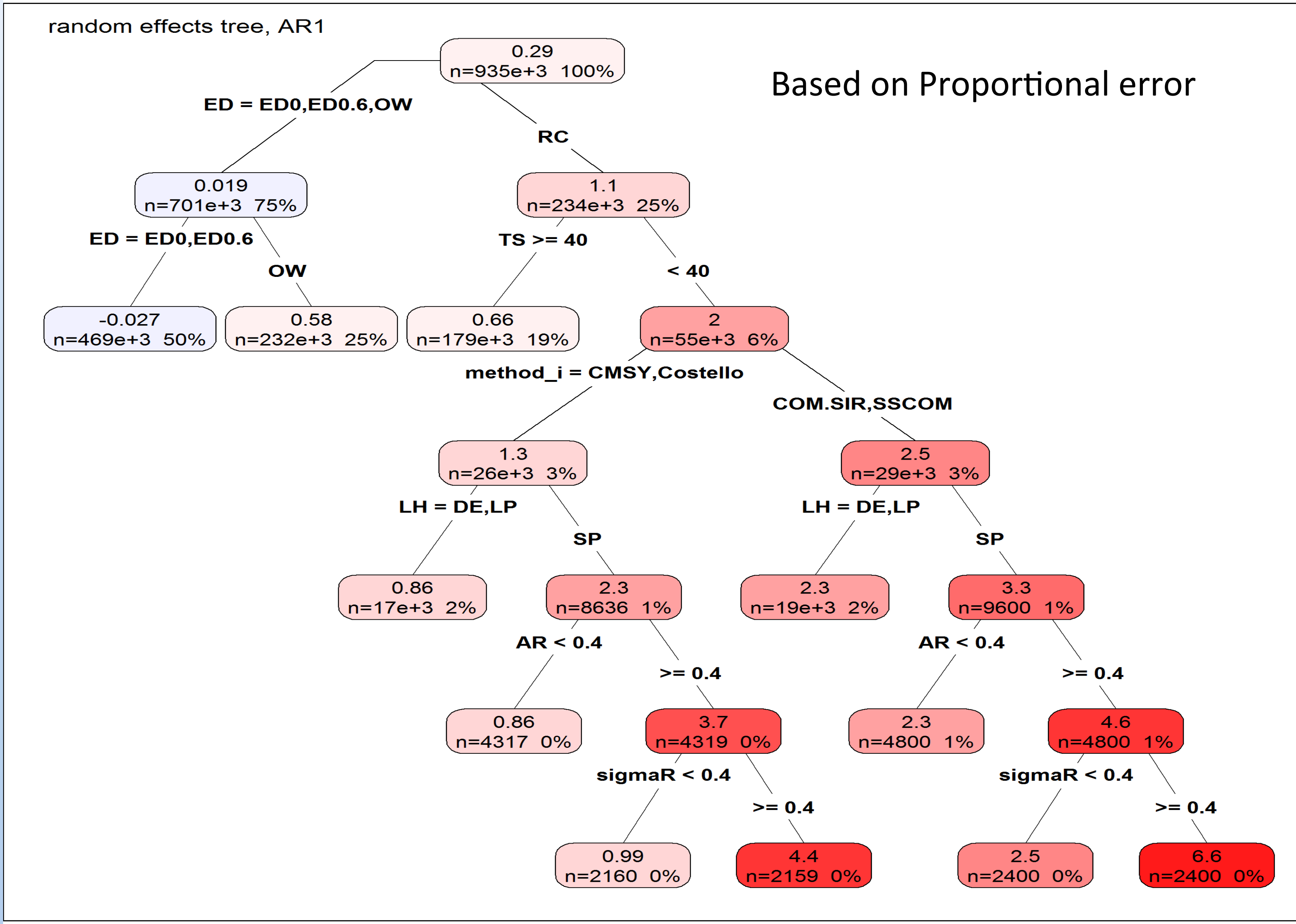

MAPE_all
20 ED0 0
20 ED0 0.8
20 ED0.6 0
20 ED0.6 0.8
20 OW 0
20 OW 0.8
20 RC 0
20 RC 0.8
60 ED0 0
60 ED0 0.8
60 ED0.6 0
60 ED0.6 0.8
60 OW 0
60 OW 0.8
60 RC 0
60 RC 0.8
Time series length
Effort dynamics
Autoregressive p.e.
Initial depletion
Life history
Recruitment variability
Catch error
Method
CMSY
COM.SIR
Costello
SSCOM

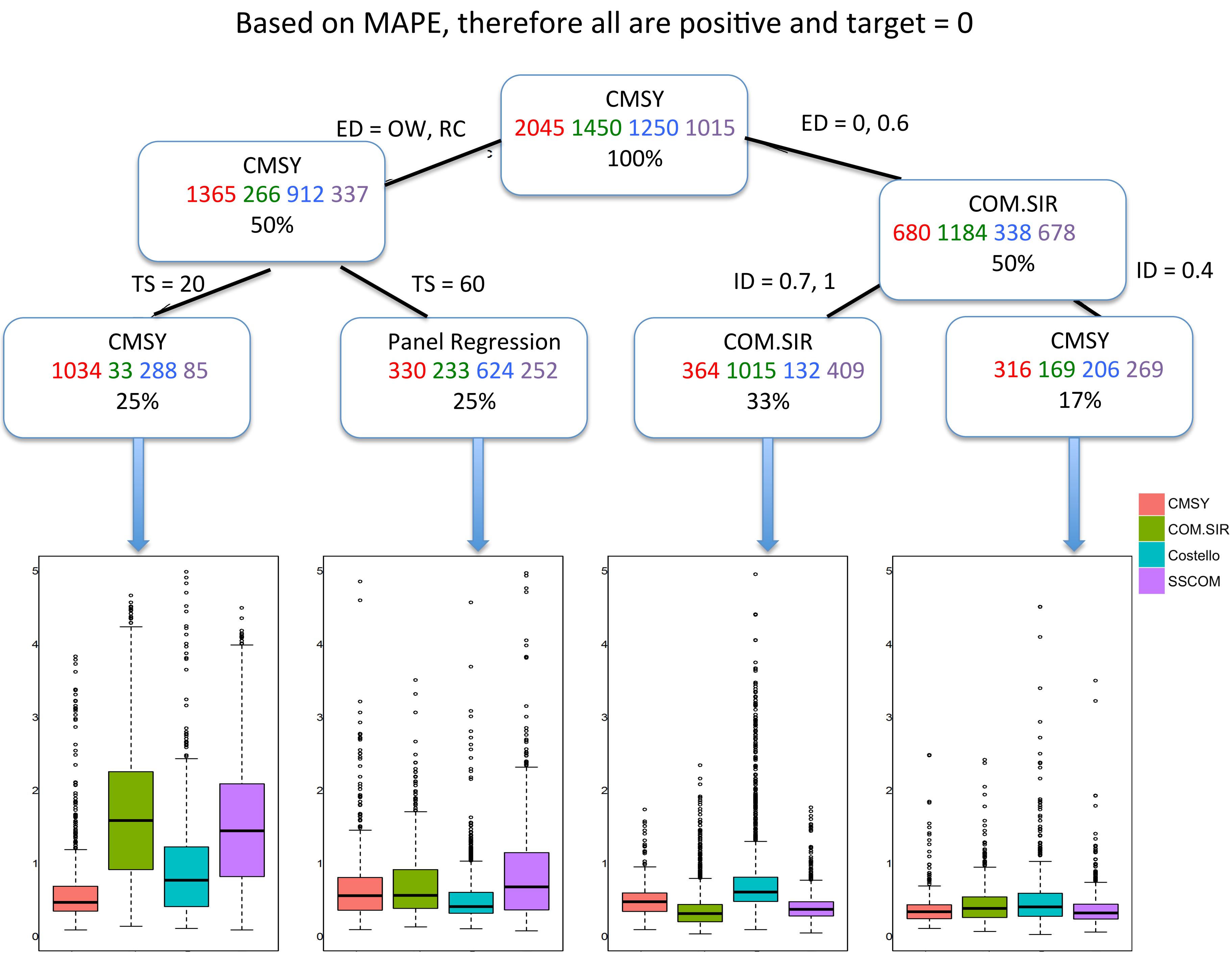
'Mondrian' plot

*Note: this is a subset of stochastic results



PLEASE DO NOT CITE WITHOUT WITHOUT PRIOR CONSENT OF THE AUTHORS




Based on MAPE, therefore all are positive and target = 0
CMSY
2045 1450 1250 1015
100%
ED = OW, RC
ED = 0, 0.6
CMSY
1365 266 912 337
50%
COM.SIR
680 1184 338 678
50%
TS = 20
TS = 60
ID = 0.7, 1
ID = 0.4
CMSY
1034 33 288 85
25%
Panel Regression
330 233 624 252
25%
COM.SIR
364 1015 132 409
33%
CMSY
316 169 206 269
17%
CMSY
COM.SIR
Costello
SSCOM

Summary of Stochastic results

- CMSY is top performer

Method	MAPE	MPE
CMSY	202	253
COMSIR	138	125
Panel regression	130	127
SSCOM	106	71

- But, Mondrian plots reflect a diverse model space
- Main trait determining performance?
  - Effort dynamics: more important than choice of method

Caveats to Diagnostics/Performance

- **Stock representivity:**
  - All life-histories not represented by 3 'types'
- **Penalized models:**
  - Model implementation constrained by simulation framework:
    - 'Reduced form' - Panel Regression
    - Uninformative priors – SSCOM, COMSIR
- **'Real life' comparability:**
  - No comparison to data-rich assessments (yet)

Limitations/Caveats contd.

- Not meant to replace full stock assessments
- Recommendation: best performers used only for understanding large-scale patterns
- For management: should have MSE first
- Applicability: some know-how needed to implement models

Acknowledgements

- FAO
- Conservation International
- Moore Foundation
- Union of Concerned Scientists
- ICES
- EU Joint Research Centre
- FLR team
- New England Aquarium
- National Center for Ecological Analysis and Synthesis
- Northwest Fisheries Science Center
- Sea Around Us project
- University of Washington
- Trond Kristiansen-- access and assistance with Hexagon
- Technical support unit for Hexagon

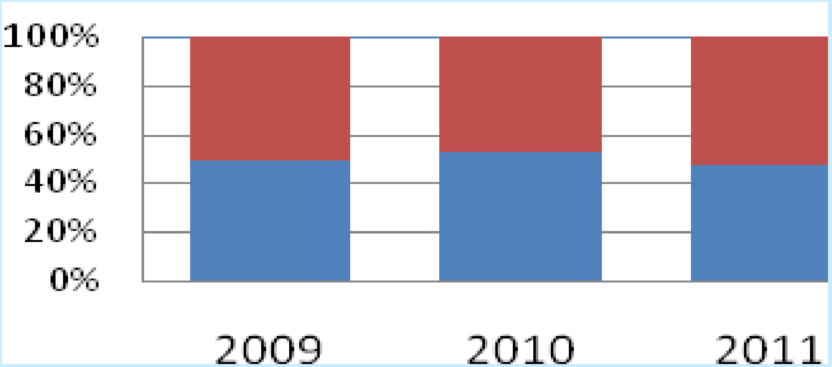
ICES' new approach to data-limited stocks aids sustainable management of fisheries and provides an extension to their advisory framework

Carl M. O'Brien, Anne M. Cooper and Iñigo Martinez

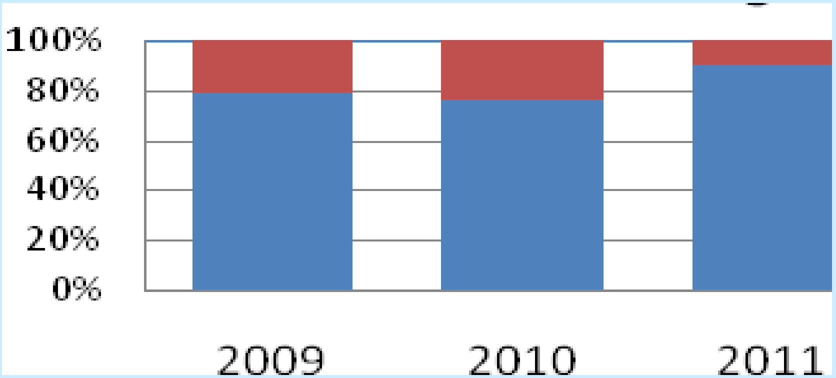
WCSAM, 17-19 July 2013
Boston, USA

Weight of landings

North-east Atlantic
and Baltic Sea



Mediterranean
and Black Sea



Assessed Not assessed

Extent of data-limited stocks in EU waters

Cefas

- Vessels less than 12 m more dependant on data-limited stocks than larger vessels.
- Pelagic stocks mostly covered by assessments; invertebrate stocks least covered by assessments.
- Limited coverage of deep-water stocks by assessments.

Data-limited stocks in EU waters

- Briefly summarise the significant achievements within ICES’ science and advice with respect to data-limited stocks

Outline of presentation

- Before 2012, ICES provided no quantitative advice for data-deficient fisheries.
- Since 2006 the European Commission's annual policy statement has defined data-deficient TAC rules
  - Increasingly formalised pragmatic rules
    e.g. 15% TAC reduction for declining stocks

Context

- Recognise different levels of data/knowledge about stocks
- Combined assessment methods and management decision rules
- Explicitly incorporate uncertainty and precaution

New approach needed!

ICES WKLIFE REPORT 2012

ICES ADVISORY COMMITTEE

ICES CM 2012/ACOM:36

Report of the Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics (WKLIFE)

13–17 February 2012

Lisbon, Portugal

ICES CIEM International Council for the Exploration of the Sea Conseil International pour l'Exploration de la Mer

The **Workshop o[…]d on LIFE history traits and exploitation […]** […]uela Azevedo (Portugal) and Carl O'Brien ([…]:

a) identify op[…]tocks without quantitative forec[…]on characteristics;

b) identify m[…]n based on available limited inf[…]ta);

c) apply the a[…]l of the report for the full list of […] this can be used and stocks for w[…]

d) identify the[…]e 1 in order to implement the ap[…]

e) identify opt[…] stocks where there is sufficient i[…] and b).

ICES' WKLIFE

Cefas

- WKLIFE attempted to categorise the amount and quality of information available for each stock which guided ICES in the process of identification of appropriate assessment methods/approaches in the advice for 2012.

ICES CM 2012/ACOM:36

- Categorisation of stocks into one of seven basis types:
  1) Data rich stocks (quantitative assessments)
  2) Negligible landings stocks
  3) Stocks with analytical assessments that are treated qualitatively
  4) Stocks for which survey indices (or unbiased CPUE) indicate trends
  5) Stocks for which reliable catch data are available for short time-series
  6) Truly data-poor stocks (landings only)
  7) Stocks caught in minor amounts as by-catch

ICES CM 2012/ACOM:36

ICES has used the following categorizations:

Category 1 – data-rich stocks (quantitative assessments)
These are the stocks that are not considered data-limited and this category includes stocks with full analytical assessments and forecasts as well as stocks with quantitative assessments based on production models.

Category 2 – stocks with analytical assessments and forecasts that are only treated qualitatively
This category includes stocks with quantitative assessments and forecasts which for a variety of reasons are merely indicative of trends in fishing mortality, recruitment, and biomass.

Category 3 – stocks for which survey-based assessments indicate trends
This category includes stocks for which survey indices (or other indicators of stock size such as reliable fishery-dependant indices; e.g. lpue, cpue, and mean length in the catch) are available that provide reliable indications of trends in stock metrics such as mortality, recruitment, and biomass.

Category 4 – stocks for which reliable catch data are available
This category includes stocks for which a time-series of catch can be used to approximate MSY.

Category 5 – data-poor stocks
This category includes stocks for which only landings data are available.

Category 6 – negligible landings stocks and stocks caught in minor amounts as bycatch
This category includes stocks where landings are negligible in comparison to discards. It also includes stocks that are part of stock complexes and are primarily caught as bycatch species in other targeted fisheries. The development of indicators may be most appropriate for such stocks.

RGLIFE & WKLIFE

the information requirement of each category/method (denoted by x) and optional information requirements (denoted by (x)):

	Information Required					
Category	Population estimate	Survey	Fishing mortality	Biomass	Discards	Landings
1	x	x	x	x	x[1]	x
2	trends	(x)	trends	trends	(x)	x
3		trends	relative	relative	x[1,2]	x[2]
4					x[1]	X
5					(x)	X
6						(x)

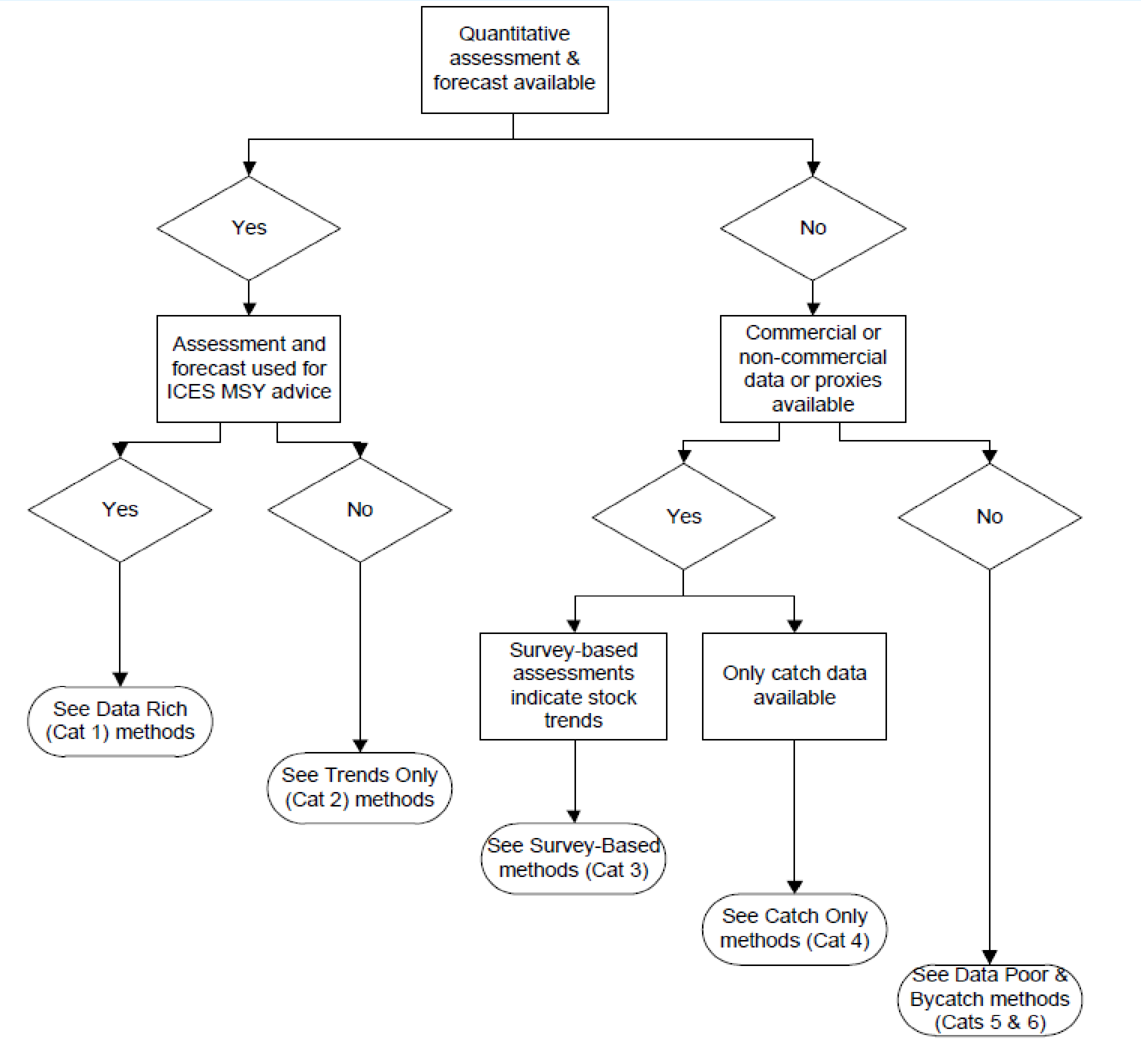
[1] Either available, or can assume to be zero.

[2] If the landings or catches are unreliable, a directional advice (qualitative) can be given.

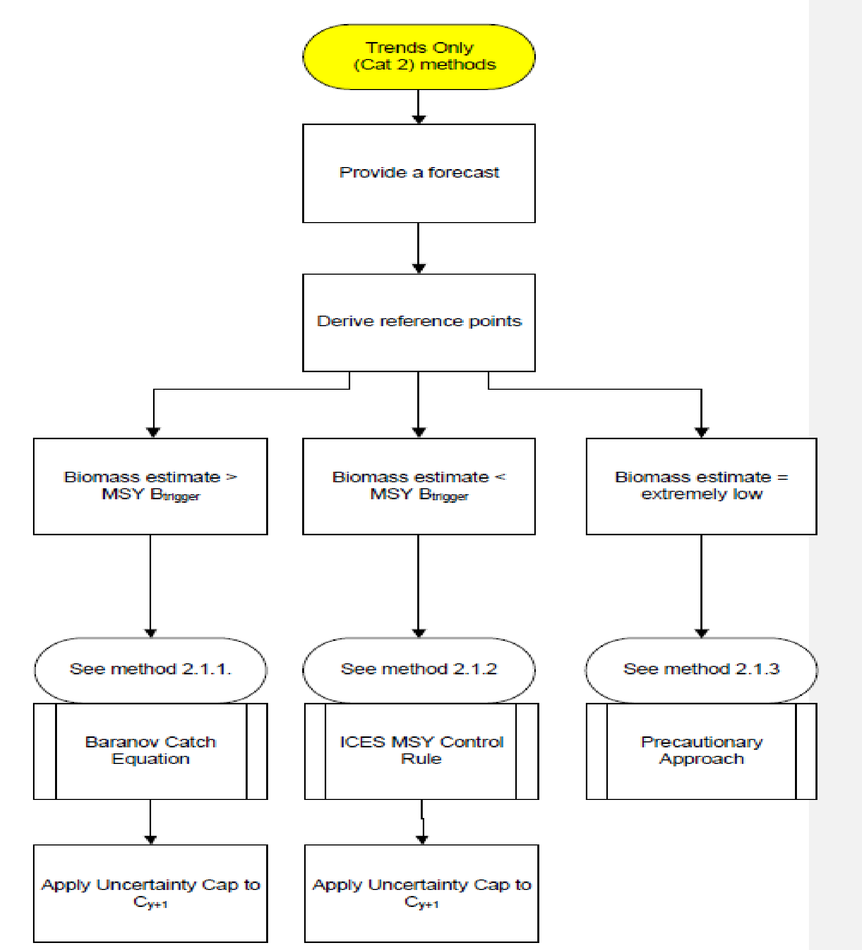
Information requirements

For each of these categories, methods have been employed to provide quantitative advice. These methods are generally based on approaches published in the scientific literature and most of the specific, quantitative forecast methods which have been applied have also been subjecedt to formal testing in simulations. The methods and the associated simulations are presented in ICES (2012b). ICES recognizes that there are alternative approaches to many of the methods proposed and it has in some cases been possible for the experts involved to provide methods which are more adequate for a specific stock while maintaining the same principle of precaution as the general framework.

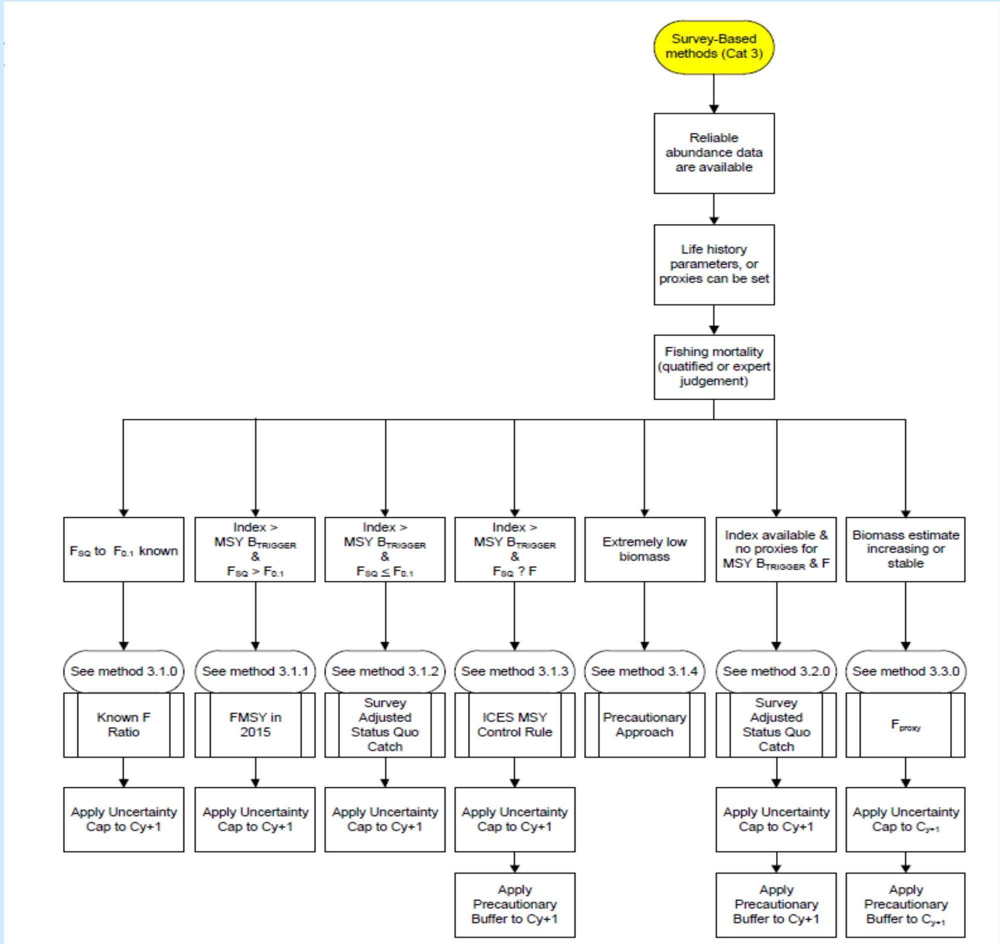
ICES' advice in 2012



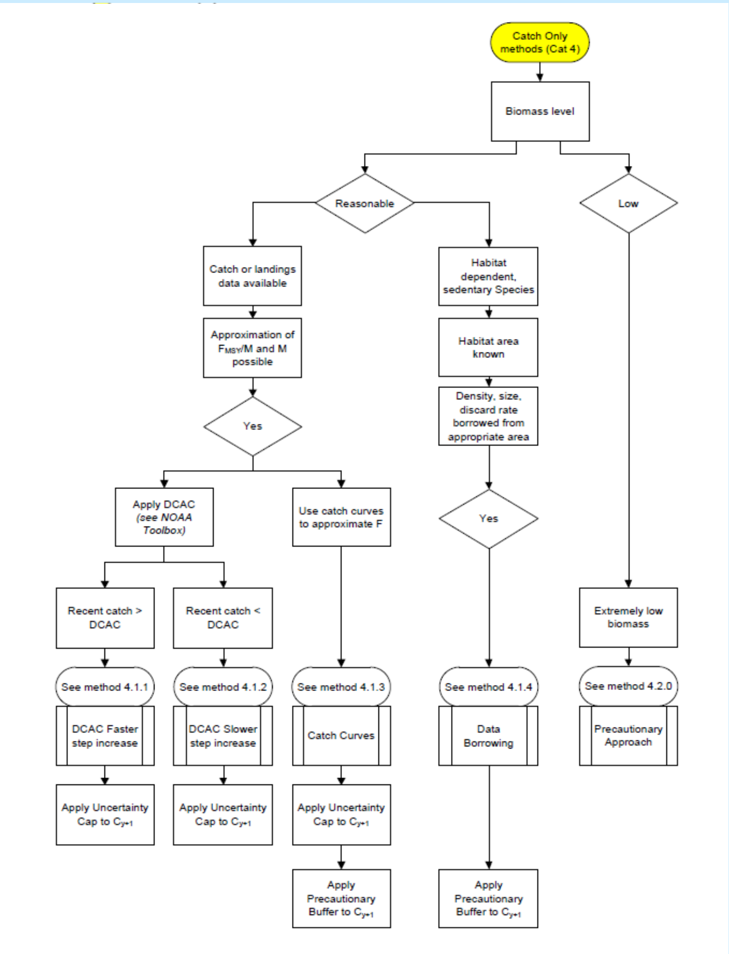
ICES CM 2012/ACOM:68



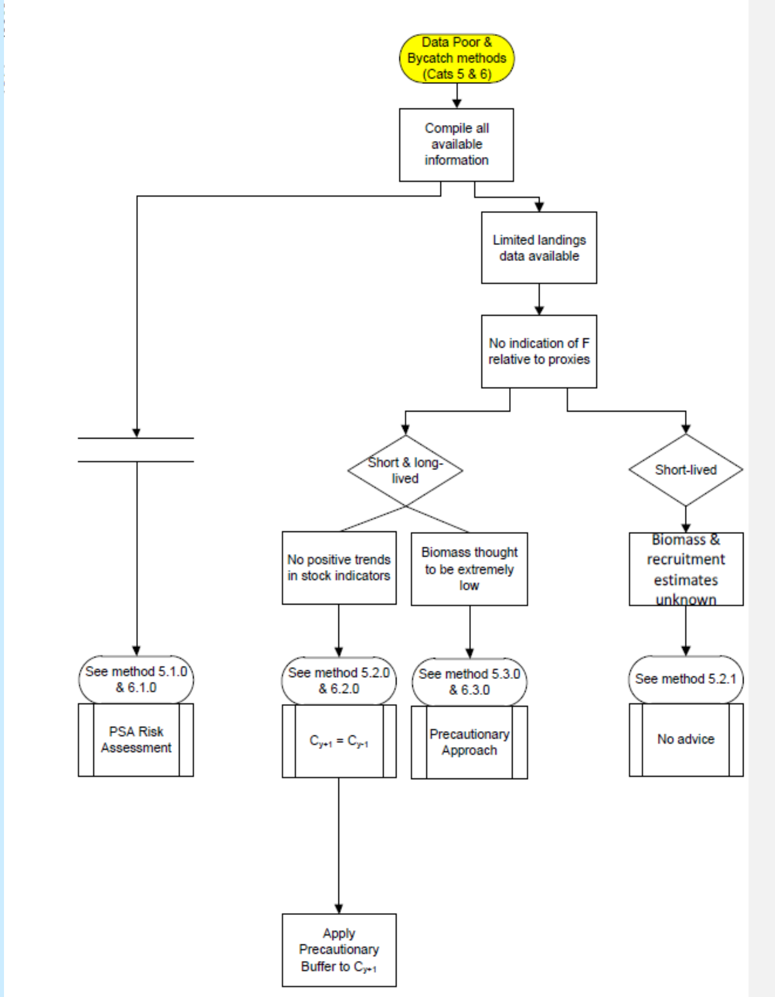
Data-limited: category 2



Data-limited: category 3



Data-limited: category 4



Data-limited: categories 5/6

DLS Category	Ecoregion Baltic Sea n=7	Bay of Biscay & Iberian Waters n=24	Celtic Sea & West Coast of Ireland n=36	North Sea n=27	Widely Distributed n=39	Total
2,1,3			2	1	1	4
3,1,0	1			1		2
3,1,2				1		1
3,1,4		3	1		2	6
3,2,0	6	7	14	6	11	44
3,3,0					4	4
4,1,2			1			1
4,1,3			2			2
4,1,4			1	5		6
5,2,0		12	6	9	8	35
5,3,0		1		1	5	7
6,2,0		1	6	1	4	12
6,3,0			3	2	4	9

ICES' advice in 2012

Method 3.2. If there are survey data on abundance (e.g. cpue over time), but there is no survey-based proxy for MSY $B_{trigger}$ and F values or proxies are not known

1) Determine catch advice from the survey adjusted *status quo* catch:

$$C_{y+1} = C_{y-1}\left(\frac{\sum_{i=y-x}^{y-1} I_i/x}{\sum_{i=y-z}^{y-x-1} I_i/(z-x)}\right)$$

2) Where I is the survey index, x is the number of years in the survey average, and $z > x$. For example, $x = 2$ would be a two year survey average, and $x = 2$ $z = 5$, which is analogous to the five steps in the ICES MSY transition from 2010 to 2015 (ICES Introduction 1.2);

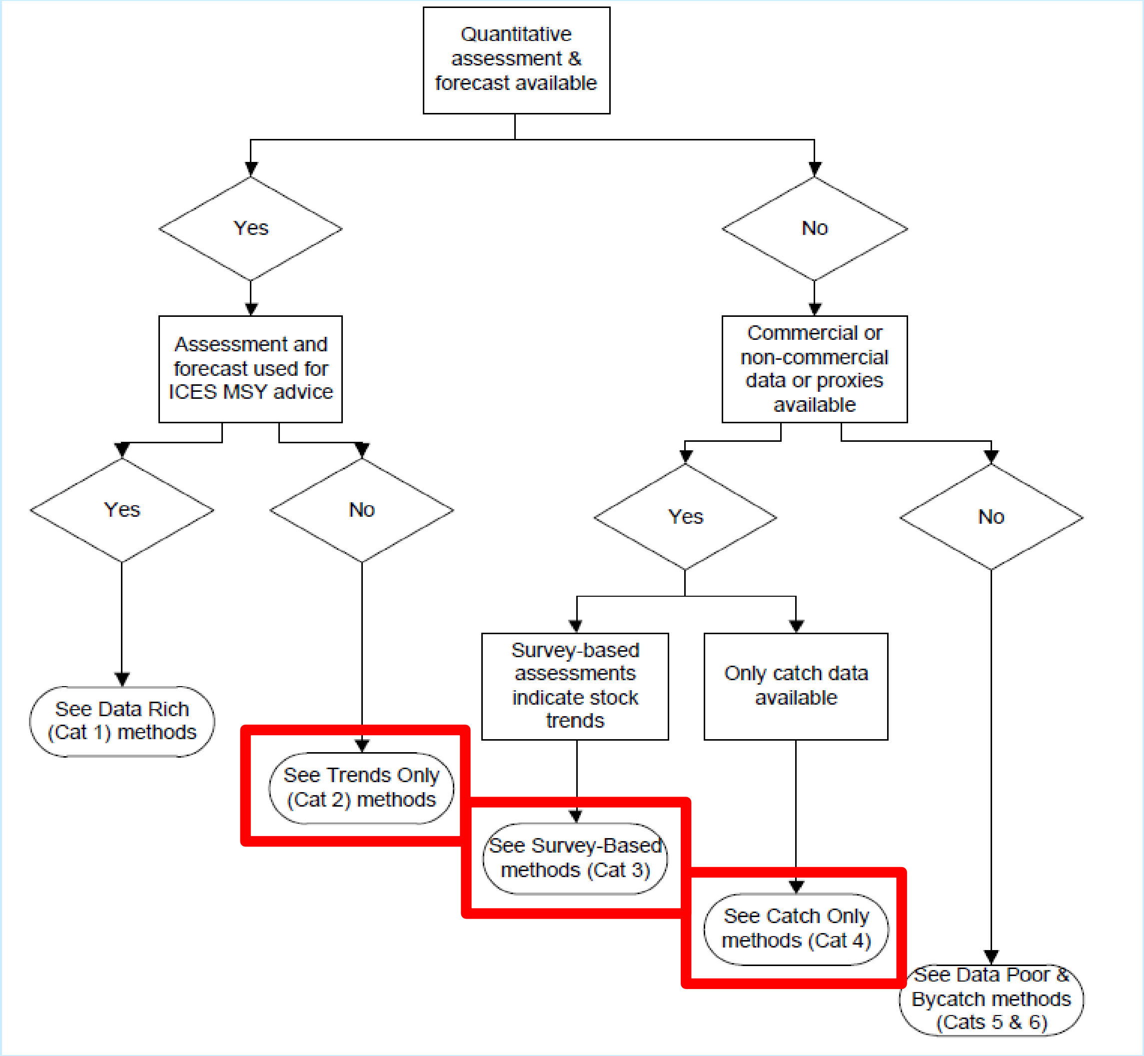
3) C_{y-1} should be the last three years unless there are justified reasons for using a longer or different time period. For example, long-lived species such as sharks and rays used ten years of data;

4) Apply the 20% Uncertainty Cap to the catch advice (see above Methods;-Definition of common terms and methods);

5) Then apply the Precautionary Buffer to the catch advice (see above Methods; Definition of common terms and methods).

Most common method

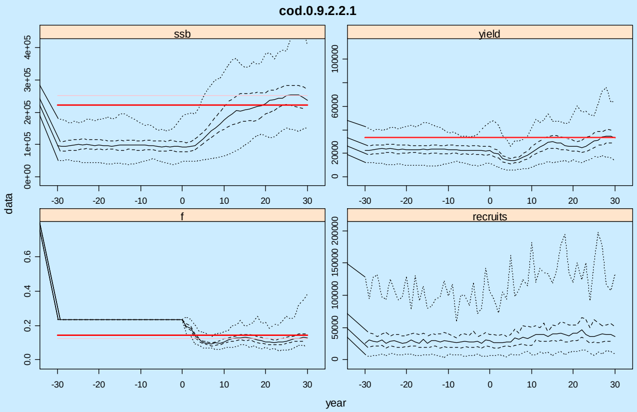
Cefas



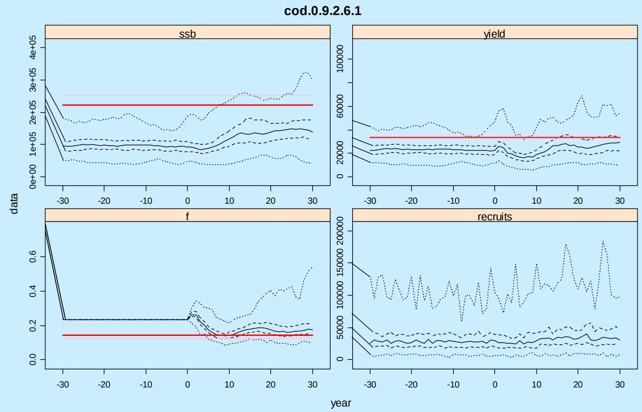
Simulation testing within MSE framework

Category 2

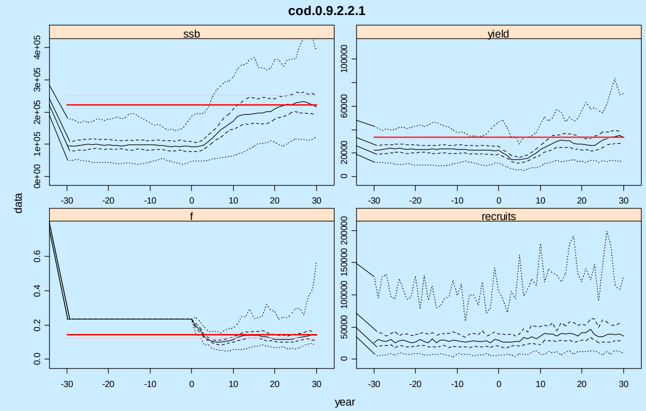
No catch bias



Catch bias

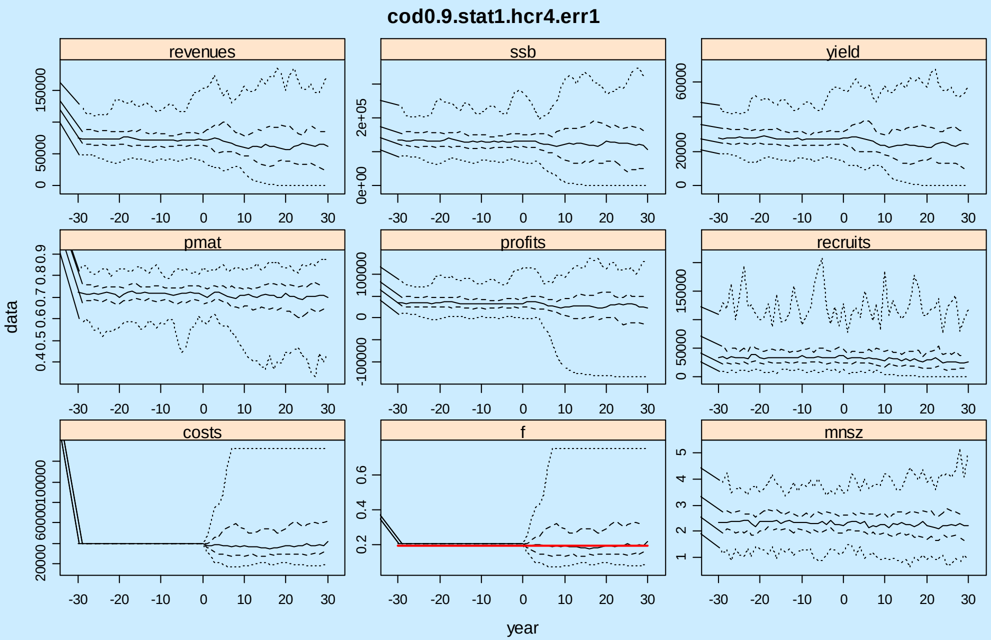


Discards bias

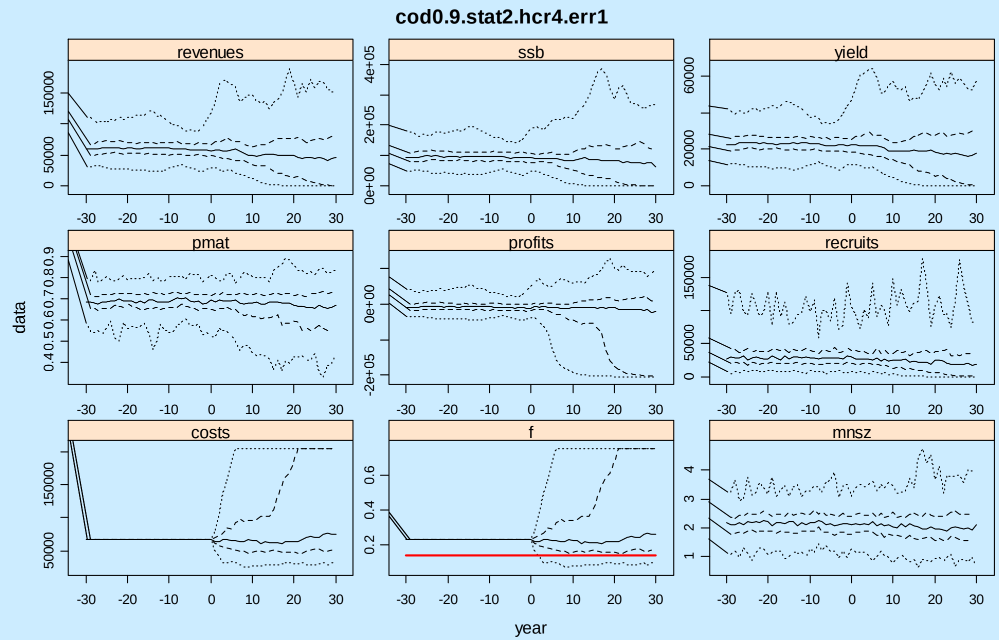


Category 3

Well managed



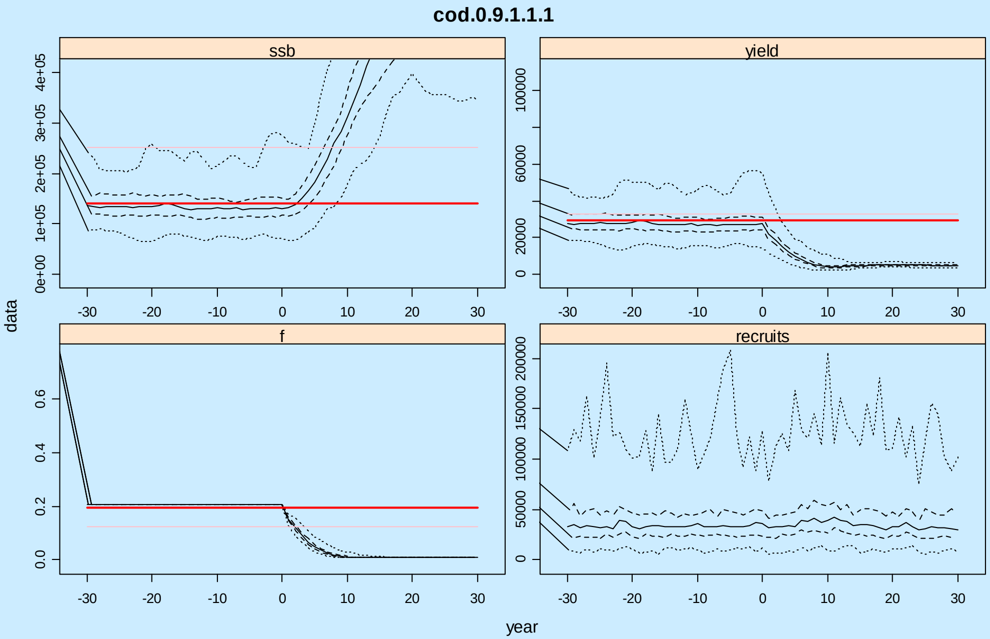
Over-fished



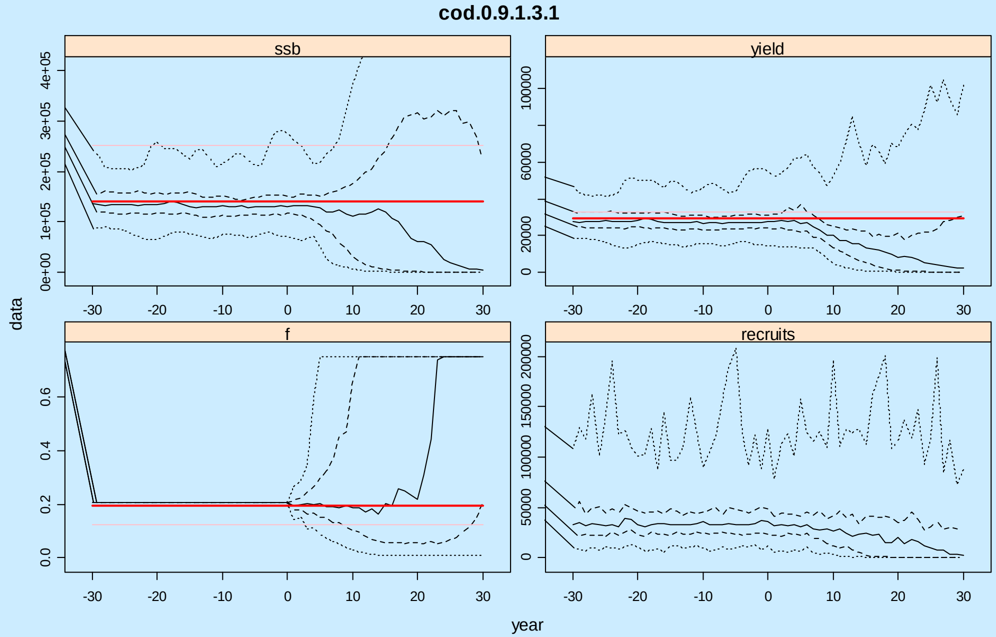
Simulation testing within MSE framework

Category 4

Catch curve analysis



Un-tuned VPA



Simulation testing within MSE framework

- Hierarchy of data categories
- Reference points defined in relation to data availability
- Increasing precaution with increasing uncertainty
- Management Strategy Evaluations recognised

Summary

- Risk of over-fishing is not consistent across all stocks:
  - A few stocks drive the main behaviour of fisheries
  - Stocks less vulnerable or less exposed not at risk
  - Strategic definition of ‘key’ stocks
  - Simplified monitoring of ‘secondary’ stocks
  - Develop robust rules harvest control rules

Summary

- Ensure compliance with data collection requirements

- Strategically cost-effective assessment framework
  - Strategic stock ‘ranking’
  - Definition of assessment-management procedures
  - Evaluate practical implications of procedures
  - Defined risk thresholds for management

- Ensure objectives are consistent with resources

Summary

- Further progress, and complete, the developments for data-limited stocks so as to include as many stocks as practicable within ICES' science and advisory framework.

- Identify preferred options for determining proxies for F_{MSY} for stocks without quantitative forecasts, using life-history traits and exploitation characteristics.

On-going activities

ICES CIEM

WKLIFE III–Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other key parameters for data-limited stocks

The Workshop on the Development of Quantitative Assessment Methodologies based on Life-history traits, exploitation characteristics, and other relevant parameters for data-limited stocks (**WKLIFE III**), chaired by Carl O'Brien (UK) and Manuela Azevedo (Portugal) and will meet at ICES HQ, 28 October to 1 November 2013 to;

a) Build on the findings of past ICES groups, including WKLIFE, RGLIFE, WKFRAME, and the Data-Limited Stocks Methods document as well as other published sources to: Identify preferred options for determining proxies for F_{MSY} for stocks without quantitative forecasts, using life-history traits and exploitation characteristics;

b) Identify key methods for estimating current exploitation based on available limited information (for instance catch and survey data);

c) Investigate/define the methods to determine the relationship between life-history traits and the variance of stock development indices;

d) Identify the synergies in (a), (b) and (c) to make further advances in the development of quantitative methodologies for data-limited stocks;

e) Review the simulation work identified at WKLIFE II and make recommendations on current and future method choices for data-limited stocks;

f) Investigate the application of PSA to inform the advice for sustainable fisheries for data-limited and data-rich stocks. It should speak directly to the application (and magnitude) of the precautionary buffer for data-limited species. The susceptibility parameter(s), weightings (note-see NMFS), vulnerability, scaling, etc. should be designed for PSA criteria relevant to start the process, formalize/quantify each by ecoregion and then drill down to finer scales as required. To do this, ICES can build on the work of WKDDRAC3 (meeting in mid-January 2013), which will identify the data needed to improve the assessments of Northeast Atlantic stocks (NWWRAC, SWWRAC, and NSRAC).

g) Based on this work, make a proposal for reopening the DLS advice in the future.

ICES' WKLIFE III

Cefas

ICES WGMG meeting 2013: Reykjavik, 30 Sep – 4 Oct

TOR 2a

With regard to the ICES Data Limited Stock (DLS) approach:

> Investigate the robustness of the DLS approach as a framework for providing advice.

4.11 - Implementing the Risk-Catch-Cost Framework for Data Poor Fisheries

Jeremy Prince & Adrian Hordyk

Biospherics P/L & Murdoch University
Western Australia

July 2013

Acknowledgements:

The Nature Conservancy
David and Lucile Packard Foundation
USAID

Stock Assessment – per Stock

Biology

Aging	3 yrs	$90k
Tagging	3 yrs	$150k
Size of Maturity	3 yrs	$30k
Stock Structure	3 yrs	$100k

Monitoring

Catch & Effort	10-20 yrs	$300k
Biomass Surveys	10-20 yrs	$1,000k

Biomass Modeling 3yrs $150k

Total Cost / stock $500 – 1,000k

Layers of Assessment	Data Requirements	Risk Management
Quantitative Stock Assessment Biomass Modeling	Catch Rate or Survey Time Series Data with: SPR@ Size Curve curve estimated & High Quality Size & Other Data	Quantitatively estimated BMSY, $B_{opt.}$, $SPR_{opt.}$ targets & risk
Risk Based Framework	Expert Based	High Risk Ranking Requires higher assessment

Layers of Assessment	Data Requirements	Risk Management
Quantitative Stock Assessment Biomass Modeling	Catch Rate or Survey Time Series Data with: SPR@ Size Curve curve estimated & High Quality Size & Other Data	Quantitatively estimated BMSY, $B_{opt.}$, $SPR_{opt.}$ targets & risk
Risk Based Framework	Expert Based	High Risk Ranking Requires higher assessment

Graduated Progression

Increasing Costs & Increasing Precision

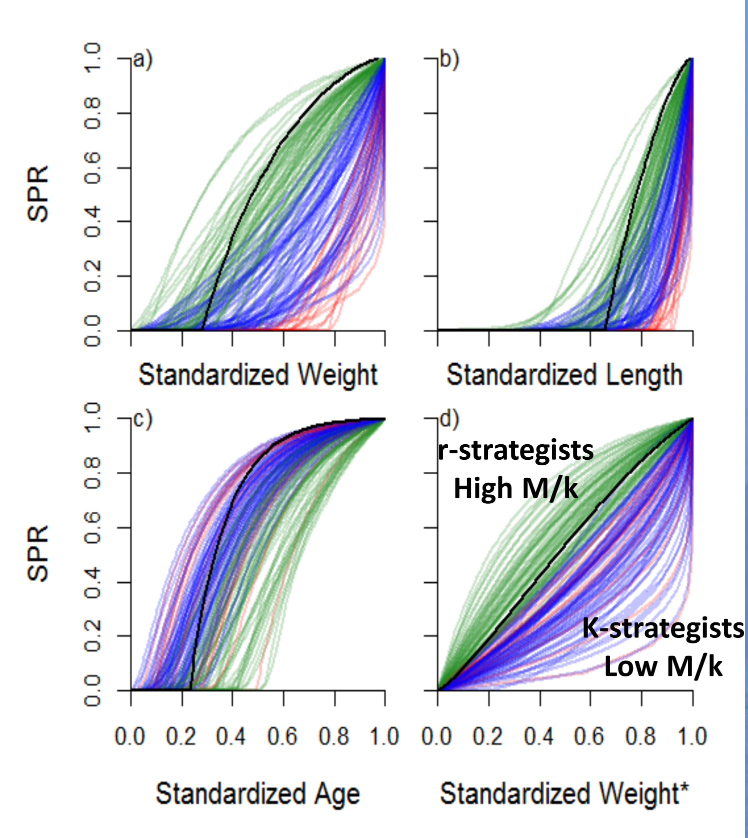
The Risk – Catch – Cost Framework

Layers of Assessment	Data Requirements	Risk Management
Quantitative Stock Assessment Biomass Modeling	Catch Rate or Survey Time Series Data with: SPR@ Size Curve curve estimated & High Quality Size & Other Data	Quantitatively estimated BMSY, $B_{opt.}$, $SPR_{opt.}$ targets & risk
Risk Based Framework	Expert Based	High Risk Ranking Requires higher assessment

Graduated Progression

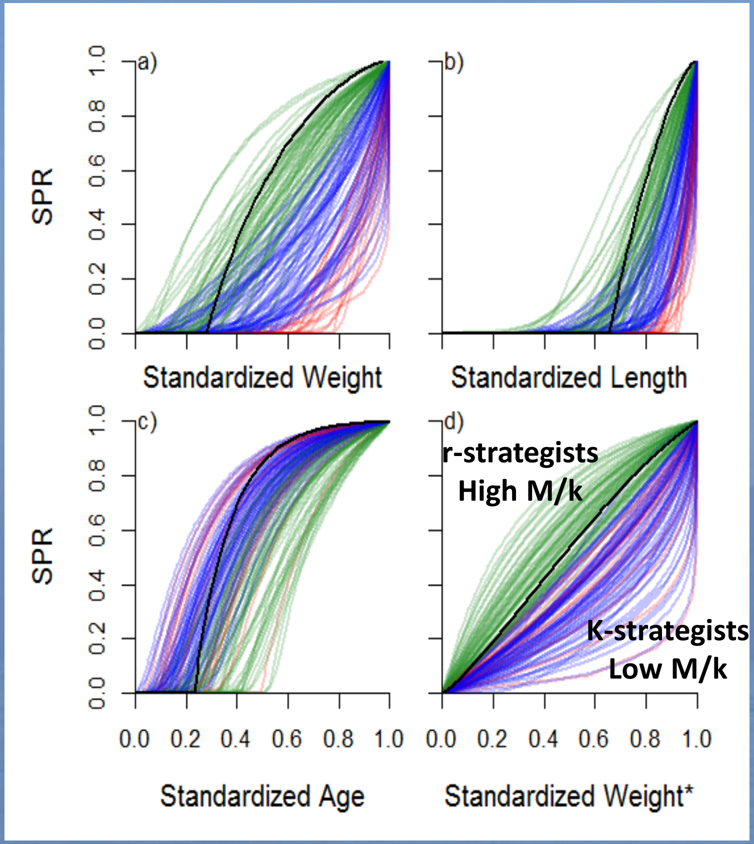
Increasing Costs & Increasing Precision

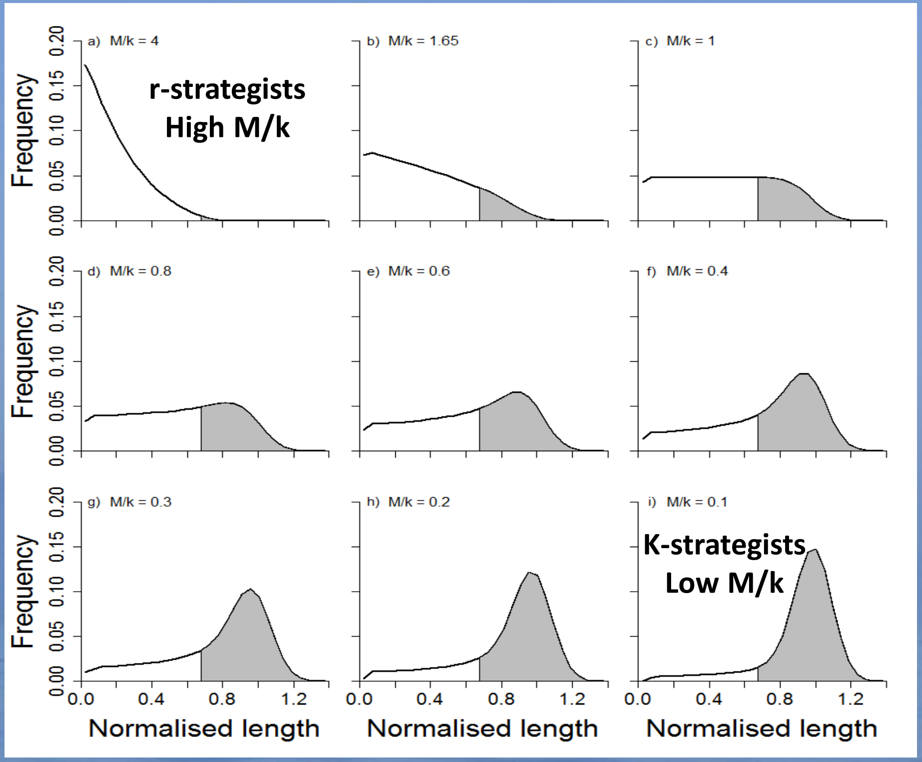
Meta-analysis



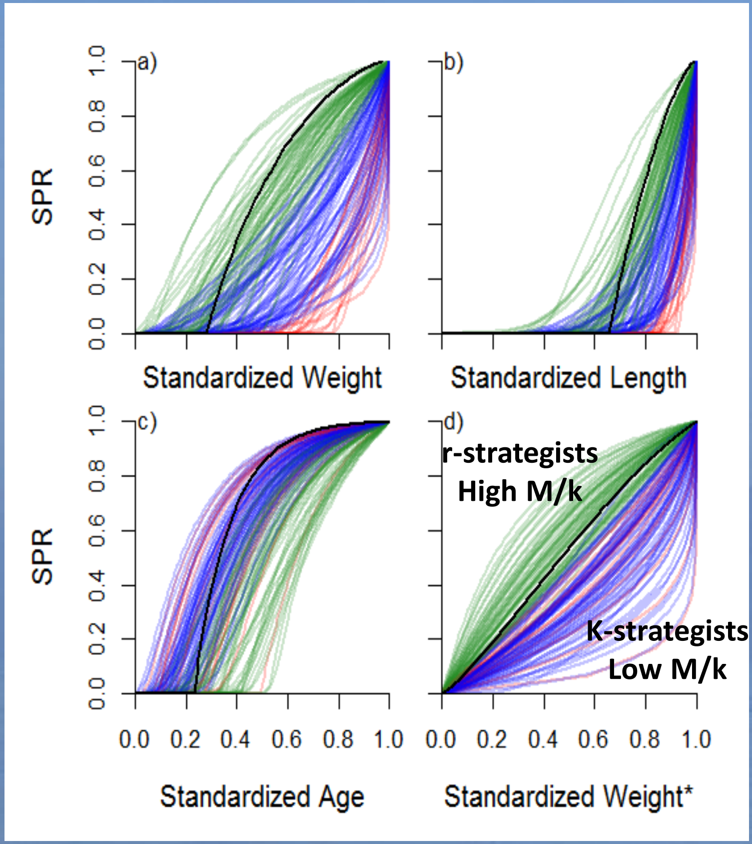
Spawning Potential Ratio (SPR)

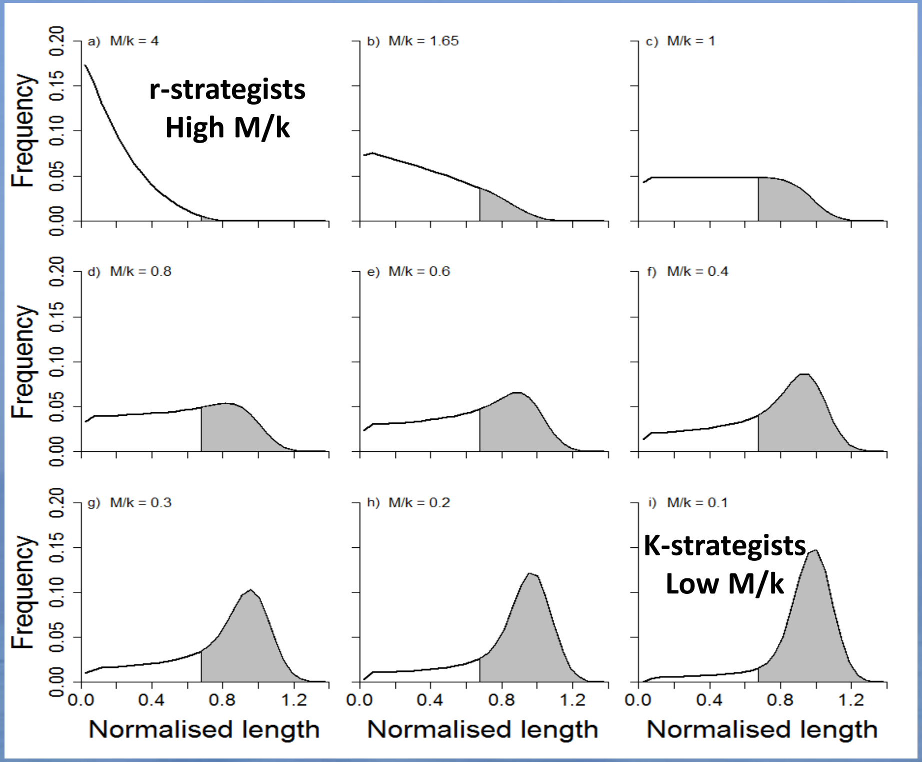
Meta-analysis + Theoretical Development





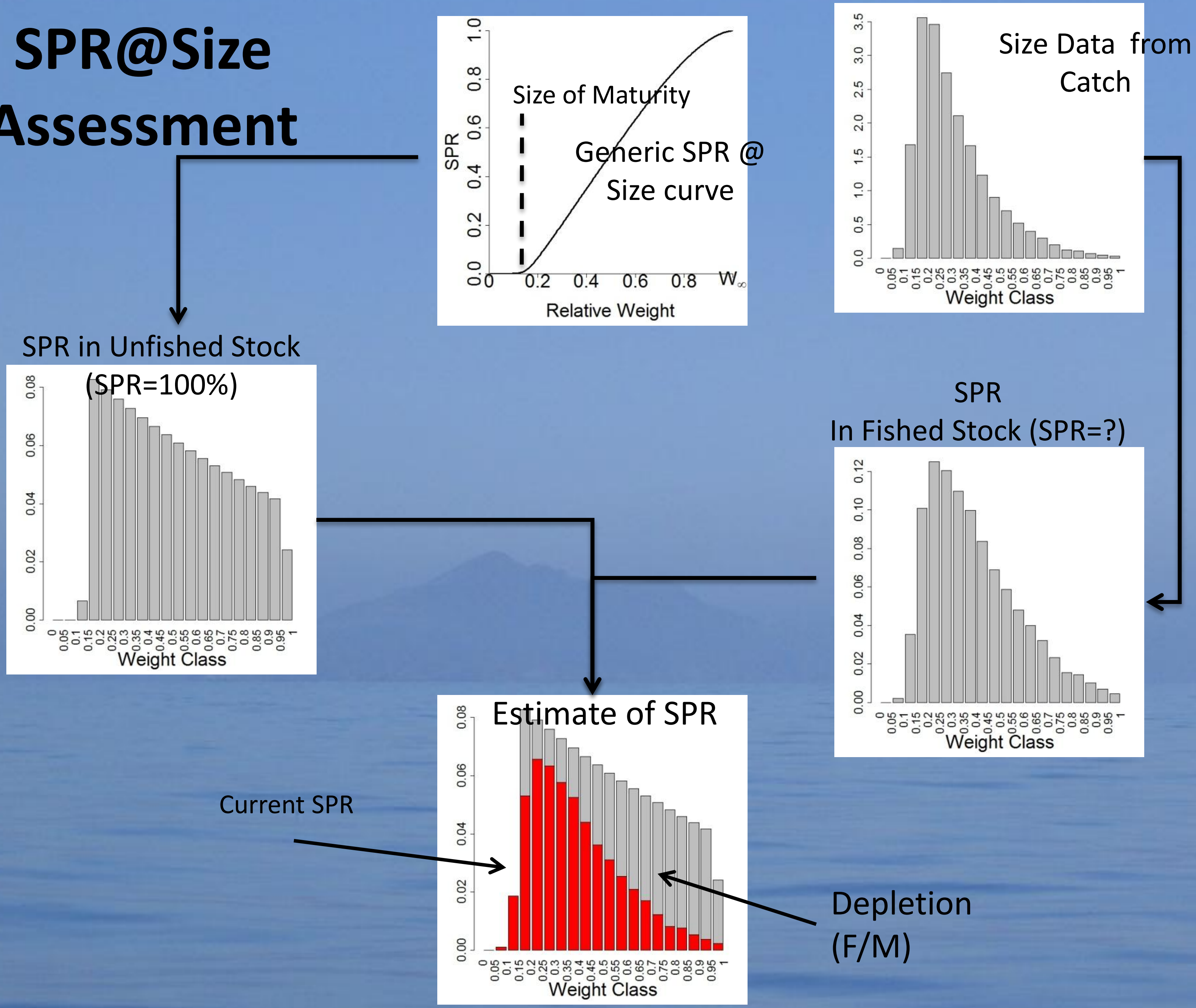
Meta-analysis + Theoretical Development





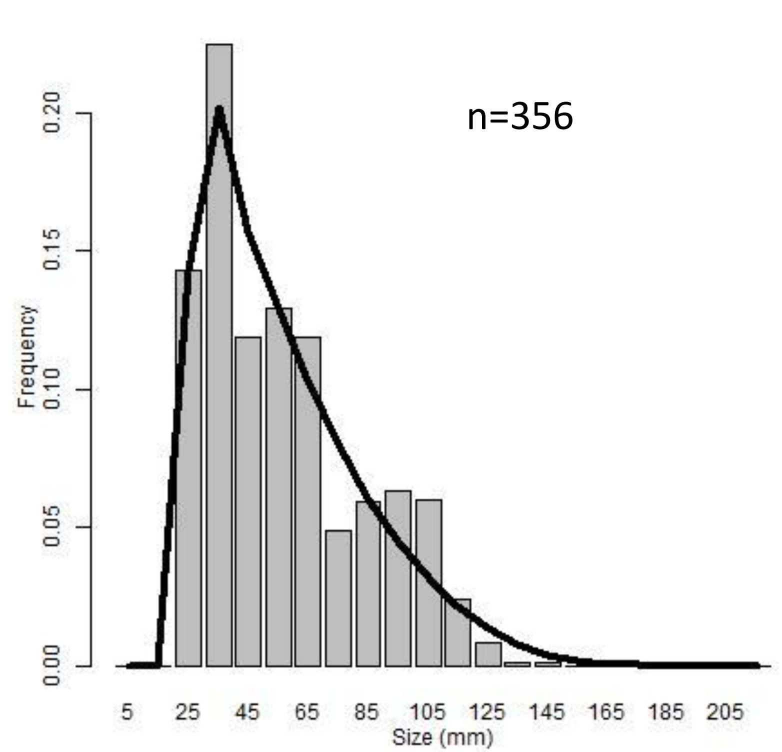
Generic Knowledge from well Studied Species Predicts Size Composition in Unstudied Stocks

SPR@Size Assessment

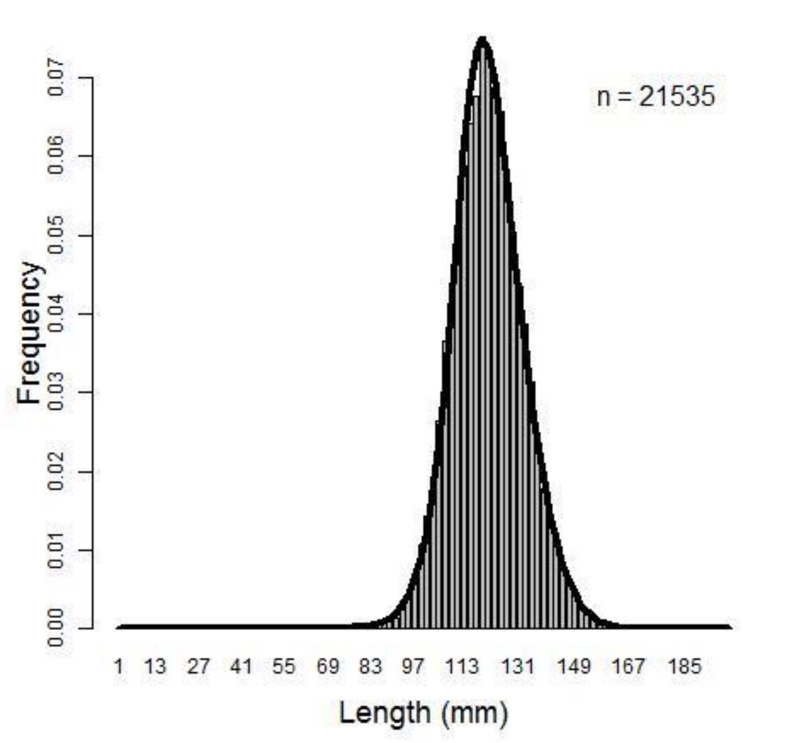


Size-based Stock Assessmment

Indonesian Blue Swimmer Crab



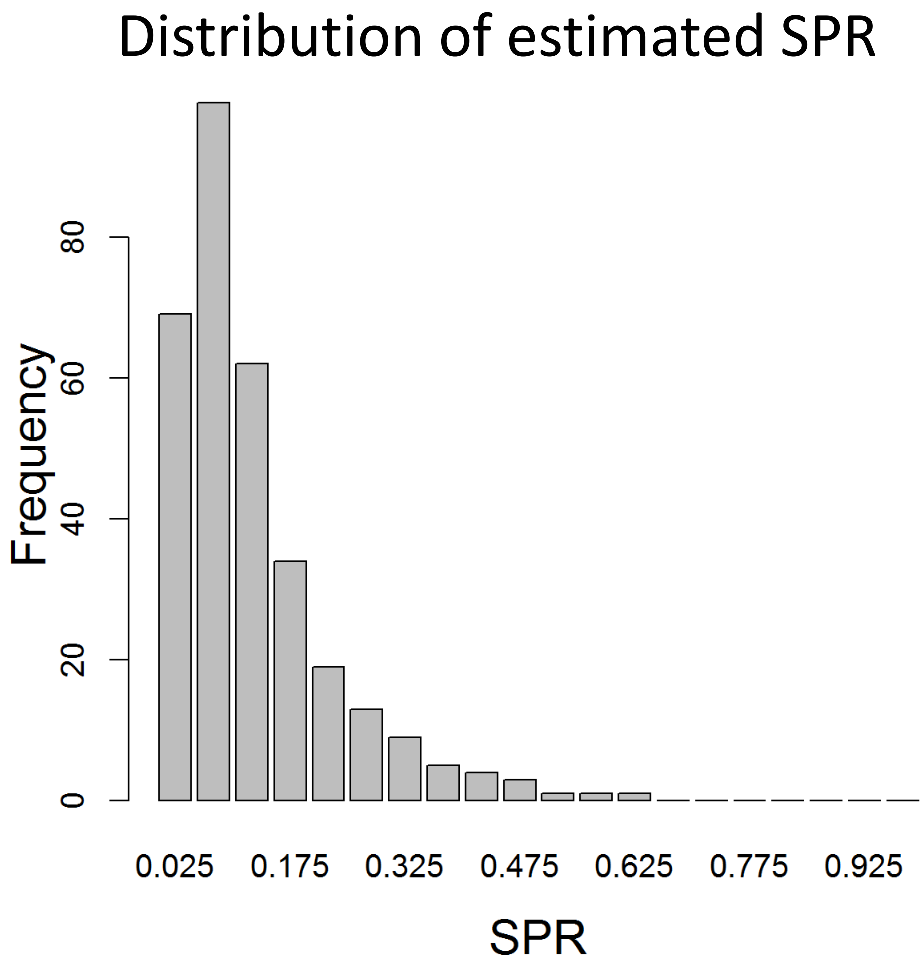
Spanish Razor Clam



SPR = 4.6% F/M = 1.96

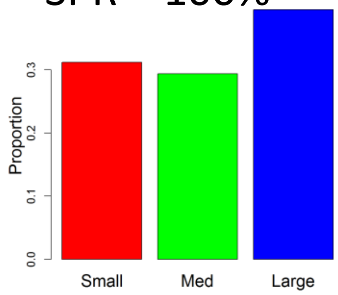
SPR = 45% F/M = 1.58

Port Fairy blacklip

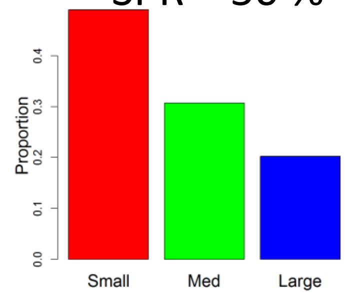


Proportions of By-catch Species in size classes

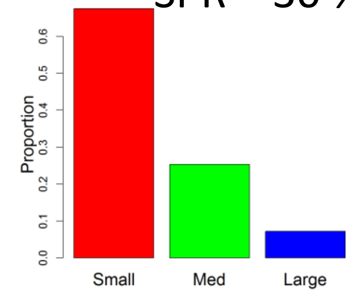
SPR = 100%

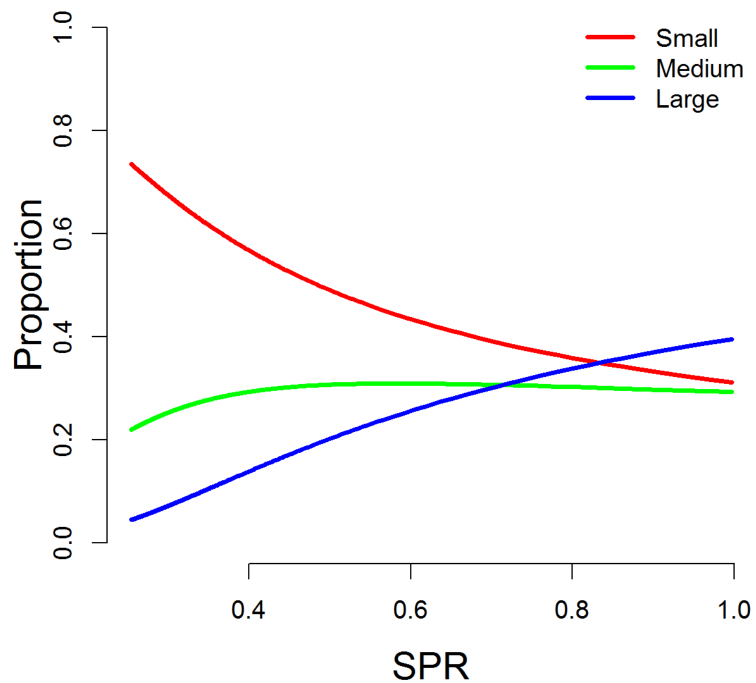


SPR = 50 %



SPR = 30 %





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SPR @ Size Analysis –Triage Equilibrium Assessment	Generic SPR@ Size Curve & Categoric analysis of rudimentary size data	$<SPR_{70\%}$ Requires higher assessment $>SPR_{70\%}$ No action Required
Risk Based Framework	Expert Based	High Risk Ranking Requires higher assessment

Graduated Progression

Increasing Costs & Increasing Precision

Harvest Control Rule

Recommend Biological Catch (RBC)

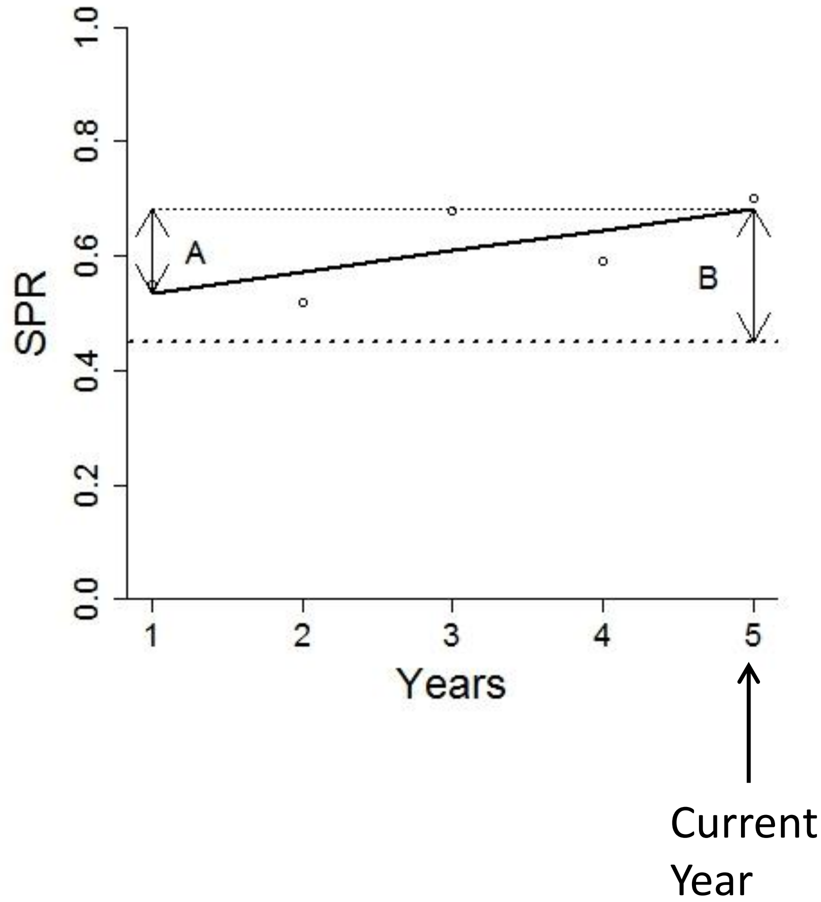
*NewRBC = pastRBC * (1+V)*

$V = k1.A + k2.B$

$A = \mathrm{SPR}_{\mathrm{CUR}} - \mathrm{SPR}_{\mathrm{CUR\text{-}5}}$

$B = \mathrm{SPR}_{\mathrm{CUR}} - \mathrm{SPR}_{\mathrm{TARG}}$

k1 & *k2* responsiveness parameters

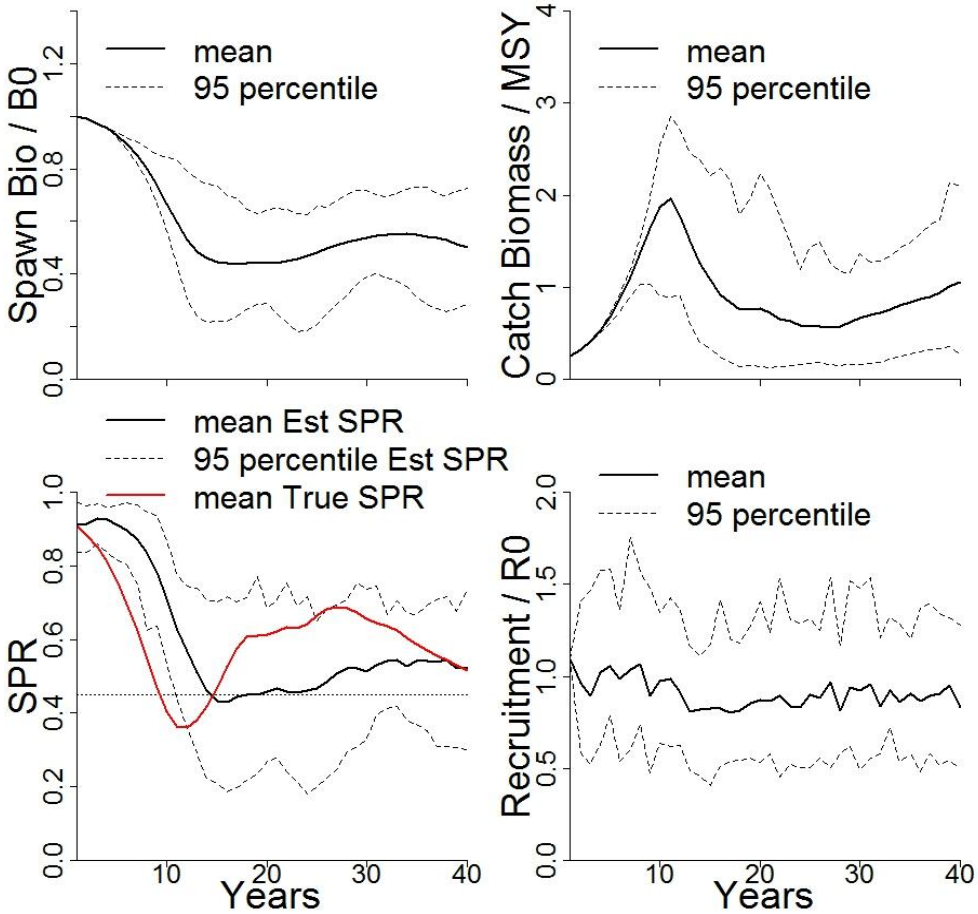


Iterative Catch Adjustments Preliminarily MSEs

30 Iterations
40 years

Low initial *F*
High initial *SPR*

k1 = 0.8
k2 = 0.7



The Risk – Catch – Cost Framework

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SPR @ Size Analysis- basic Equilibrium Assessment	Generic SPR@ Size Curve & Better Quality Size Data	Generic SPR @ Curve assumes worst-case productivity for species
SPR @ Size Analysis –Triage Equilibrium Assessment	Generic SPR@ Size Curve & Categoric analysis of rudimentary size data	$<SPR_{70\%}$ Requires higher assessment $>SPR_{70\%}$ No action Required
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Graduated Progression

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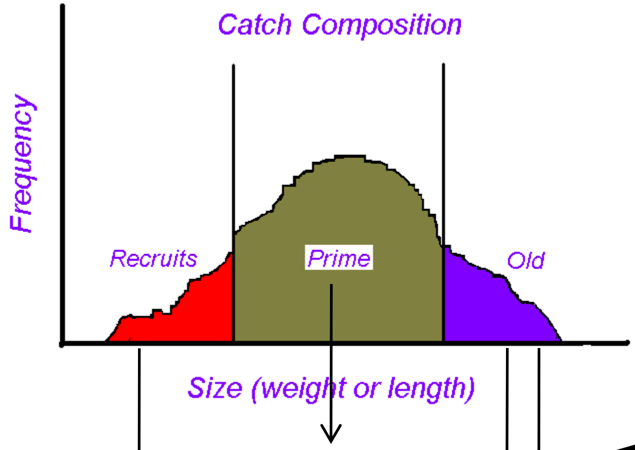
Scale-less Assessment

Local Spawning Potential Ratio

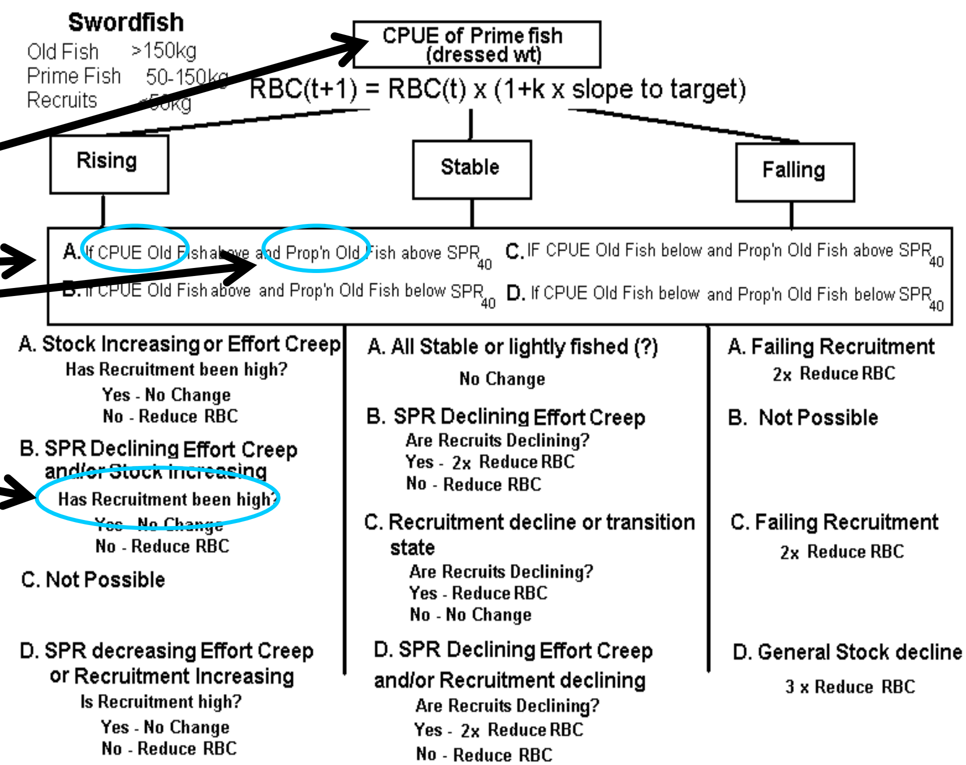


CPUEprime

CPUEold

PropOld

CPUErecruits



Size based CPUE Indicators

Target Level of SPR

Iteratively establish local catch levels

Froese, R. (2004). Keep it simple: three indicators to deal with overfishing. Fish Fish. 5, 86-89.

Prince, J. D. et al. (2011). A simple cost-effective and scale-less empirical approach to harvest strategies. *ICES J. Mar. Sci.* 68: 947-960.

Layers of Assessment	Data Requirements	Risk Management
Quantitative Stock Assessment Biomass Modeling	Catch Rate or Survey Time Series Data with: SPR@ Size Curve curve estimated & High Quality Size & Other Data	Quantitatively estimated BMSY, $B_{opt.}$, $SPR_{opt.}$ targets & risk
SPR @ Size Decision Tree Dynamic Pool Assessment	Catch Rate Data with: SPR@ Size Curve curve estimated & High Quality Size Data	Incremental catch adjustment around $SPR_{50\%}$ Size & CPUE Targets Dynamic assessment more accurate, less precautionary more catch
SPR @ Size Analysis – advanced Equilibrium Assessment	SPR@ Size Curve curve estimated & High Quality Size Data	Incremental catch adjustment around $SPR_{50\%}$ Size Target.
SPR @ Size Analysis- basic Equilibrium Assessment	Generic SPR@ Size Curve & Better Quality Size Data	Generic SPR @ Curve assumes worst-case productivity for species
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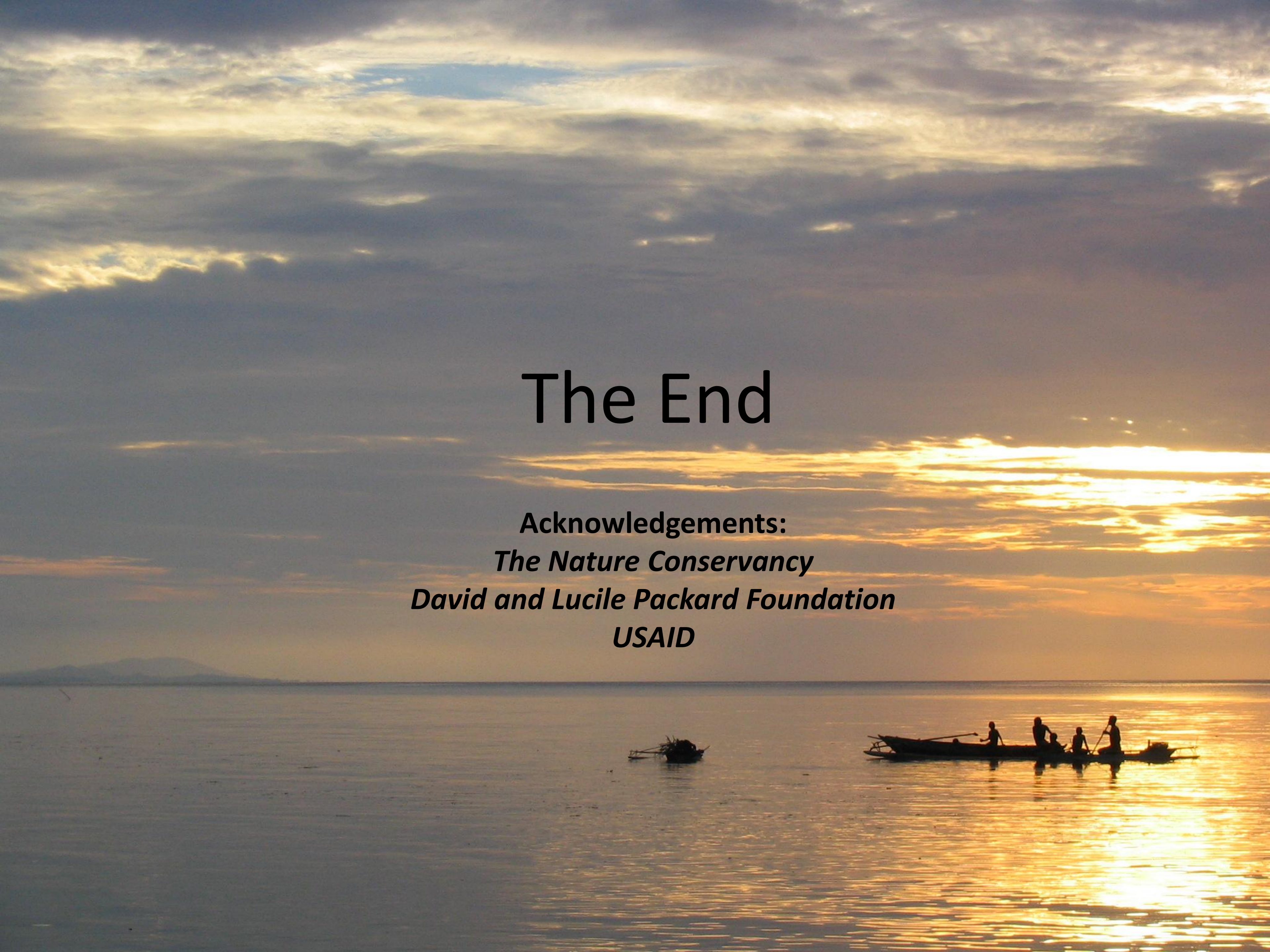
Increasing Costs & Increasing Precision

The Risk – Catch – Cost Framework



The End

Acknowledgements:
The Nature Conservancy
David and Lucile Packard Foundation
USAID

Recommendations for estimating total mortality rate from cohort sliced catch at length data

Matthew W. Smith, Amy Y. Then, Lisa E. Ailloud, Kristen Omori, Gina M. Ralph and John M. Hoenig

VIMS | William & Mary
Virginia Institute of Marine Science

- Don’t

Presentation outline

- Cohort Slicing
  - Effect on catch at age
  - Need for a plus group
  - Implications for catch-curve analysis

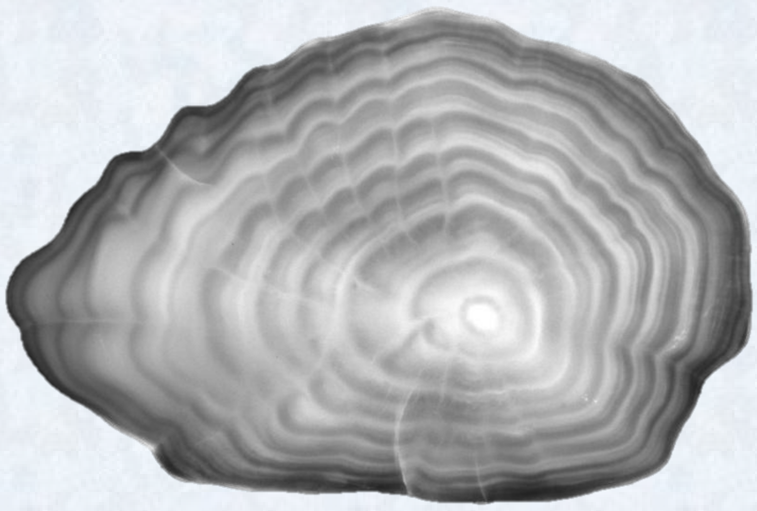
- Simulation Design
  - Method for evaluating performance

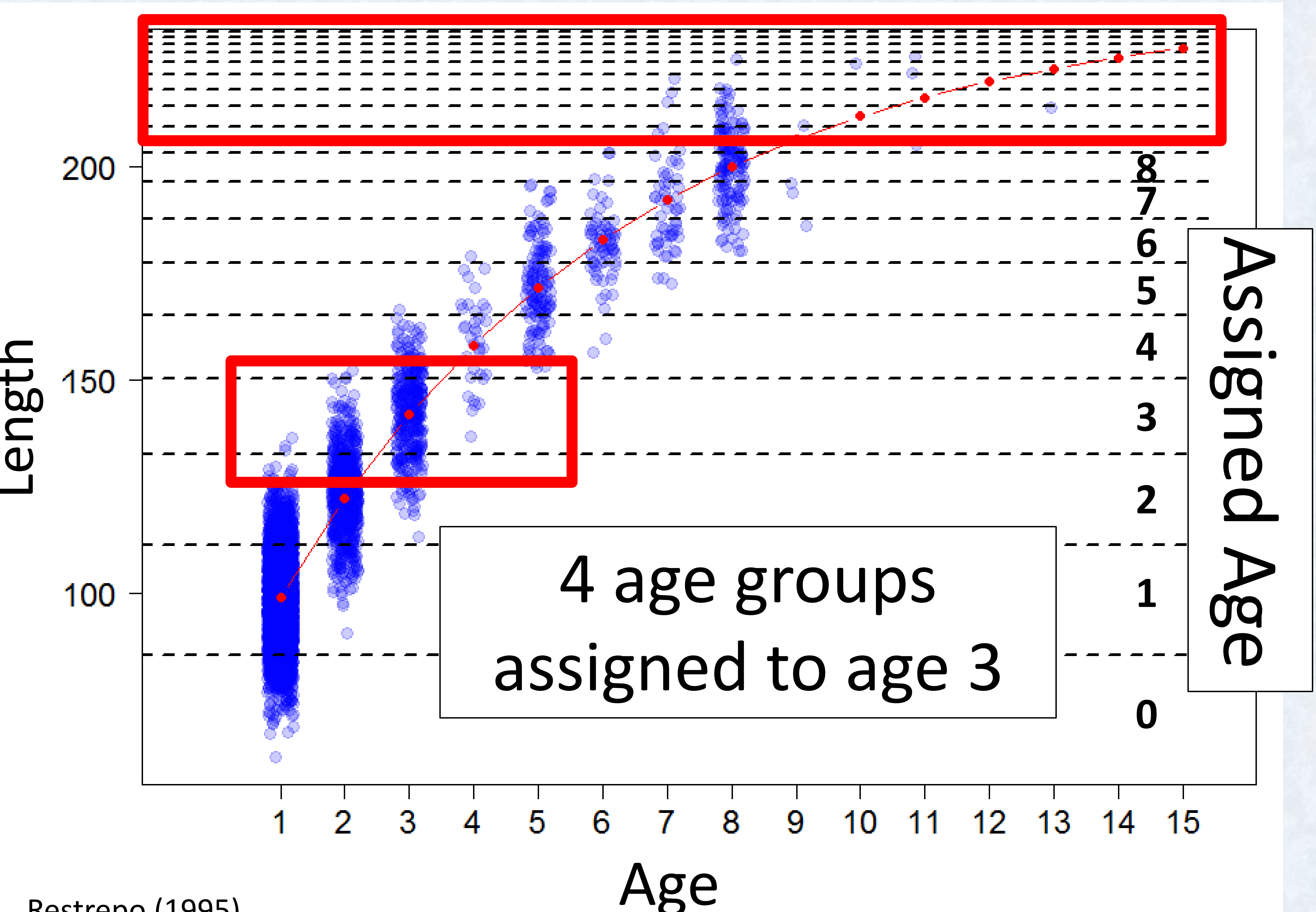
- Results & Conclusions

Data poor assessment

- We Have
  - Length

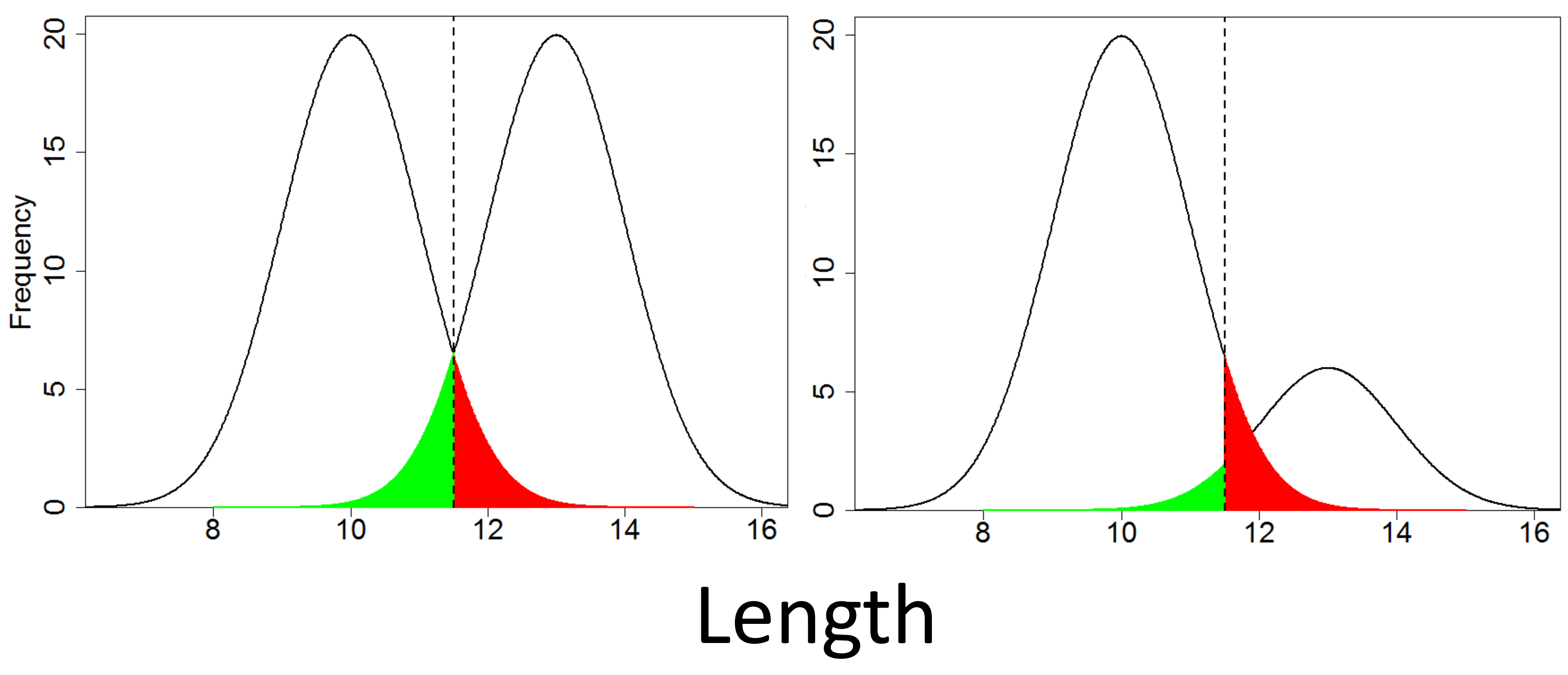
- We Want
  - Age

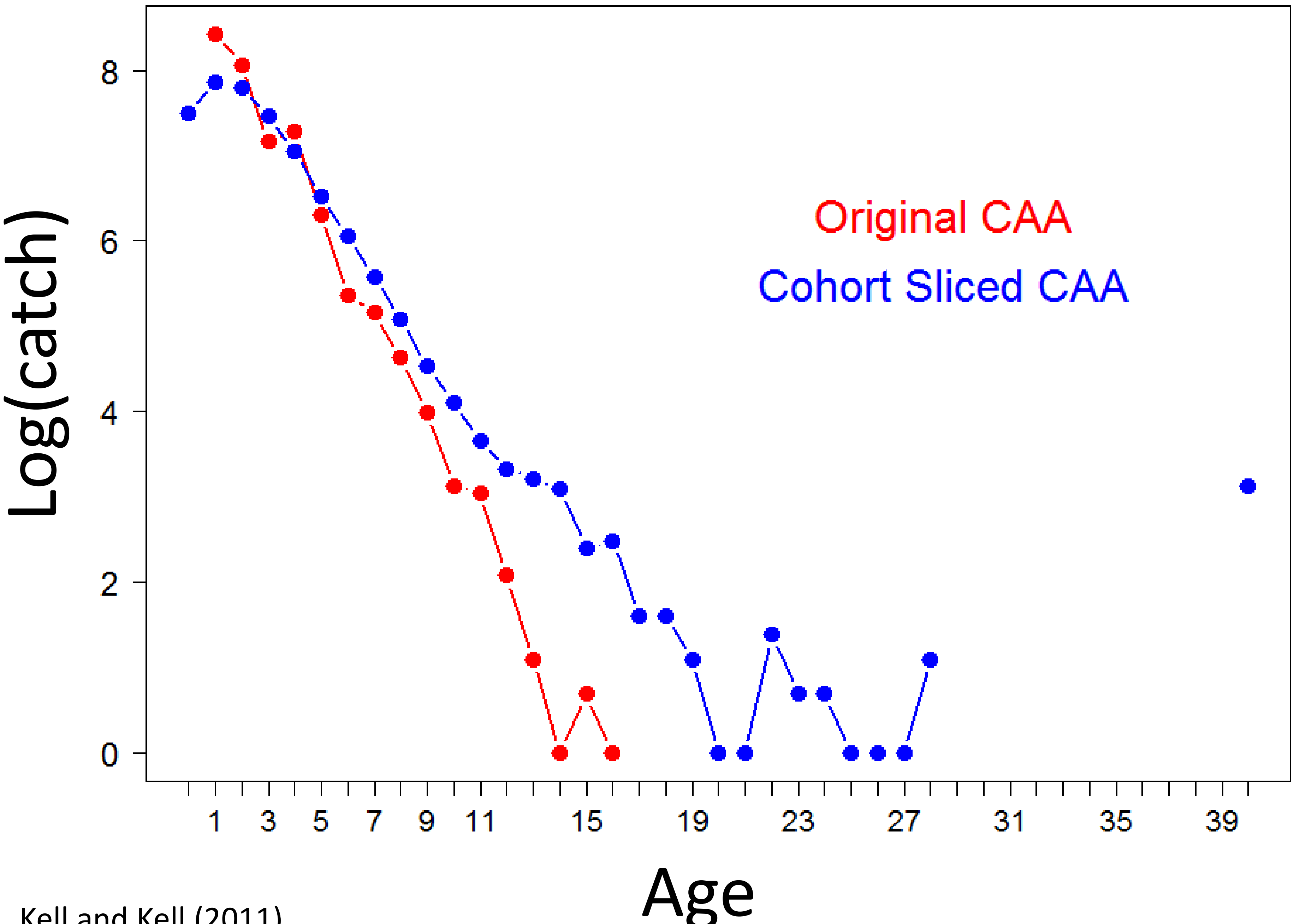




Restrepo (1995)

Misclassified age bias





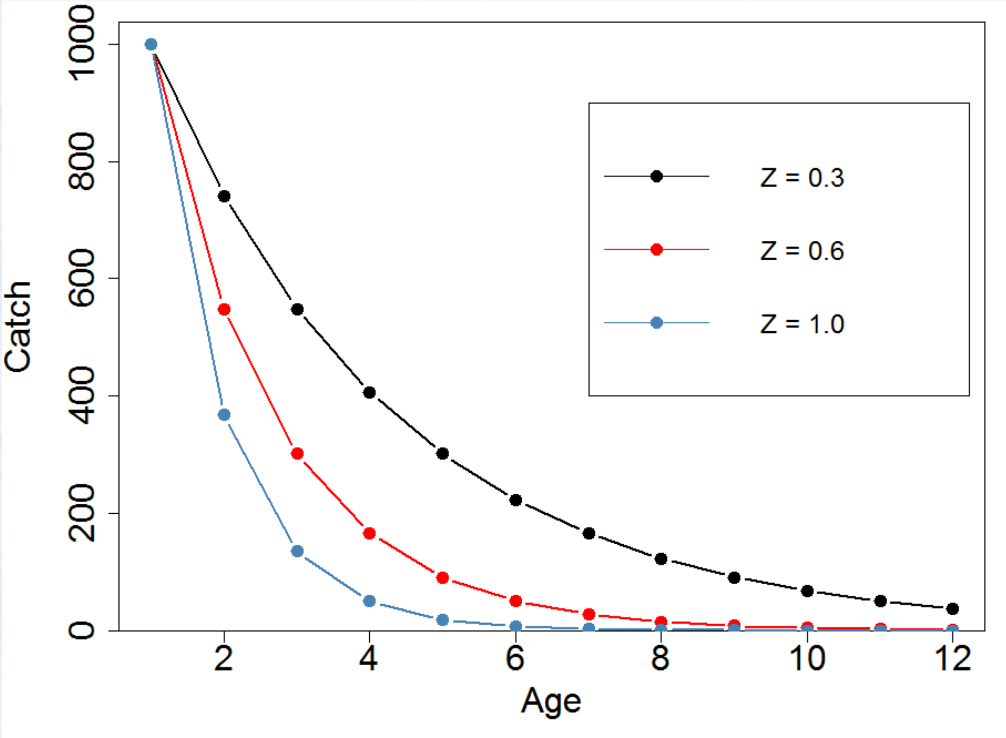
Kell and Kell (2011)

Study Questions

- What are the accuracy & precision of total mortality rate estimators?
- What conditions produce large errors?
- Do any methods perform better in general?

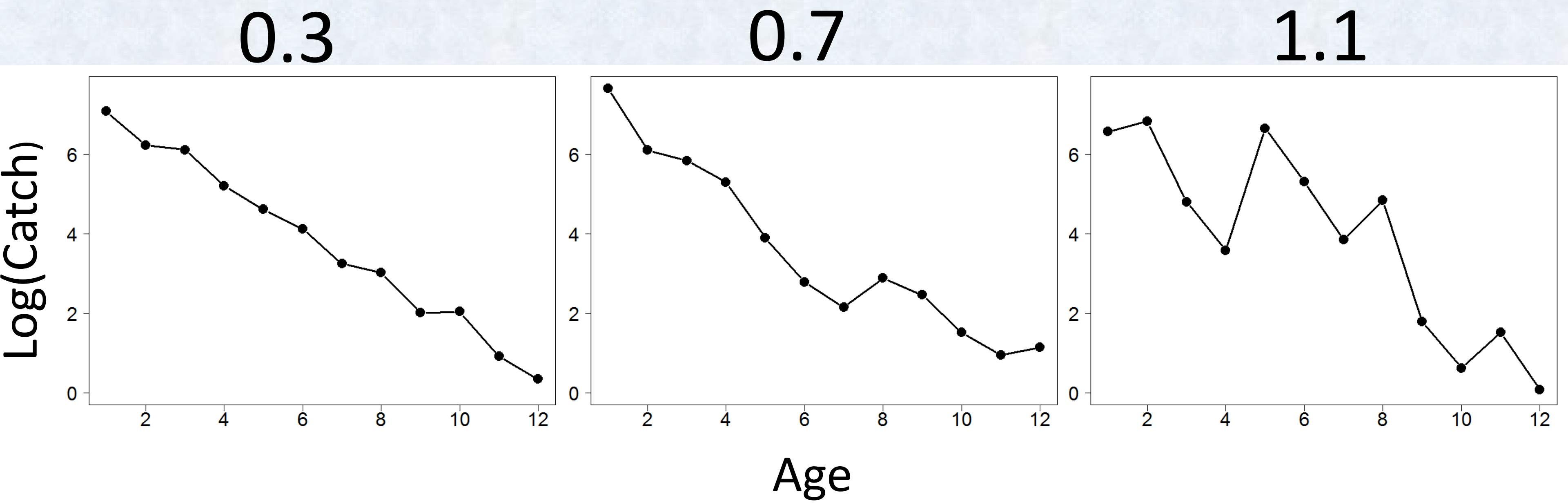
Simulation

- Monte Carlo simulation
  - Z = 0.3, 0.6 or 1.0 $^{-yr}$



Simulation

- Monte Carlo simulation
  - Z = 0.3, 0.6 or 1.0 $^{-yr}$
  - Recruitment error = 0.3, 0.7 or 1.1 *



* Myers et al. 1995

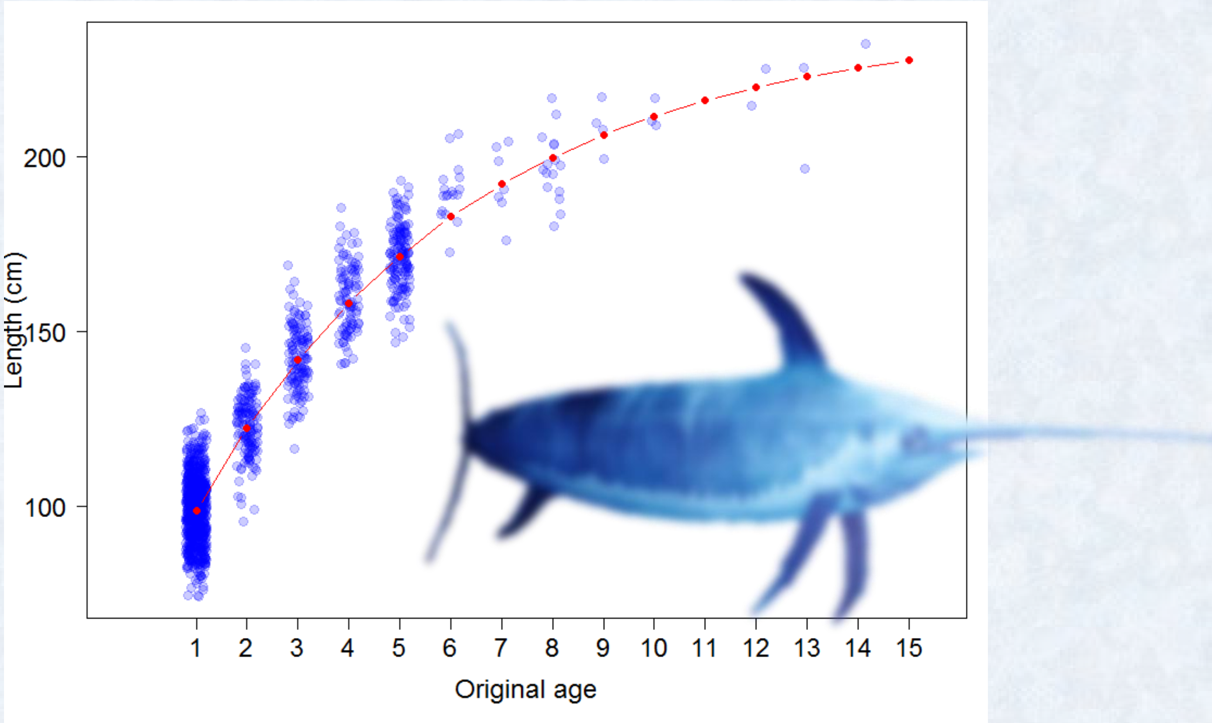
Simulation

- Monte Carlo simulation
  - Z = 0.3, 0.6 or 1.0 $^{-yr}$
  - Recruitment error = 0.3, 0.7 or 1.1
  - Swordfish growth model *

L_{∞} = 238 cm

t_o = -1.404

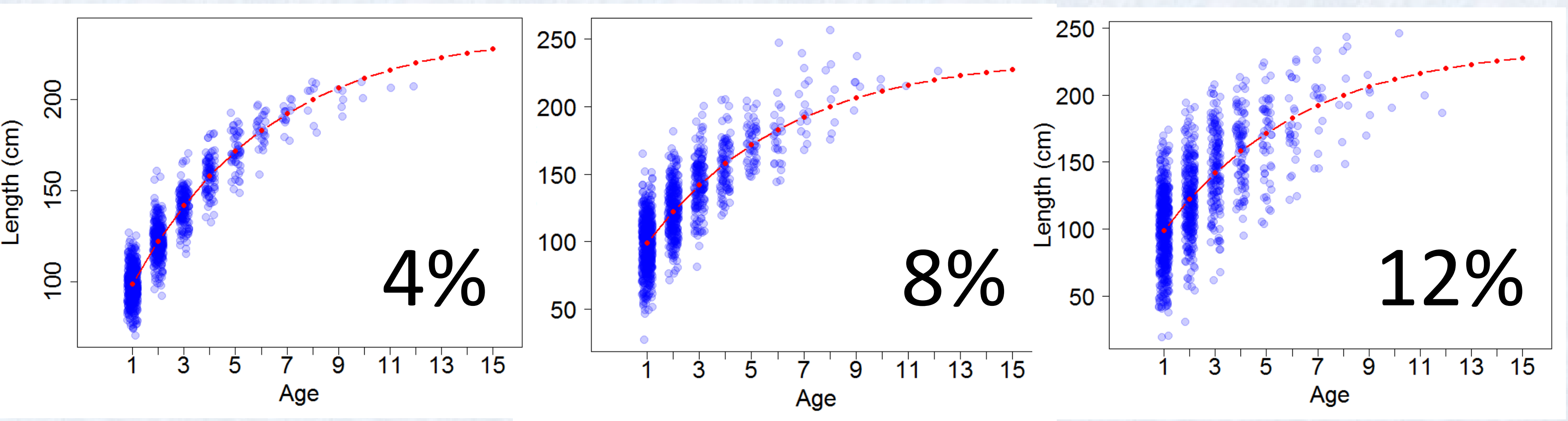
K = 0.185



* Tserpes & Tsimenides (1995)

Simulation

- Monte Carlo simulation
  - $Z = 0.3, 0.6 \text{ or } 1.0^{-yr}$
  - Recruitment error = 0.3, 0.7 or 1.1
  - Swordfish growth model
  - Length at age error = 4, 8 or 12 % L_{∞} *



* Amy Then personal communication

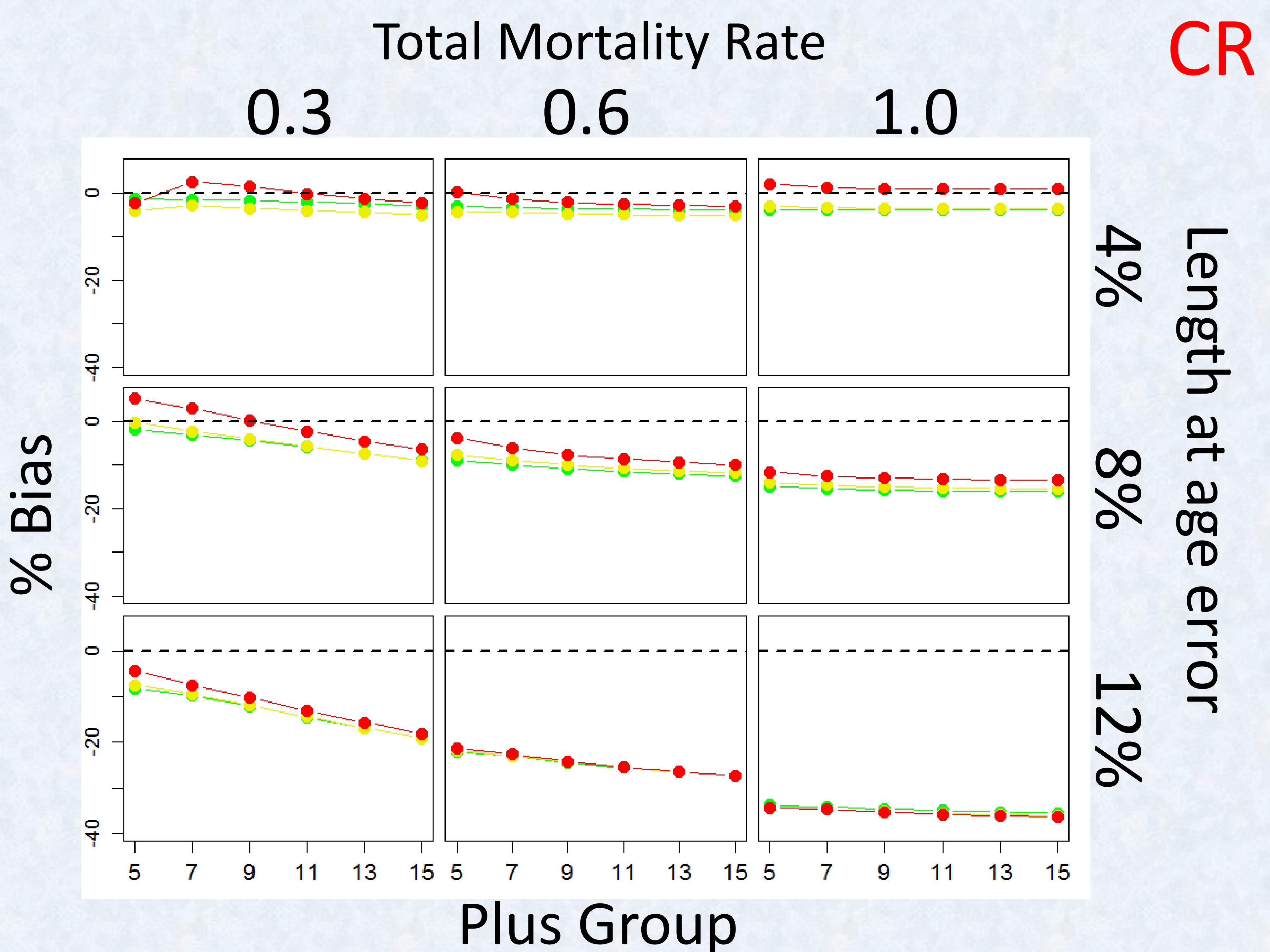
Simulation

- Generate 1000 populations

- Chapman & Robson (Right Censored) ǂ
  - Peak plus *
- Weighted regression (w_i)
  - Peak *
- Regression (Not Shown)

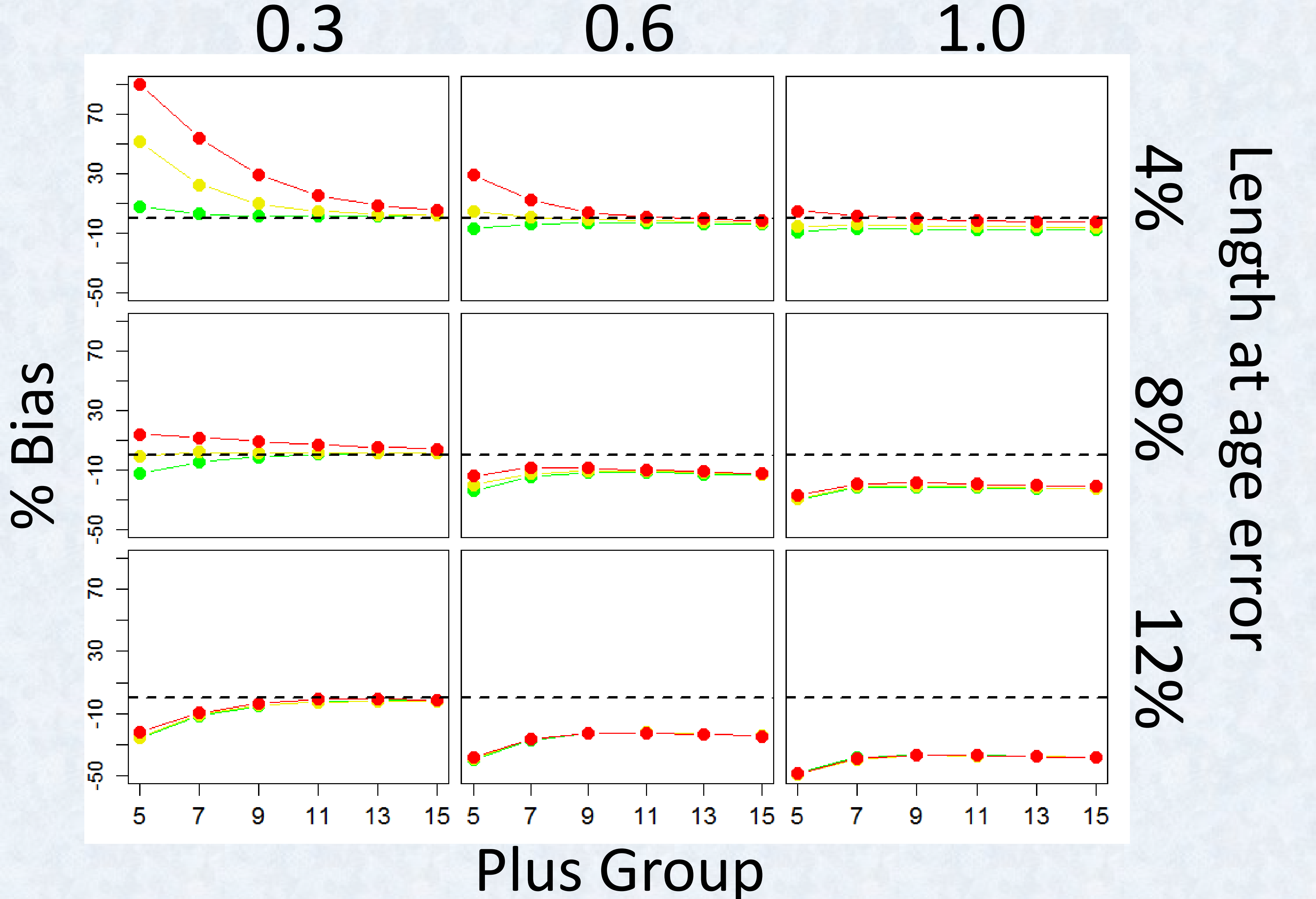
- Plus groups 5, 7, 9, 11, 13 & 15

ǂ Robson and Chapman (1961)
* Smith et al. (2012)


Total Mortality Rate
CR
0.3
0.6
1.0
% Bias
Length at age error
4%
8%
12%
Plus Group
0
-20
-40
5
7
9
11
13
15

Total Mortality Rate

WR



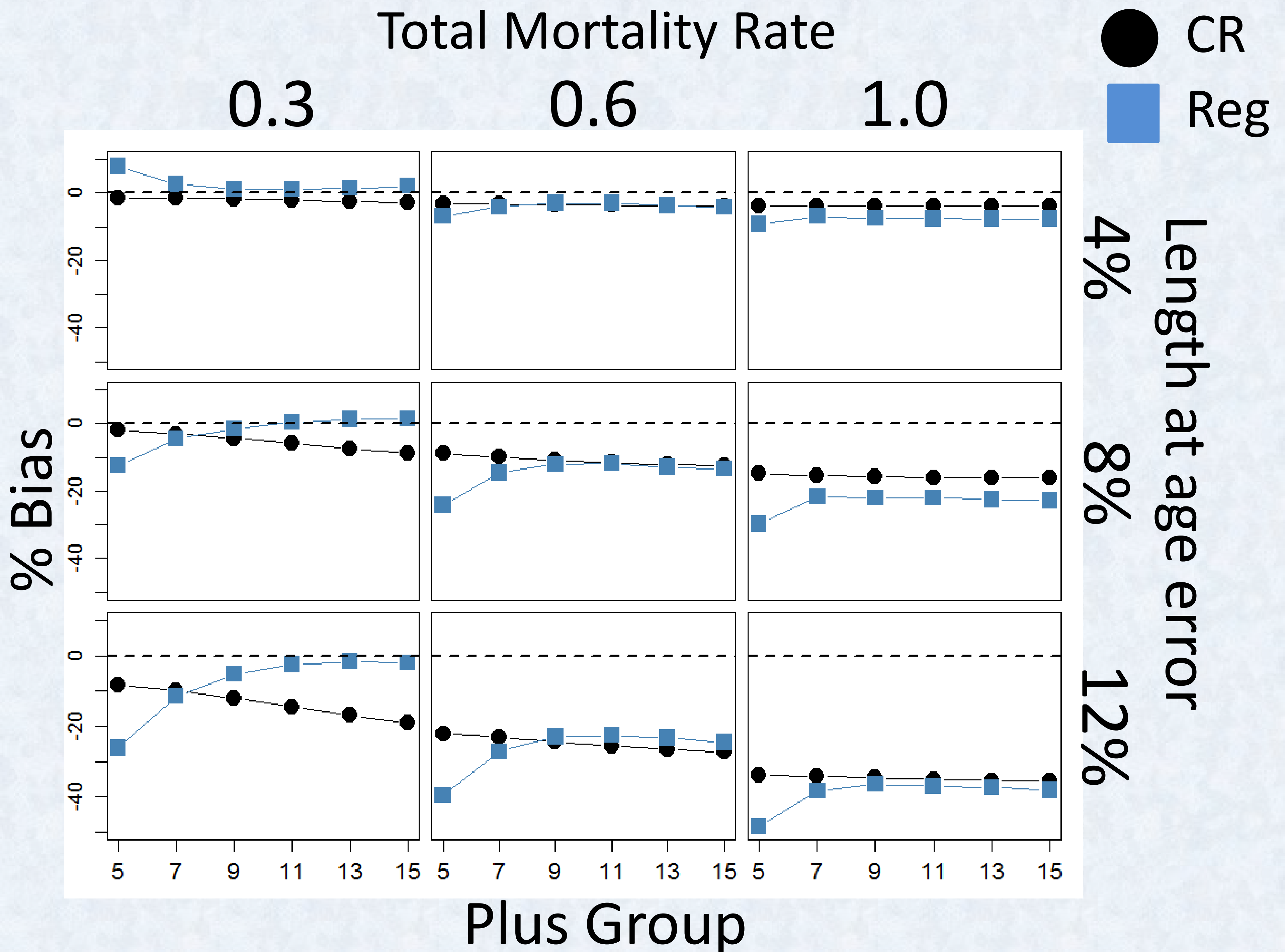
Comparative Results

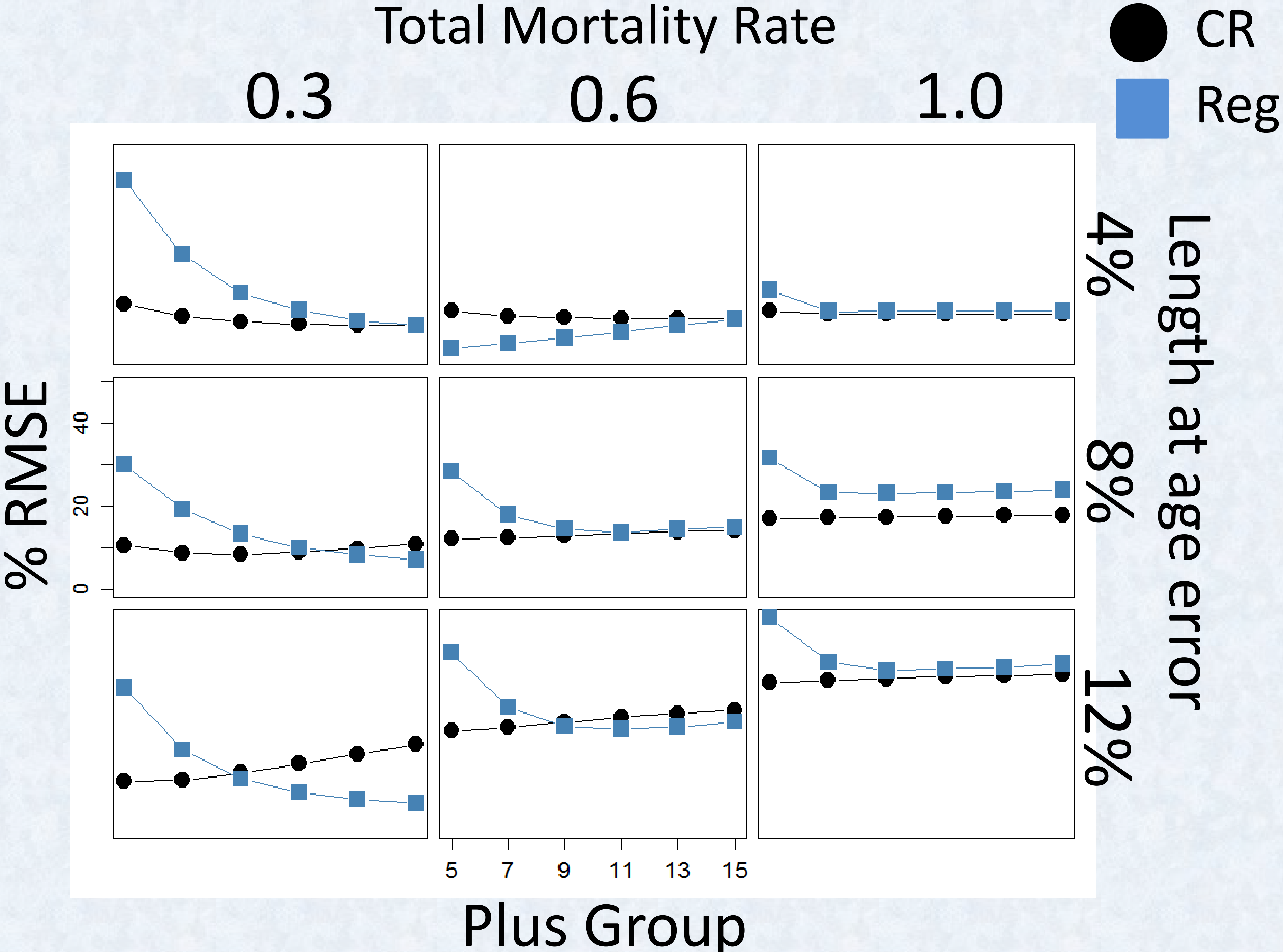
- Compare CR and WR

● - Chapman Robson

■ - Weighted Regression

Only showing low recruitment error (0.3) scenarios


Total Mortality Rate
CR
Reg
0.3
0.6
1.0
4%
8%
12%
Length at age error
% Bias
Plus Group
0
-20
-40
5
7
9
11
13
15



Total Mortality Rate
0.3
0.6
1.0
CR
Reg
% RMSE
0
20
40
Length at age error
4%
8%
12%
5
7
9
11
13
15
Plus Group

Conclusions

- Cohort slicing shifts catch to older age groups
- For Catch curve analysis
  1. CR method, with young plus group, preferred
  2. If *Z* and length-at-age error are high, estimate may have significant negative bias (20 – 40%)
  3. Otherwise, bias low < 10%
- Given Z from cohort slicing, → check bias by simulation
- Best plus group depends on method. (For VPA?)

Thank You

- NMFS population dynamics fellowship

- Funding from NMFS Southeast Fisheries Science Center through the Cooperative Institute for Marine and Atmospheric Studies, University of Miami

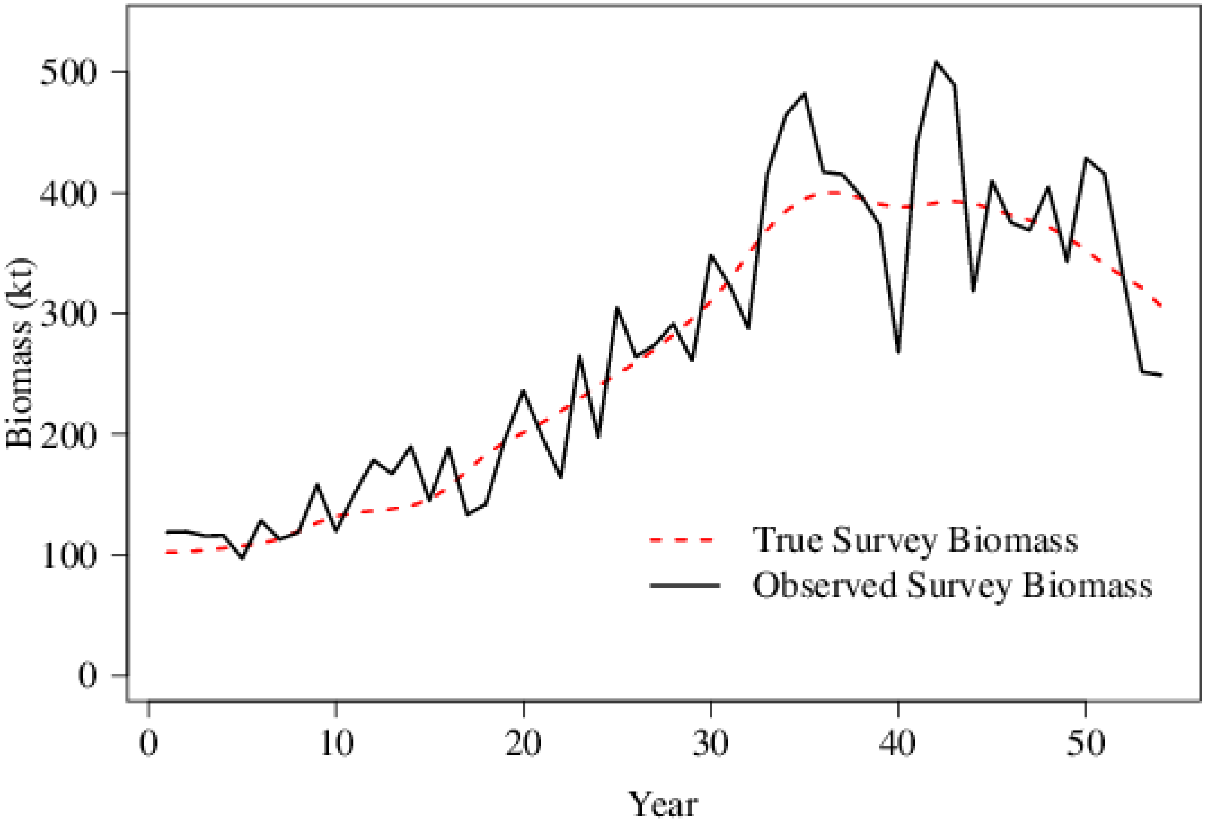
Random walk models for estimating abundance from a series of resource surveys

Paul Spencer, Grant Thompson, Jim Ianelli
and Jon Heifetz

National Marine Fisheries Service
Alaska Fisheries Science Center
Seattle, WA

A signal to noise problem

1) We want to remove the observation error
2) We do not want to "smooth" the underlying "signal"
3) The last data point is most important (for management)



State-space representation

$$z_t = f(z_{t-1}) + a_t$$

$$y_t = g(z_t) + e_t$$

z = Population size (unobserved)

Y = Survey index

Process and observation errors are represented by *a* and *e*, respectively

One example of special interest is the random walk model with uncorrelated noise (RWPUN ; Stockhausen and Fogarty (2007))

$$z_t = z_{t-1} + a_t$$

$$y_t = z_t + e_t$$

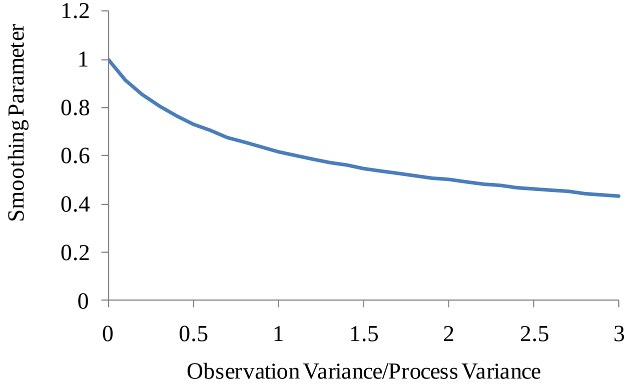
Exponential smoothing

$$\hat{z}_t = \hat{y}_t(1) = (\alpha)y_t + (1-\alpha)\boxed{\left[\alpha y_{t-1} + \alpha(1-\alpha)y_{t-2} + \alpha(1-\alpha)^2 y_{t-3} + \ldots\right]}$$

This is a Kalman Filter with constant observation error variance

For the random walk model with constant variances:

1) α = f(process variance/observation variance) (Pennington 1986, Thompson)
2) Exponential smoothing is the optimal forecast method (Pennington 1986)



Random effects model

Considers the process errors as “random effects” (i.e., drawn from a overlying distribution) and integrated out of the likelihood.

The state-space random walk plus noise can be formulated as a random effects model.

Differences between the Kalman Filter and Random Effects models

1) Exact solution (KF) vs fine numerical approximation (RE)

2) Different statistical approaches –Bayesian updating equations vs hierarchical random effects model

3) The random effects model can provide more flexibility with non-linear processes and non-normal error structures

ARIMA modeling notation

ARIMA models (auto-regressive integrated moving average)

$$y_t = \alpha_1 y_{t-1} + \ldots \alpha_p y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-q} \ldots \beta_q \varepsilon_{t-q}$$

α -- p auto-regressive parameters
β -- q moving average parameters
ε -- random errors

The data can also be differenced *d* times to achieve stationarity.

The structure of the ARIMA model is referred to (*p,d,q*).

The random walk plus uncorrelated noise (RWPUN) model is a (0,1,1) ARIMA model.

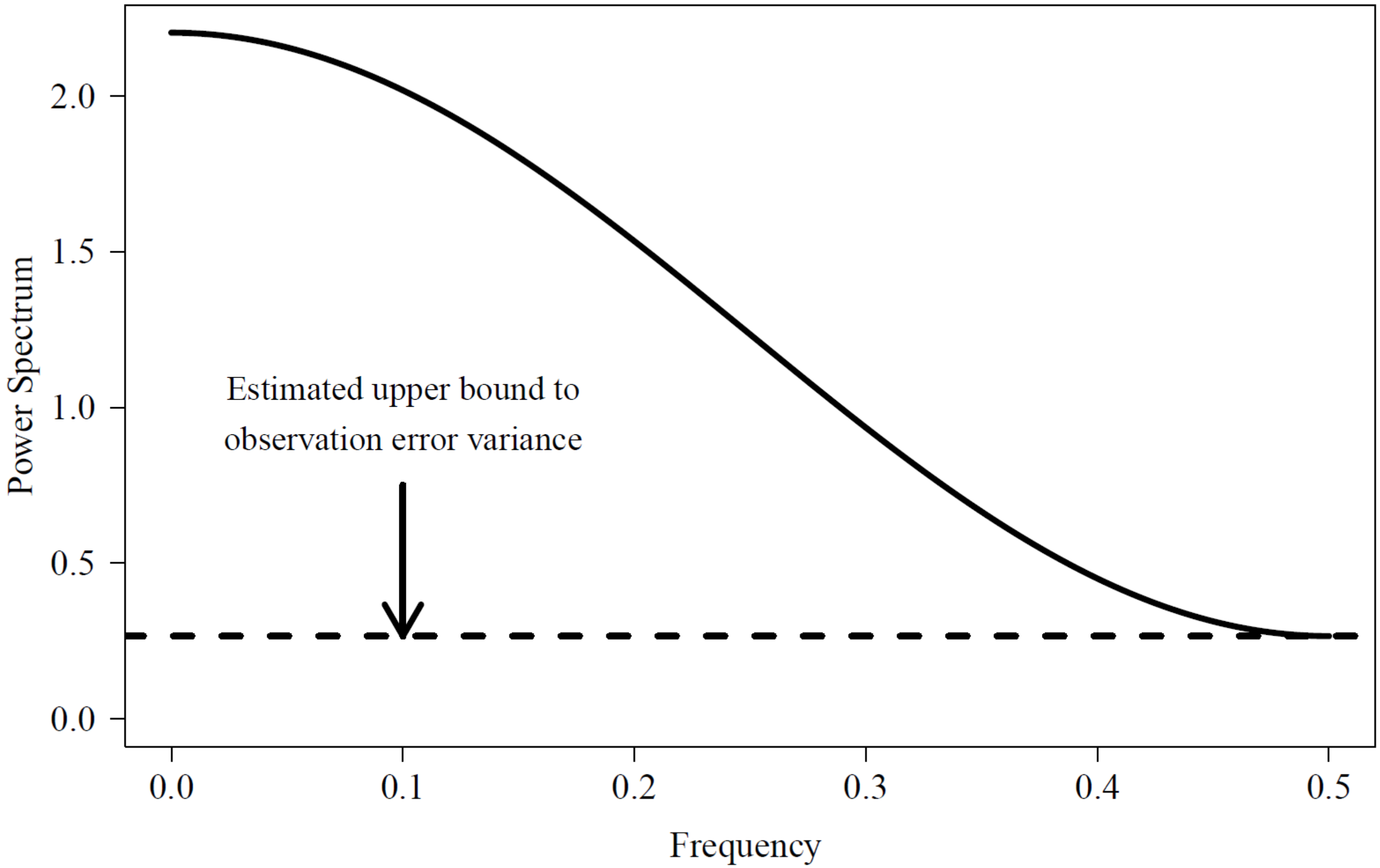
Models where we do not assume the underlying state is a random walk

Stockhausen and Fogarty (2007) applied a smoothing procedure based on generalized ARIMA models:

1) Fit a series of candidate ARIMA models to survey data.
2) Use model selection criteria to identify the best *p,d,q* ARIMA model.
3) Estimate the power spectrum for the ARIMA process, which gives an estimate of the upper bound of the observation variance (K^*).
4) From ARIMA parameters and K^*, estimate smoothing weights to be used in a symmetric moving average.

Important point – the Q dimension we estimate for the observed data must be equal or greater than (P + D).

Example estimation of power spectrum and *K**



Conditions for applying generalized ARIMA smoothing

1) A time series long enough to get reliable parameter estimates (Stockhausen and Fogarty suggest 40 years)

2) Estimated Q >= (P+D)

3) Not white noise

4) Other (stationarity of autoregressive parameters, invertability, variance reduction)

Description of Simulation Study

Objective: How does generalized ARIMA modeling compare to exponential smoothing and random effects model?

Two life-history types: Pacific ocean perch (long-lived) and walleye pollock (shorter-lived)

Recent population:

Increasing
Flat
Decreasing

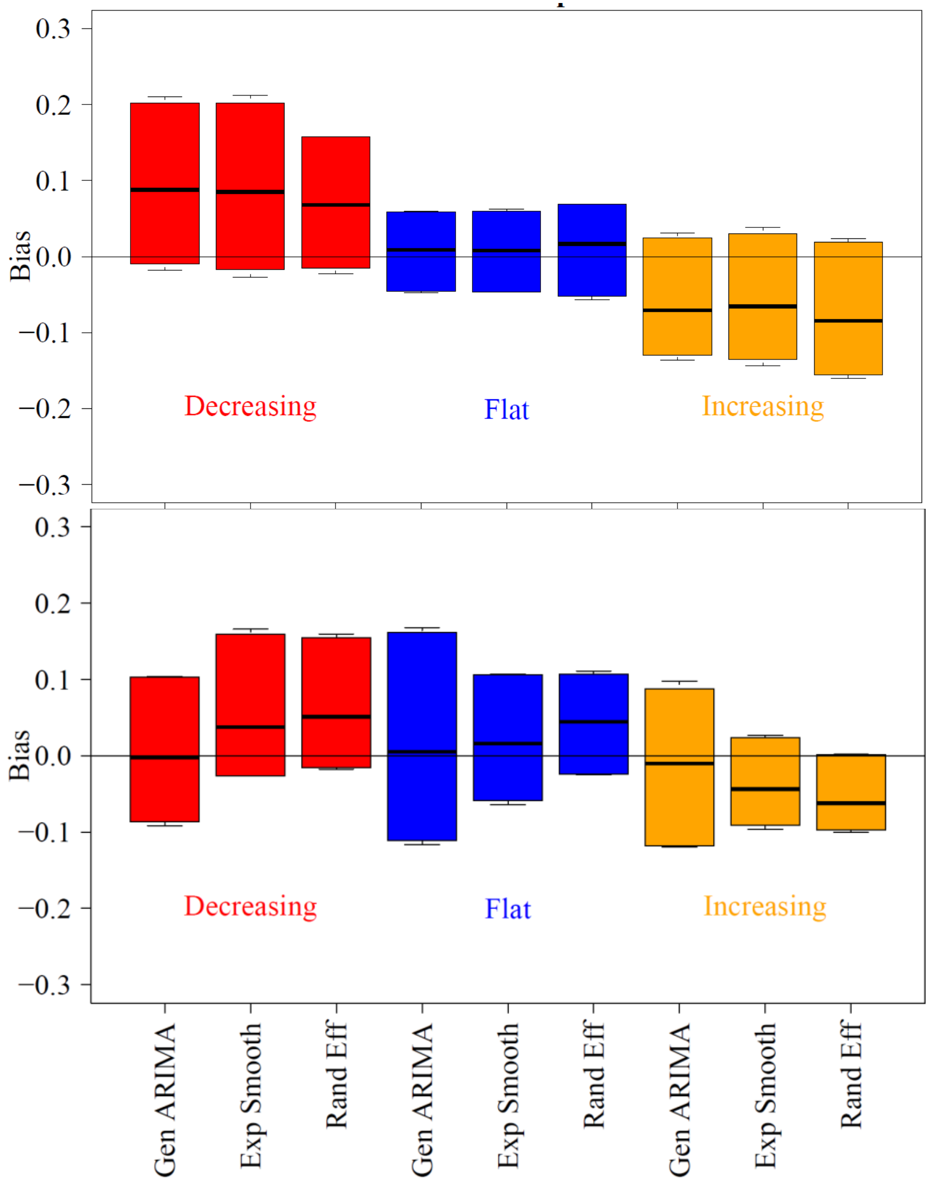
Process errors – two levels of recruitment variance (sigma_r)

Observation errors – two levels for CVs of survey biomass estimates

Three levels of survey frequency

Classification of ARIMA model results

Bias and variance of relative errors of recent smoothed biomass estimate



Best ARIMA model is (0,1,1)

Generalized ARIMA model performs about as well as exponential smoothing and random effects models

Best ARIMA model is not (0,1,1)

Generalized ARIMA modeling reduces mean bias, but can increase variance relative to other methods

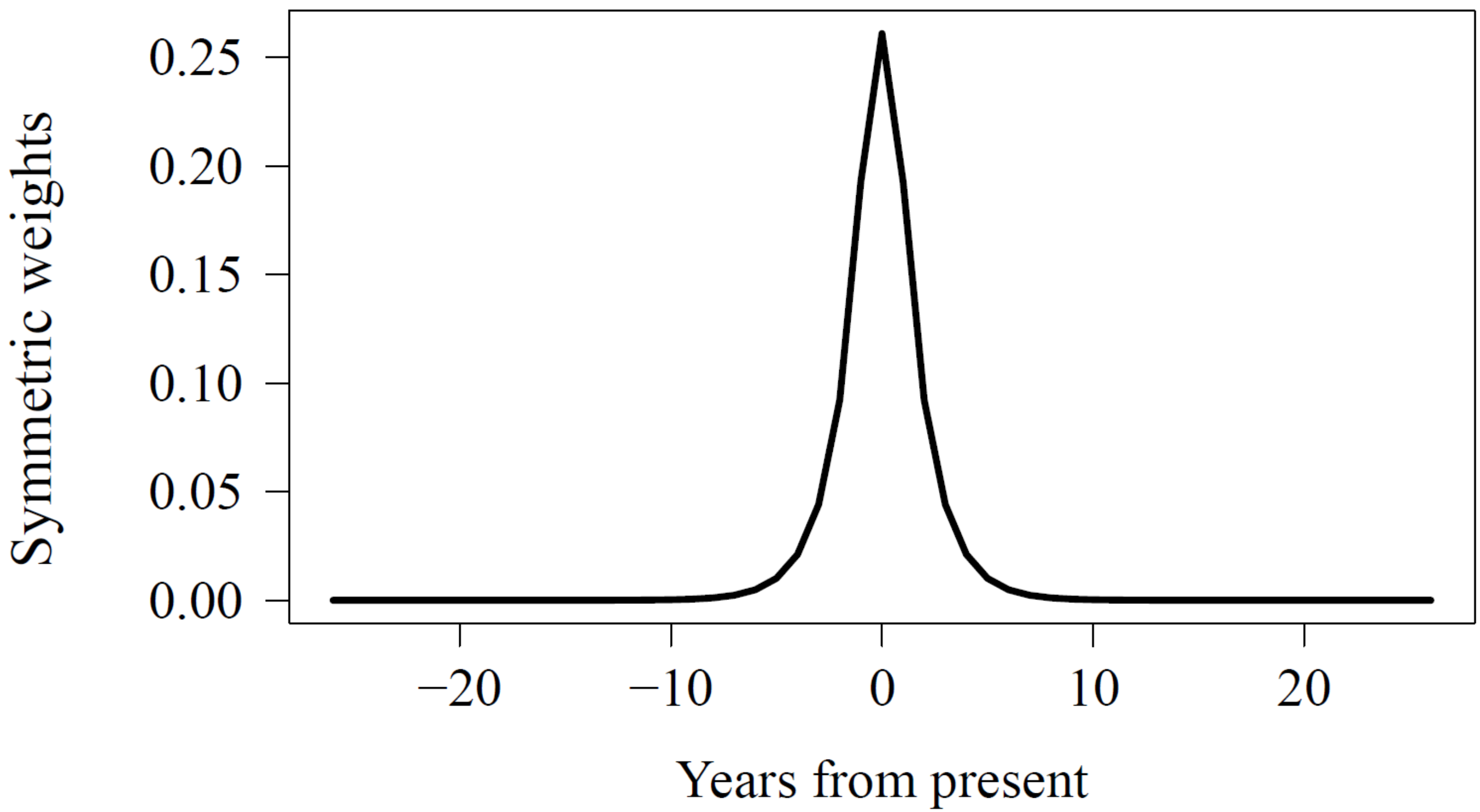
Conclusions

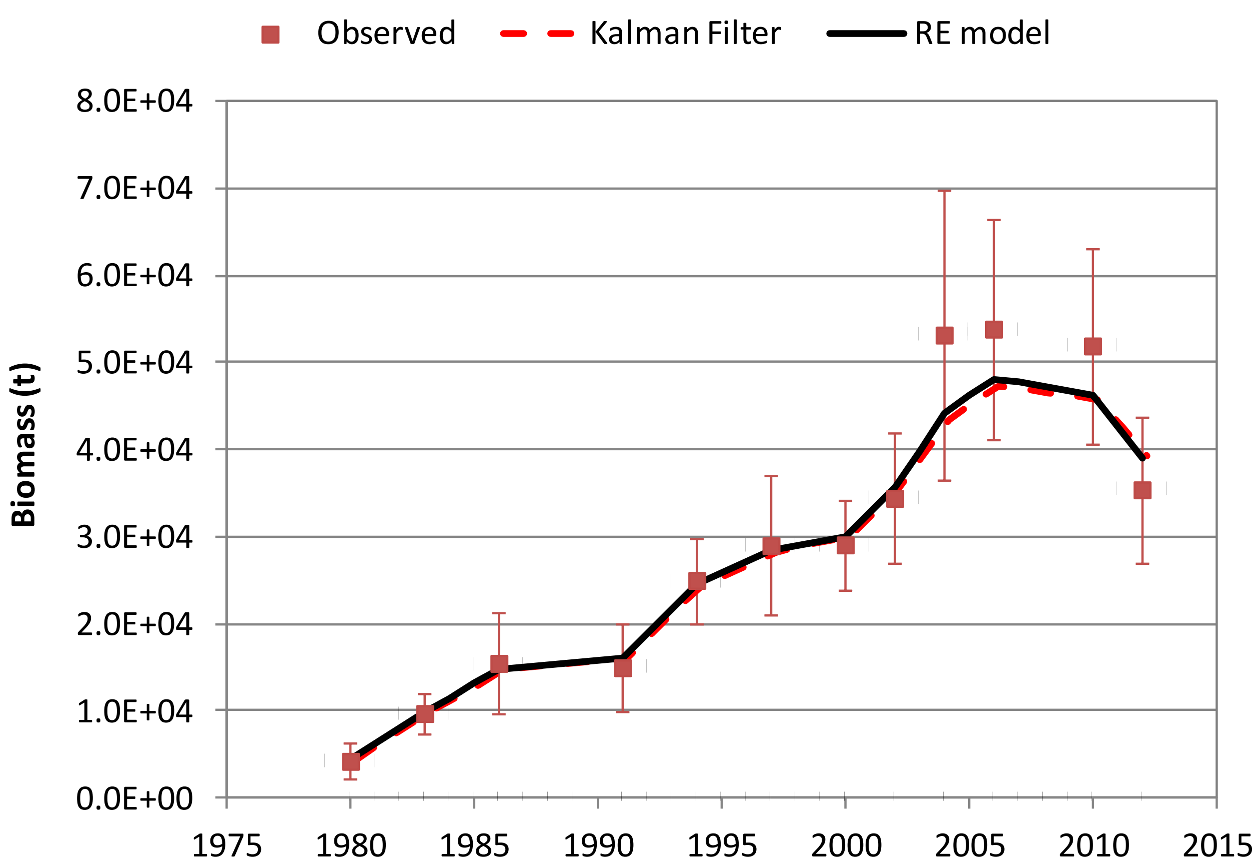
1) The Random Walk model described many of our datasets. For these cases, the three smoothing methods perform similarly.

2) Some cases may not be conducive to generalized ARIMA smoothing.

3) If the best ARIMA model is not ARIMA (0,1,1) model, then generalized ARIMA smoothing could reduce the bias but may increase the variance of the estimated error.

Example of symmetric smoothing weights





Observed
Kalman Filter
RE model
Biomass (t)
8.0E+04
7.0E+04
6.0E+04
5.0E+04
4.0E+04
3.0E+04
2.0E+04
1.0E+04
0.0E+00
1975
1980
1985
1990
1995
2000
2005
2010
2015

Classification of linear models for survey time series (considered by Alaska Fisheries Science Center)

Estimation of state dynamics?

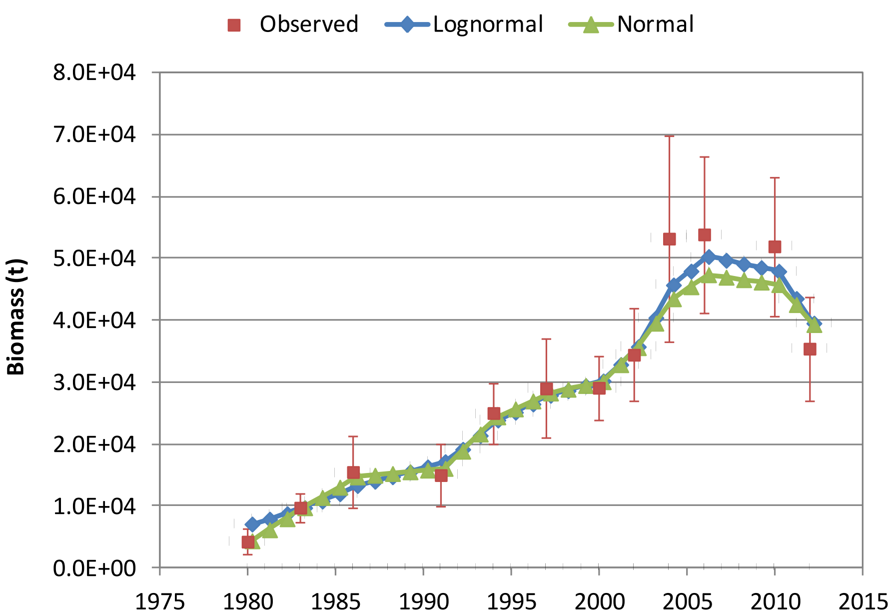
Assumed constant observation errors?	yes	no
no		Random Effects model Kalman Filter
yes	Generalized ARIMA modeling	Exponential weighting/Kalman filter/ARIMA (0,1,1)

A random walk Kalman filter

1) Measurement error can differ over time
2) Observations may not be evenly spaced

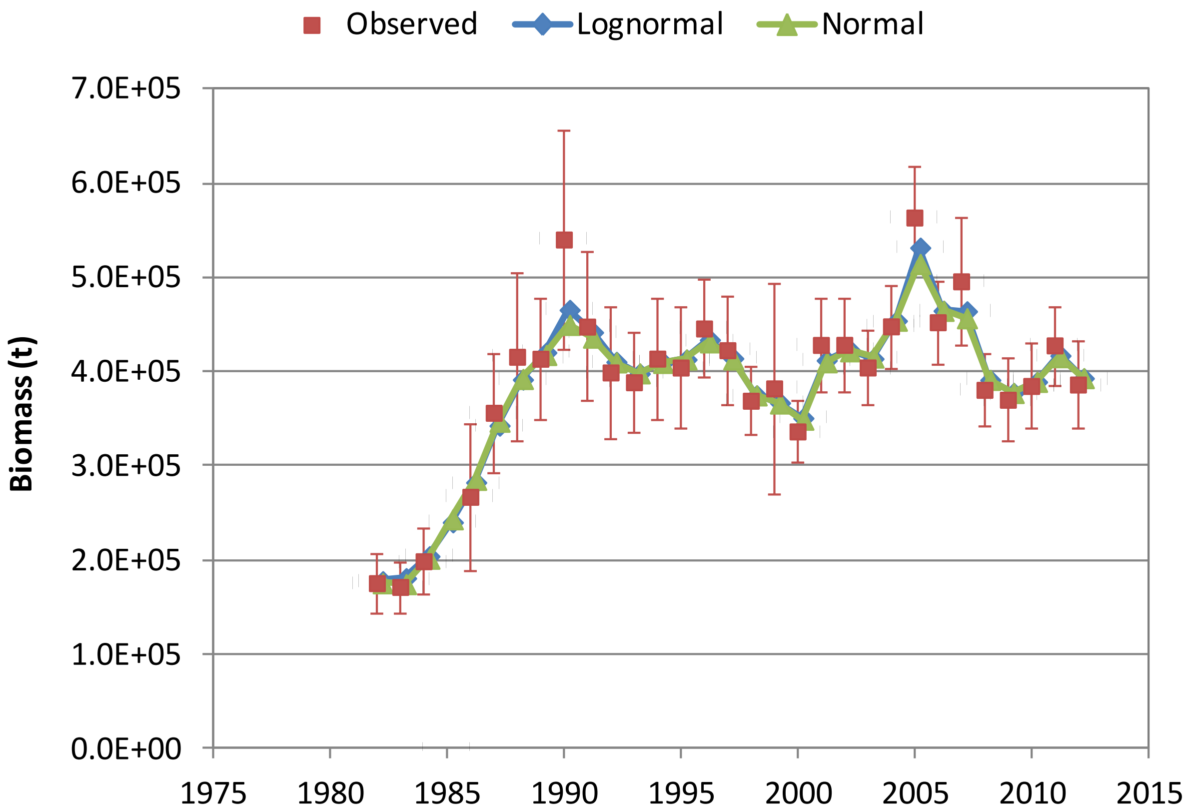
$$X_t = X_{t-1} + \eta_{t-1} \qquad \eta_{t-1} \sim N(0, \sigma^2)$$ State equation

$$Y_t = X_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, SE_t^2)$$ Observation equation

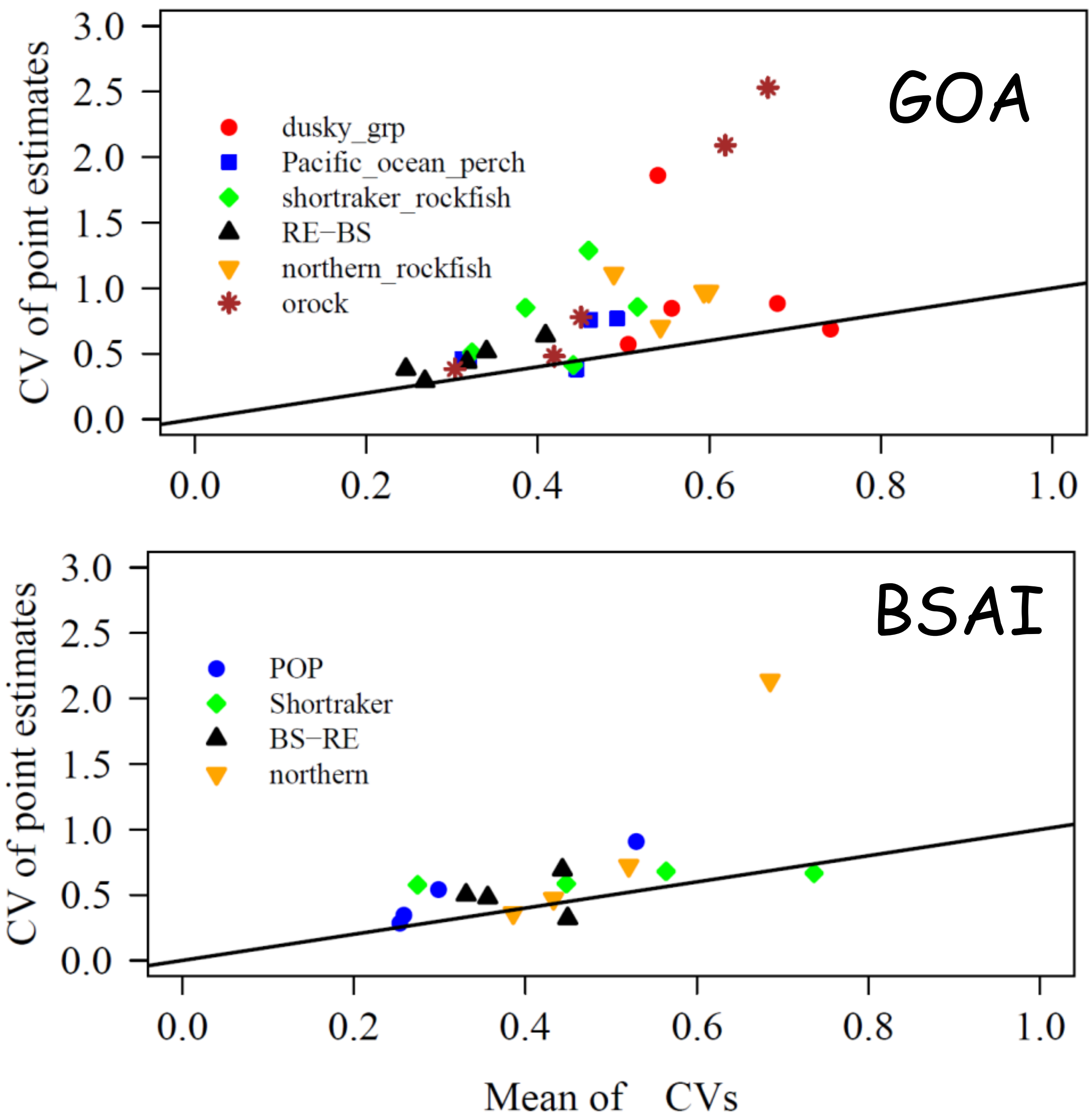


Example application to AI skates

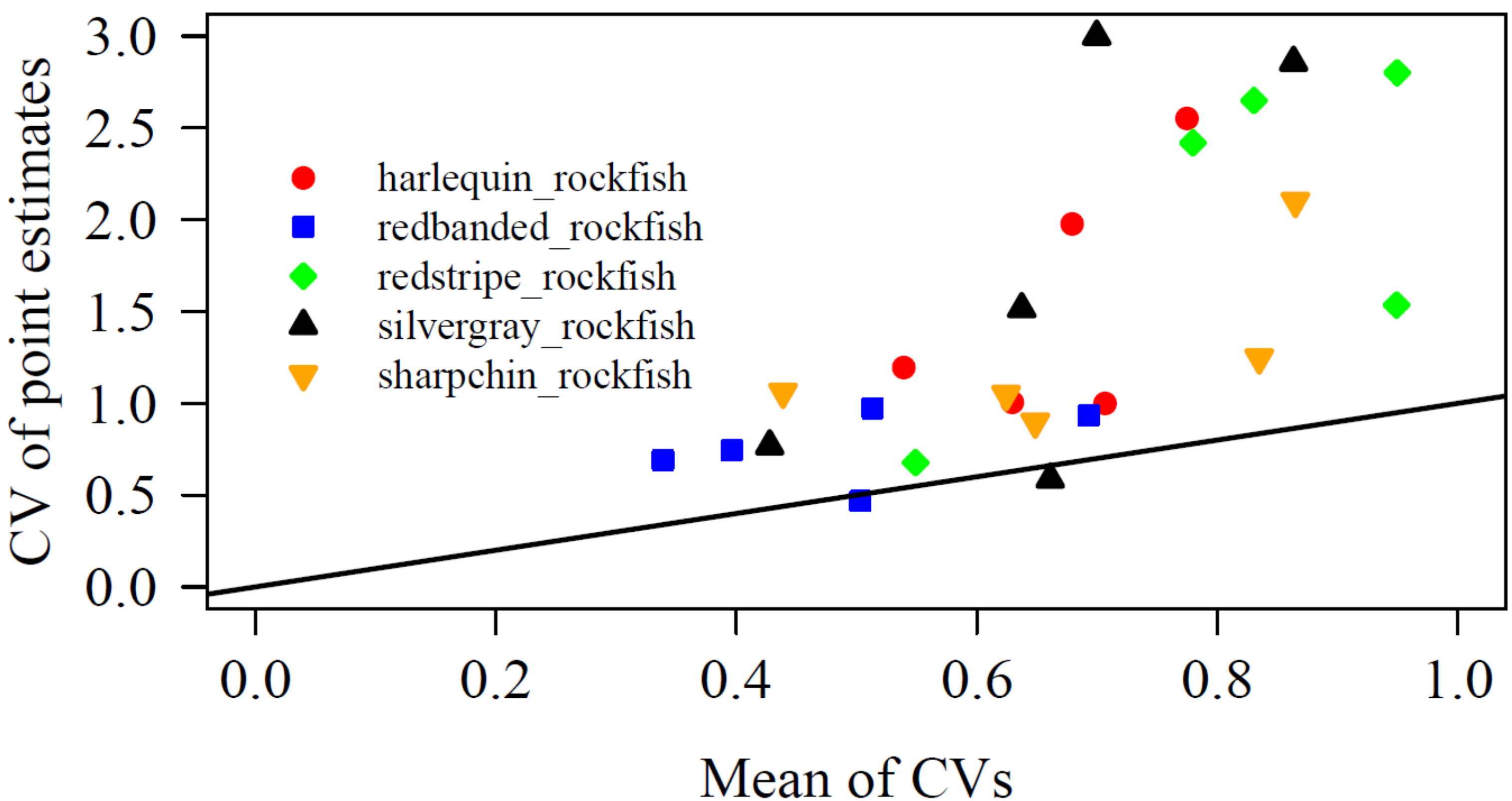
EBS skates


Observed
Lognormal
Normal
Biomass (t)
7.0E+05
6.0E+05
5.0E+05
4.0E+05
3.0E+05
2.0E+05
1.0E+05
0.0E+00
1975
1980
1985
1990
1995
2000
2005
2010
2015

How variable are the subarea biomass estimates?



Subarea variability for some GOA "other rockfish" species



Integrating marine reserves into data-poor stock assessments:

Assessing tradeoffs between models that rely on reserve-based indices

Sarah Valencia

World Conference on Stock Assessment Methods

Boston, USA

July 17-19, 2013

Stock assessments rely on contrasts in historical data

Current

McClanachan 2008

Historical

McClanachan 2008

Using reserves as reference areas

Outside Reserve

Inside Reserve

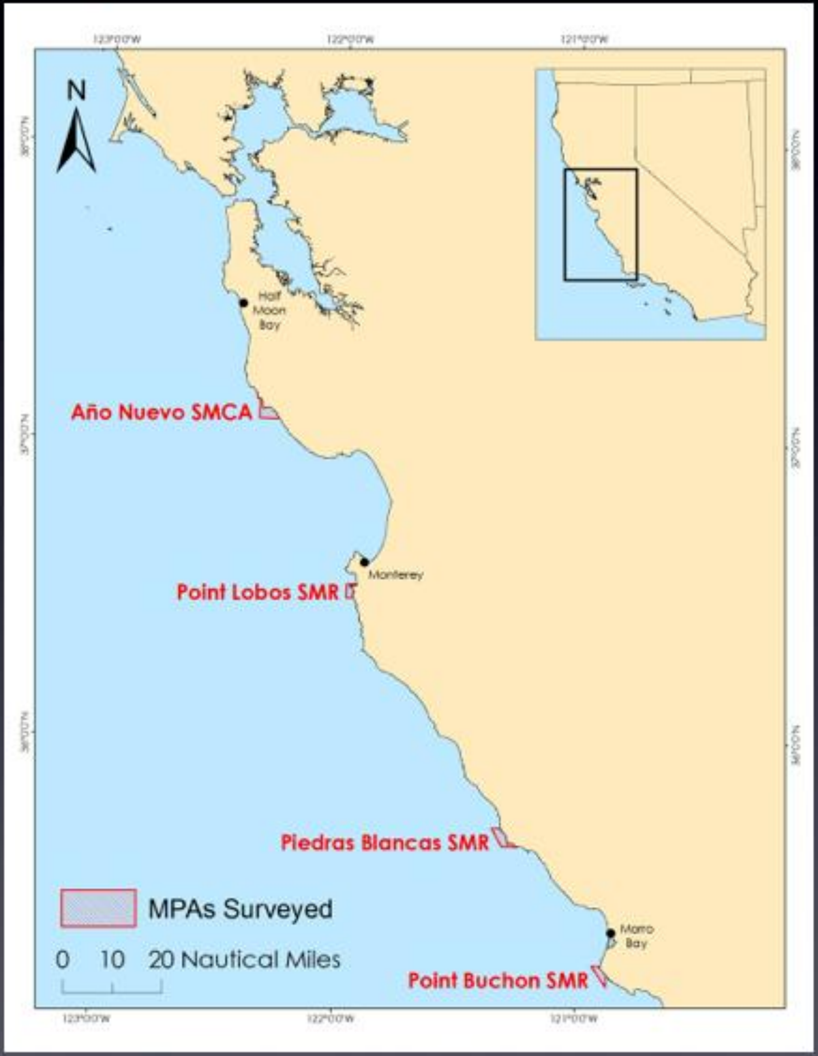
Can contrasts between reserves and fished areas help with data-poor assessments?

Questions

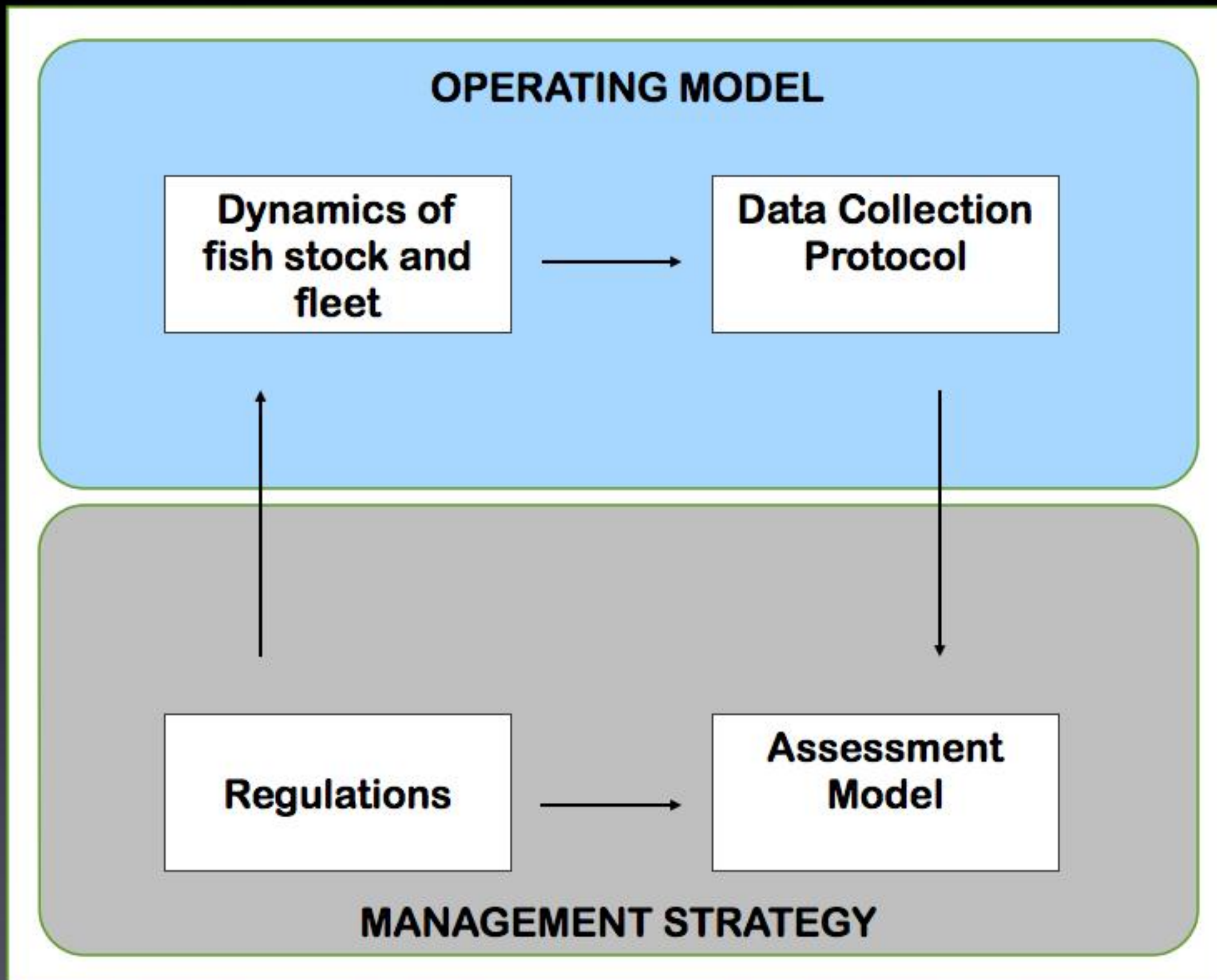
- What are the trade-offs between methods that rely on different information streams?
- Do improvements to management offset monitoring costs?
- What data collection protocols and assessment methods might work best for California's nearshore stocks?

California Collaborative Fisheries Research Project

- Since 2007, 4 marine reserves monitored in central CA
- What can this tell us about the status of fisheries?
- Incorporating marine reserves into fisheries management

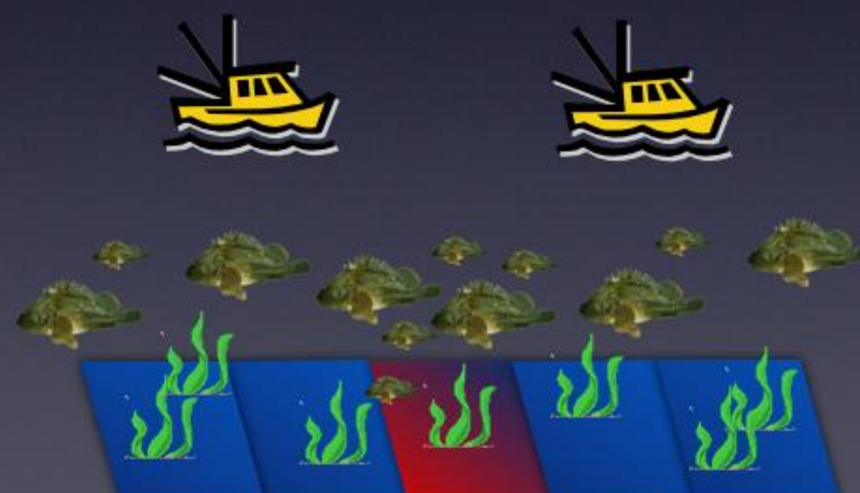


Management Strategy Evaluation



Operating Model

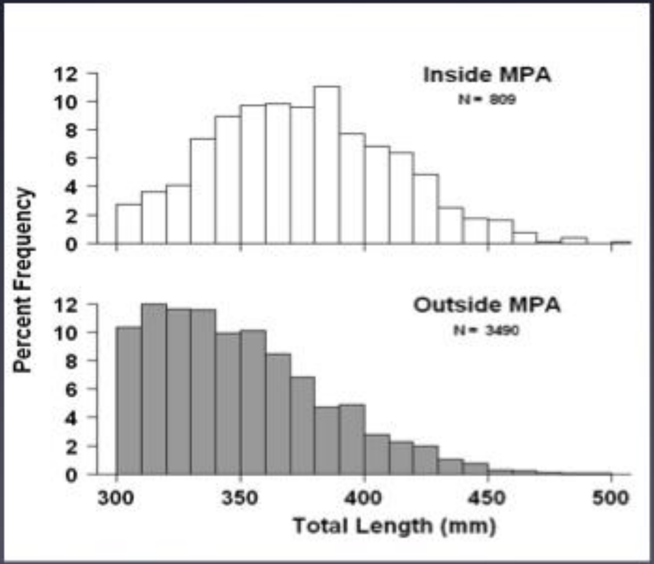
- Age-based, spatial, stochastic operating model to simulate harvest of nearshore species
- MPA created in 20% of available habitat



Simulating CCFRP's Data Collection Protocol

Generate samples from inside and outside marine reserves

- Size composition
- Catch-per-unit-effort



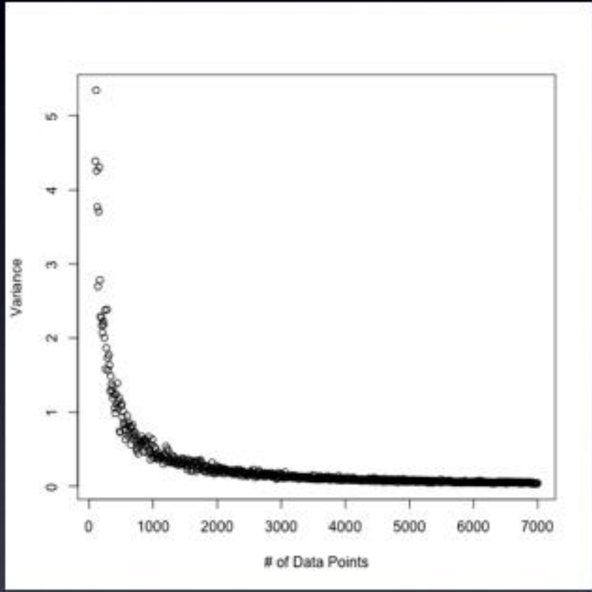
Different Assessment Methods Require Different Data

No Monitoring	CPUE Only	Size Only	Size and CPUE
50% of historical catch	Density Ratio Control Rule	Length-Based SPR, Bounded Mortality Estimator	Decision Tree

Comparing Apples to Apples

Optimization procedure

- Determine the minimum amount data required to stabilize variance
- Optimize the control rule parameters for every scenario run



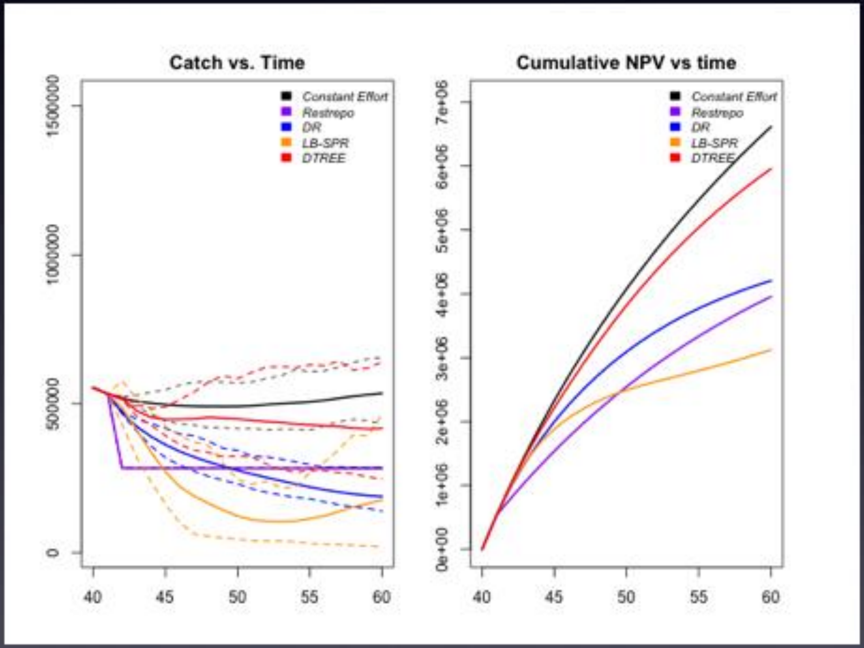
Scenarios

Test how well each management strategy performs under a range of scenarios

- Historical fishing pressure
- Trends in recruitment
- Alternative connectivity patterns
- Density-dependence

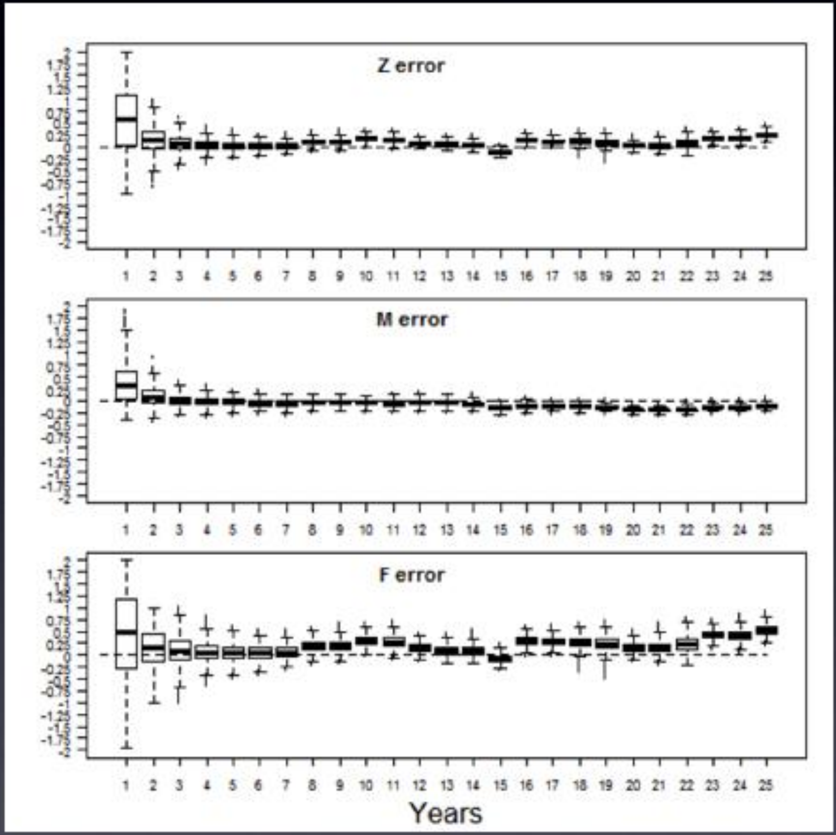
Is it worth it to survey reserves?

- Some stocks could see performance gains that offset costs
- Benefits to recreational fisheries less clear
- Multi-species sampling program is most cost effective



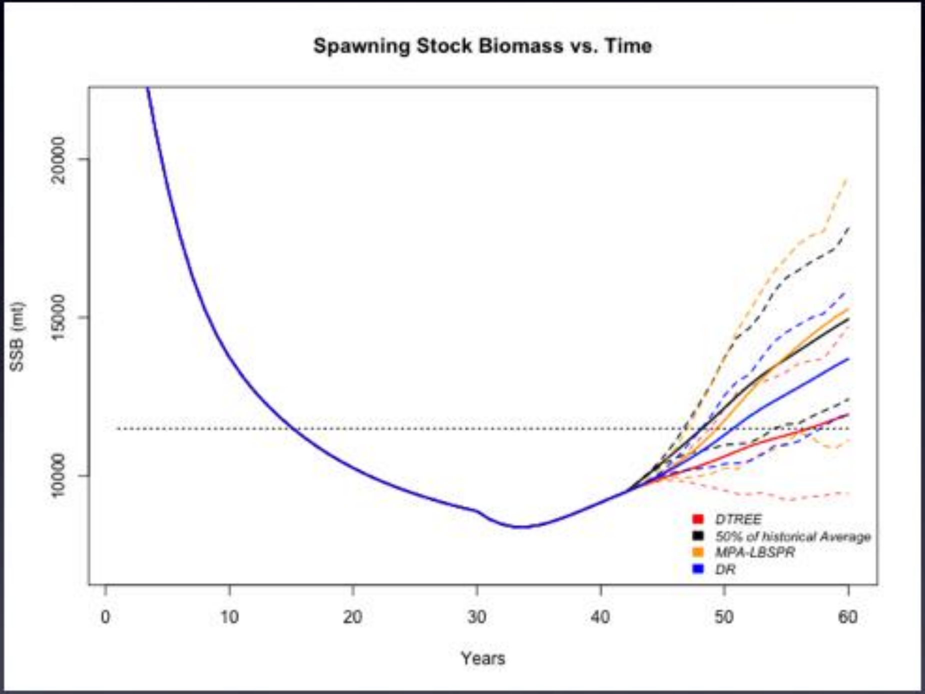
How well do these methods work?

- Some estimation methods may be consistently biased
- In measuring performance of data-poor methods, long term performance matters



Harvest Control Rules

- Successful indicators must be able to detect change
- Harvest control rule determines how you respond to changes
- Important to simulate entire management procedure



Questions?

Thank you

CERTIFIED SUSTAINABLE SEAFOOD

Marine Stewardship Council

Assessing the Assessment Methods

Megan Atcheson, Cassie Leisk, Nicolas Gutierrez, Dan Hoggarth, David Agnew

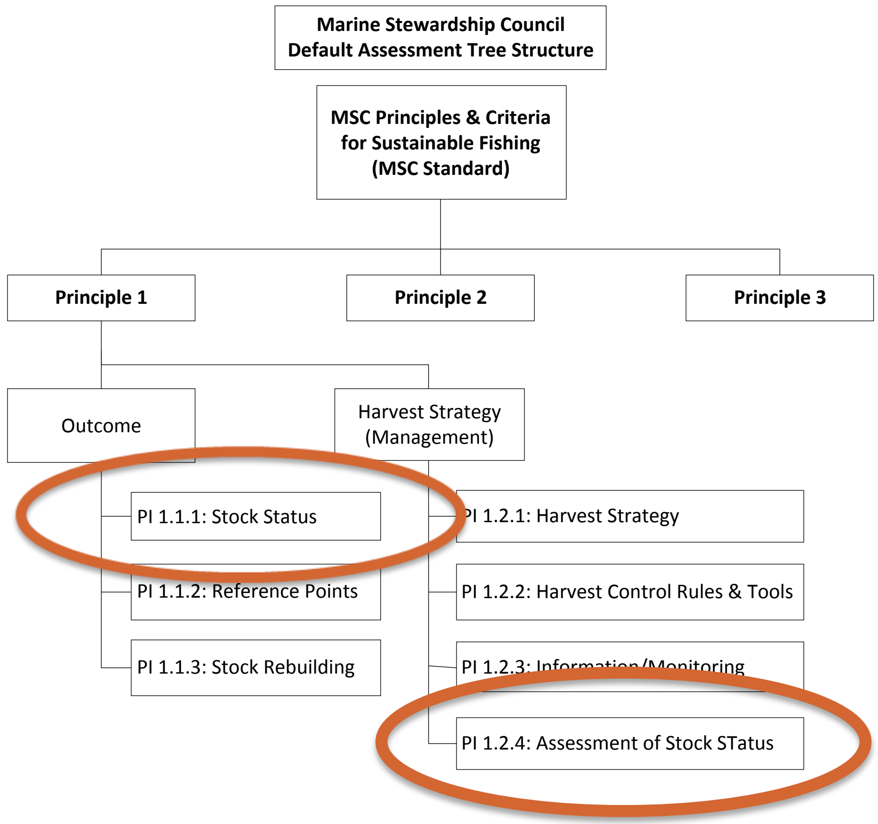
WCSAM July 2013

Marine Stewardship Council (MSC)

- Independent non-profit
- Meets FAO guidelines for ecolabels
- Scope – wild capture fisheries
- Objective and scientifically verifiable standard
- Third-party independent, accredited certifiers
- Voluntary
- Open to fisheries of all sizes, scales, geography, & gear
- Fish from successfully certified fisheries can be marketed with MSC ecolabel once "chain of custody" is completed

The MSC Standard

Default Assessment Tree: Principle 1



Principle 1 considers the sustainability and management of the target stock (as identified within the unit of certification).

CB2.8 Assessment of Stock Status PI (PI 1.2.4) ◙

Table CB7: PI1.2.4 Assessment of stock status PISGs

Component	PI	Scoring issues	SG60	SG80	SG100
Harvest strategy	**Assessment of stock status** **1.2.4**	a. Appropriateness of assessment to stock under consideration		The assessment is appropriate for the stock and for the harvest control rule.	The assessment takes into account the major features relevant to the biology of the
		assessment			assessment has been tested and shown to be robust. Alternative hypotheses and assessment approaches have been rigorously explored.
		e. Peer review of assessment		The assessment of stock status is subject to peer review.	The assessment has been **internally and externally** peer reviewed.

What if there is no stock assessment?

Risk-Based Framework (RBF)

What is the RBF?

- Set of assessment methods
- Insufficient data for standard assessment tree
- Highly precautionary risk-based approach
- Based on Ecological risk assessment for the effects of fishing (ERAEF, Hobday et al. 2007, 2011).

Why was the RBF developed?

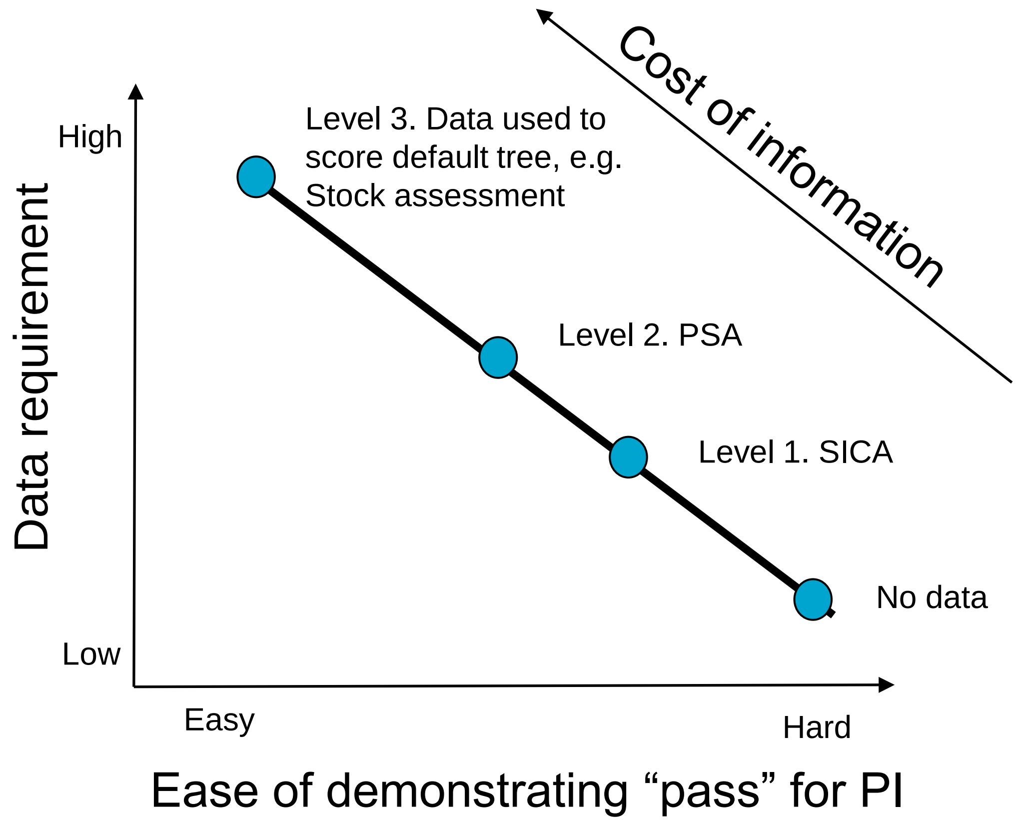
- Accessibility

"…the use of less elaborate methods for assessment of stocks should not preclude fisheries from possible certification for ecolabelling". (FAO Guidelines on Ecolabelling for Fisheries and Fisheries Products from Marine Capture Fisheries)

Data Gaps

1. Assessments in which there is no stock assessment data.
2. Assessments in which stock status data is available but target and limit reference points have not been defined.
3. Assessments for which stock assessment information is available and reference points may be defined but there are concerns about the quality and/or currency of the data.
4. 20 fisheries in total have used the RBF for P1 – less than half are from developing countries or small scale (but 50% of these are bivalves).

Hierarchical approach



The RBF extends the range of tools available to an assessment team

Scale Intensity Consequence Analysis (SICA)

Qualitative information

- **Diverse** range of stakeholders

Evaluation of risk

- Scale (**temporal** and **spatial**) and **intensity** of fishery's activities on the target stock
- **Consequence** of activity for the species

If risk levels unknown:

- Highest plausible risk score results
- Highly **precautionary**

Productivity Susceptibility Analysis (PSA)

Semi-quantitative information

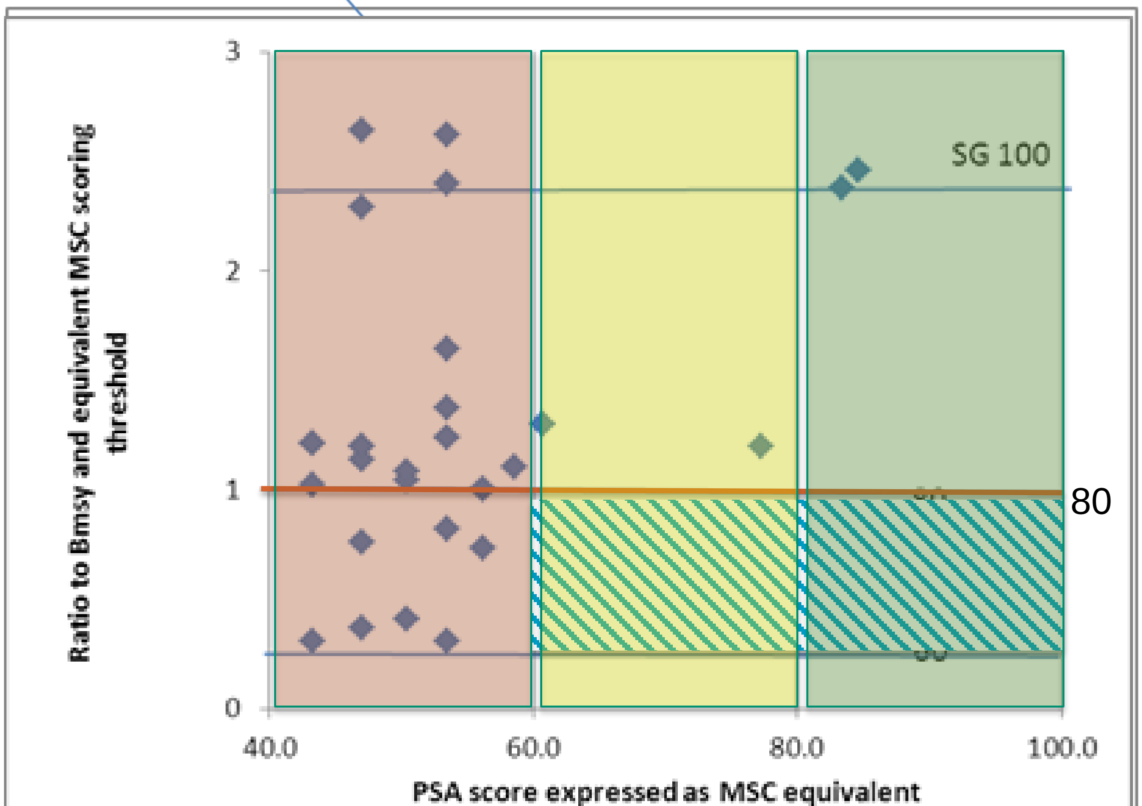
- **Diverse** range of stakeholders

Assumes risk to a species depends on:

- **Productivity** of unit
- **Susceptibility** of unit to fishing activity
  - Areal overlap
  - Vertical overlap
  - Selectivity
  - Post-capture mortality

Is the RBF Really Precautionary?

Industrial fisheries that would be given GREEN under normal MSC get RED under PSA



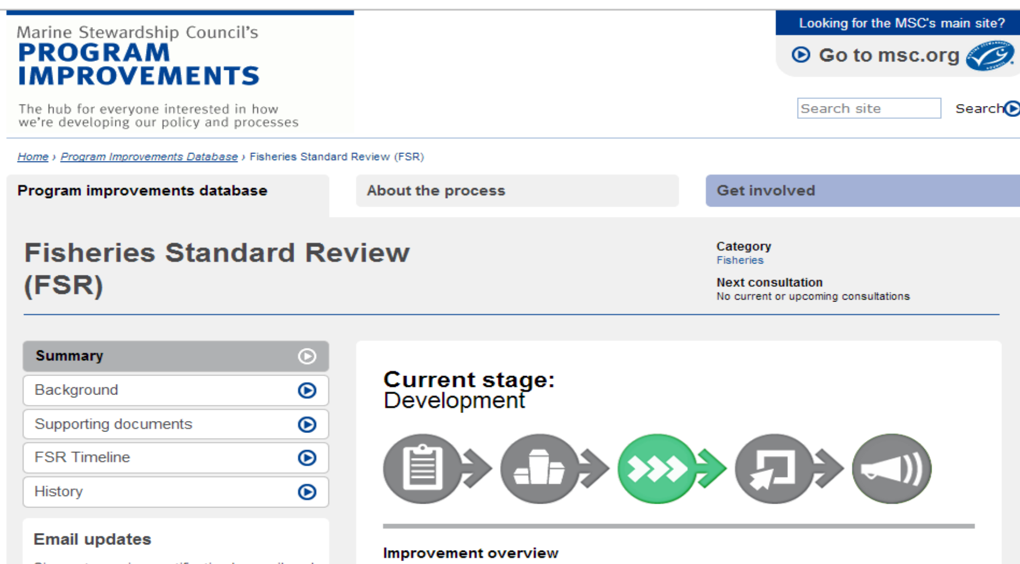
Equivalence is effectively shifted down by 20 points (normal 80 would only score 60)

PSA scores expressed as MSC equivalent demonstrating the high levels of precautionary built into the RBF. The PSA scores for all 59 fisheries resulted in more precautionary scores than those that would have resulted using the standard assessment approach. Horizontal lines represent approximate MSC scores that would be expected when using B/BMSY ratios in PI 1.1.

Summary

- Data-rich assessment ✓
- Data-poor assessment ✓
- Data-semi-deficient assessment ?

- Fisheries Standard Review: improvements.msc.org



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Questions?

Megan Atcheson

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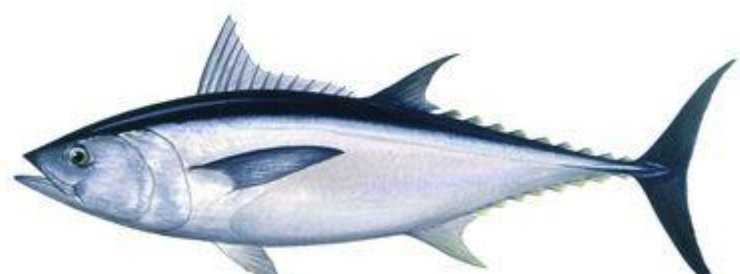
www.msc.org

Indian Ocean Tuna Commission
Commission des Thons de l'Océan Indien
iotc ctoi

Surplus Production Models and SRA Based techniques for Kawakawa & Longtail Tuna Assessments

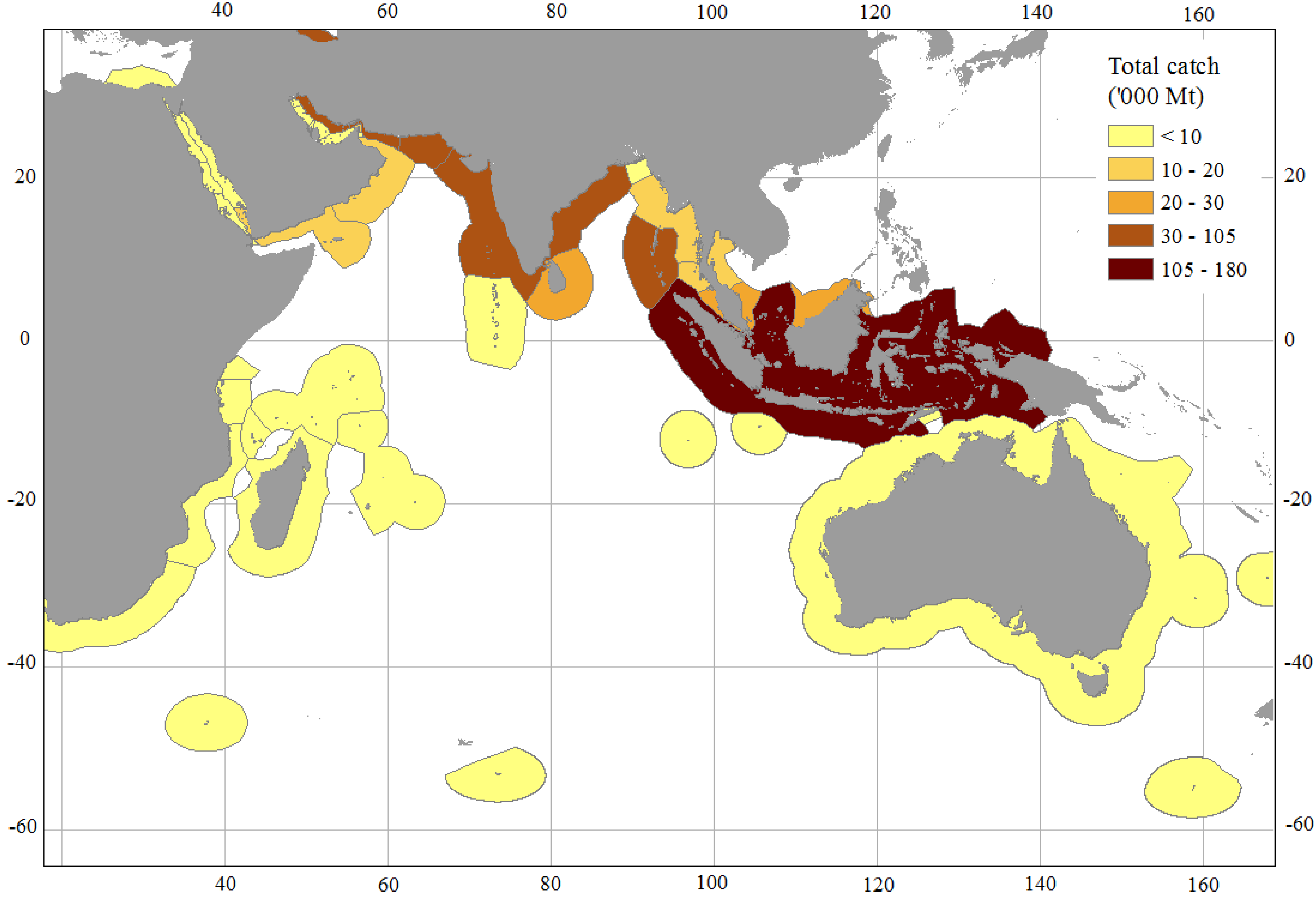
Rishi Sharma, IOTC, Victoria, Seychelles

Shijie Zhou, CSIRO, Brisbane, Australia



Outline of Talk

- Stock assessment Traditional approaches:
  - Surplus production models
  - Age Structured Models
- Issues on catch increases in IO
- Data poor Stock Reduction Analysis Methods
- Kawakawa & Longtail Assessments


Total catch
('000 Mt)
< 10
10 - 20
20 - 30
30 - 105
105 - 180
40
60
80
100
120
140
160
20
0
-20
-40
-60


06/02/2013

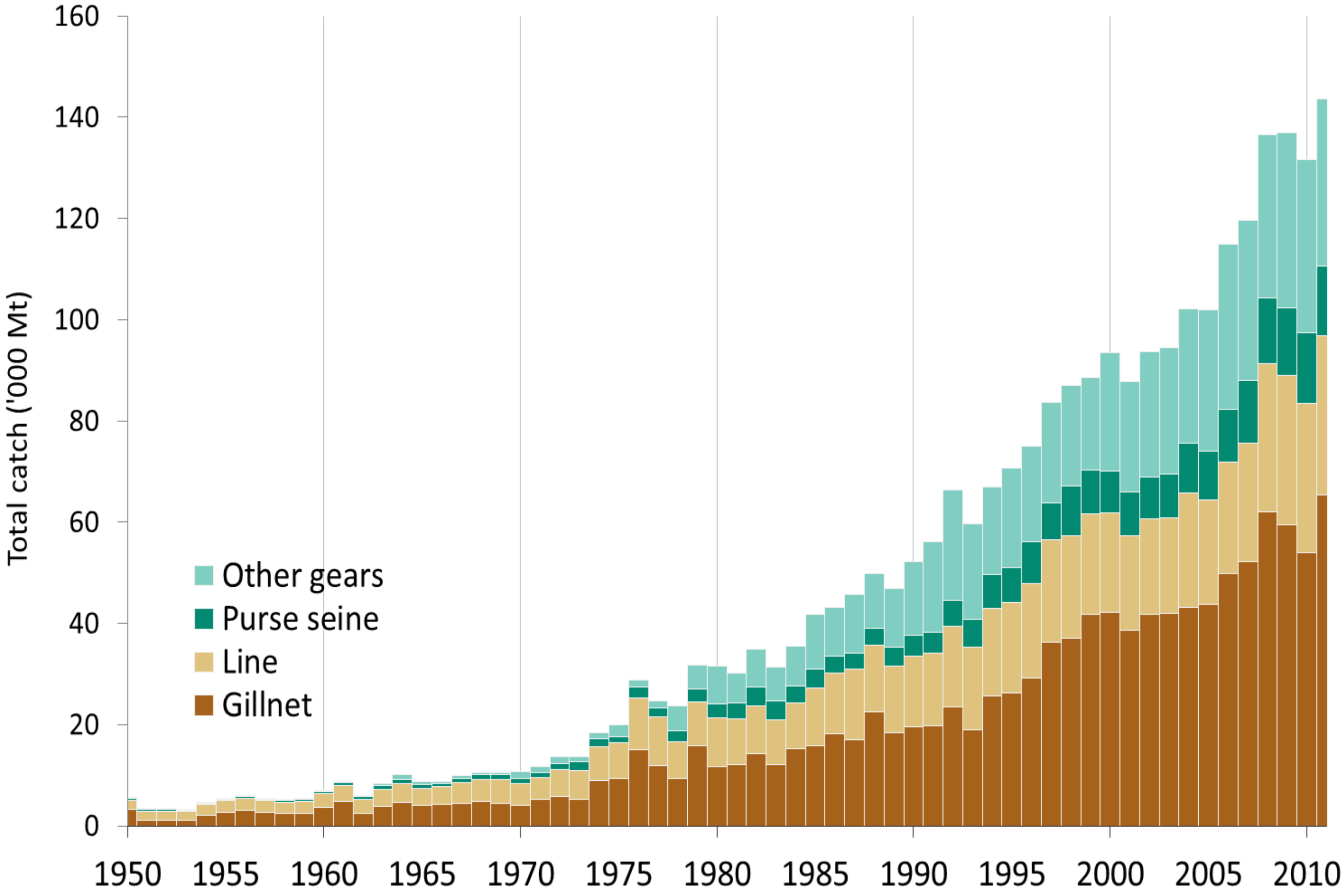
skiff(Fiber glass) 8－10m

launch15－25m

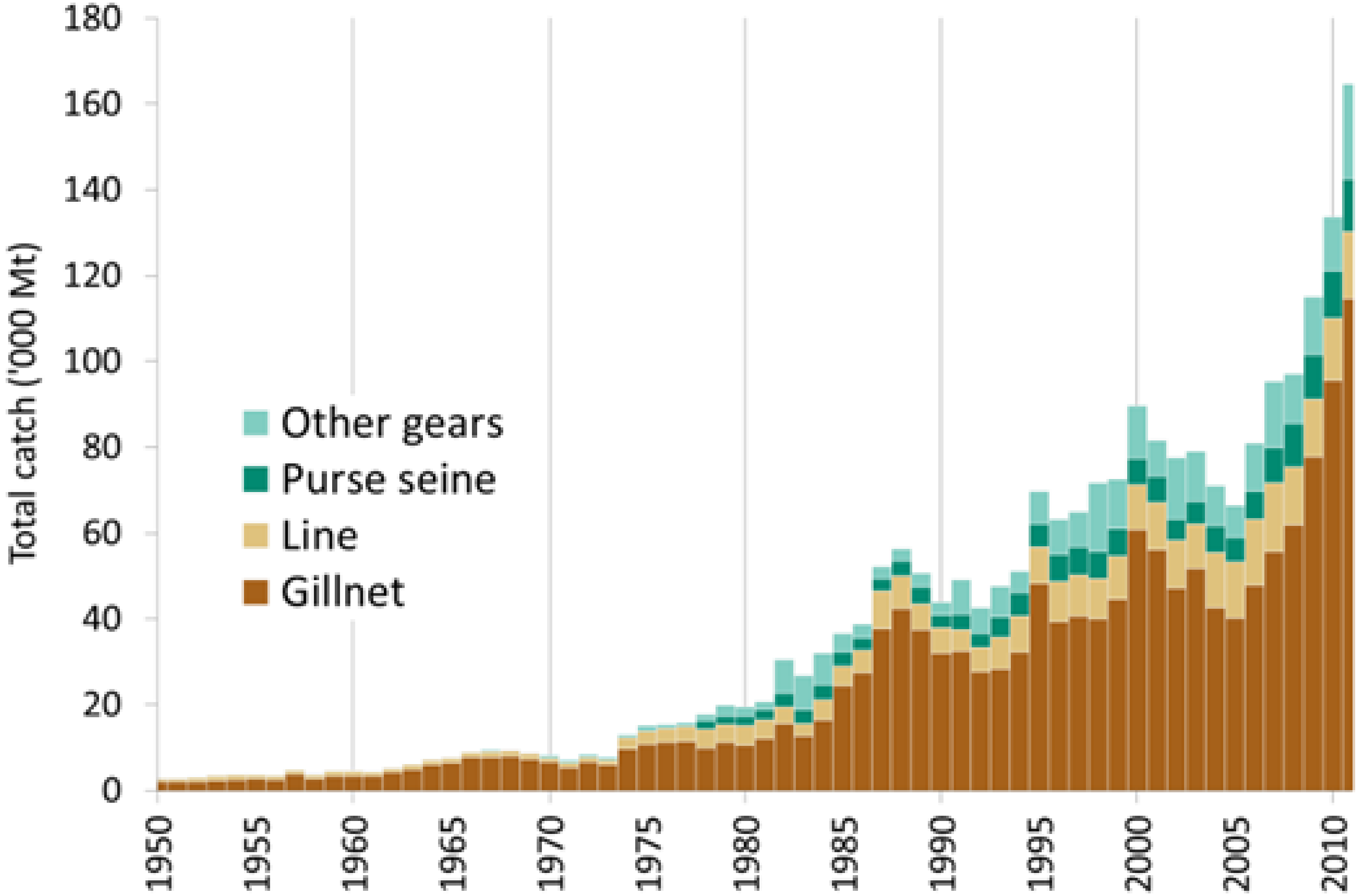
houri

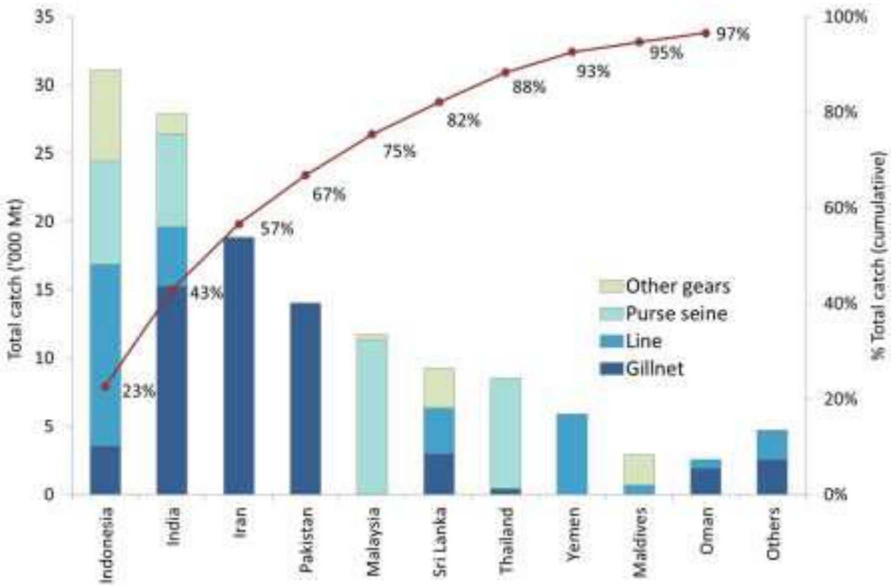
shasha

Catch Trends-Kawakawa (***Euthynnus affinis***)



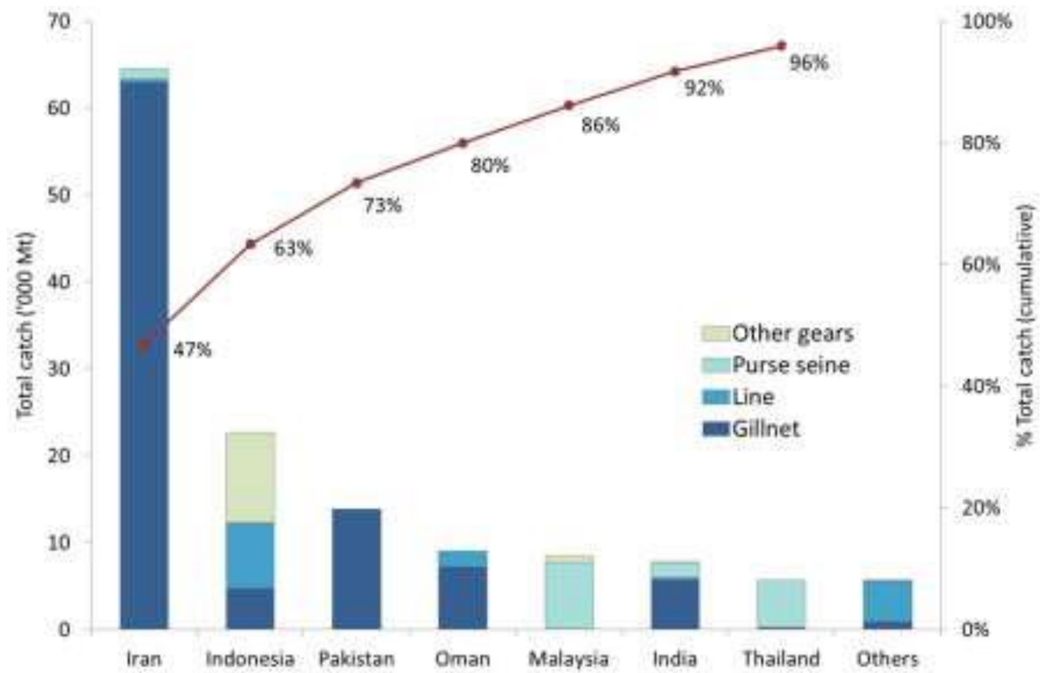
Longtail (***Thunnus tonggol***)





Kawakawa

Longtail



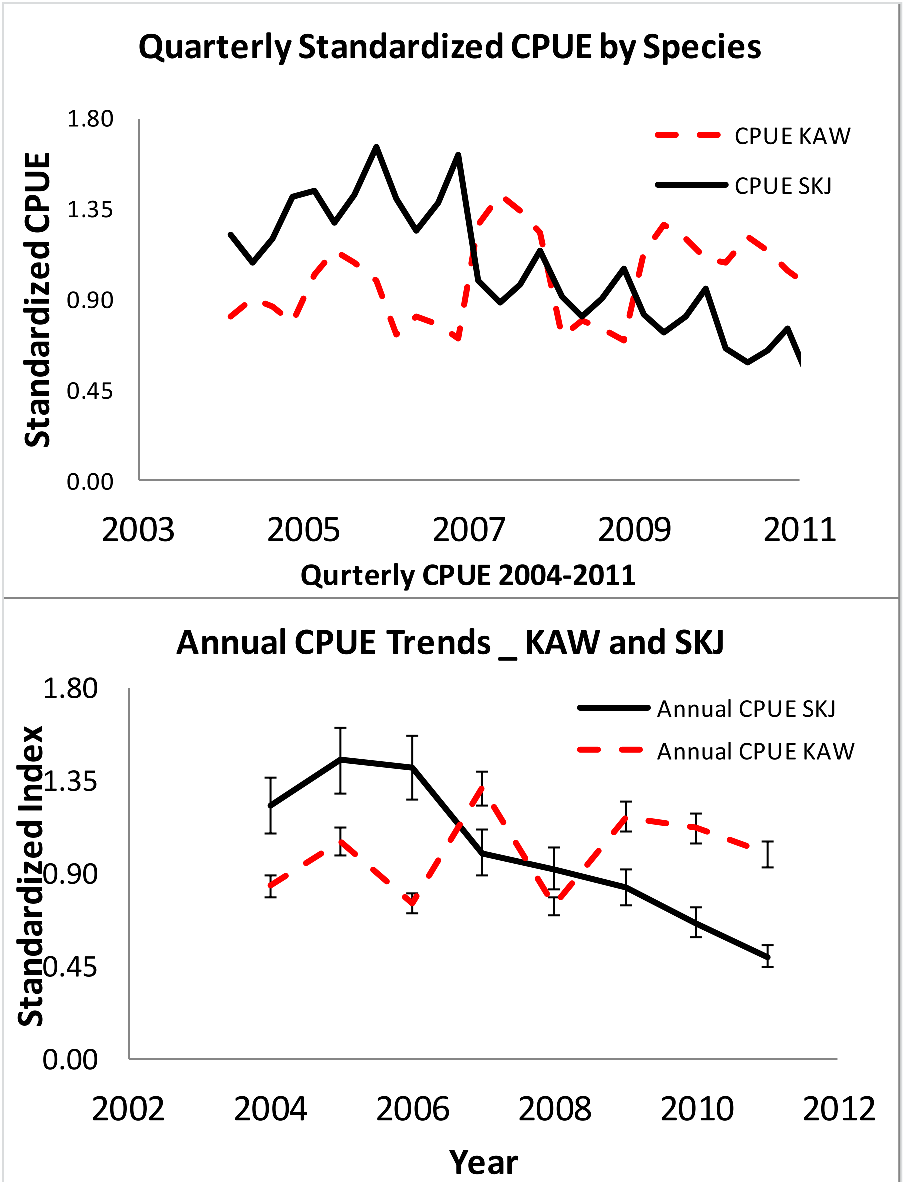
Traditional Approach: Parameters estimated

- Catchability parameters from closed form solution
- r and K.
- Data used, Catch, Standardized Index of Abundance and Effort.

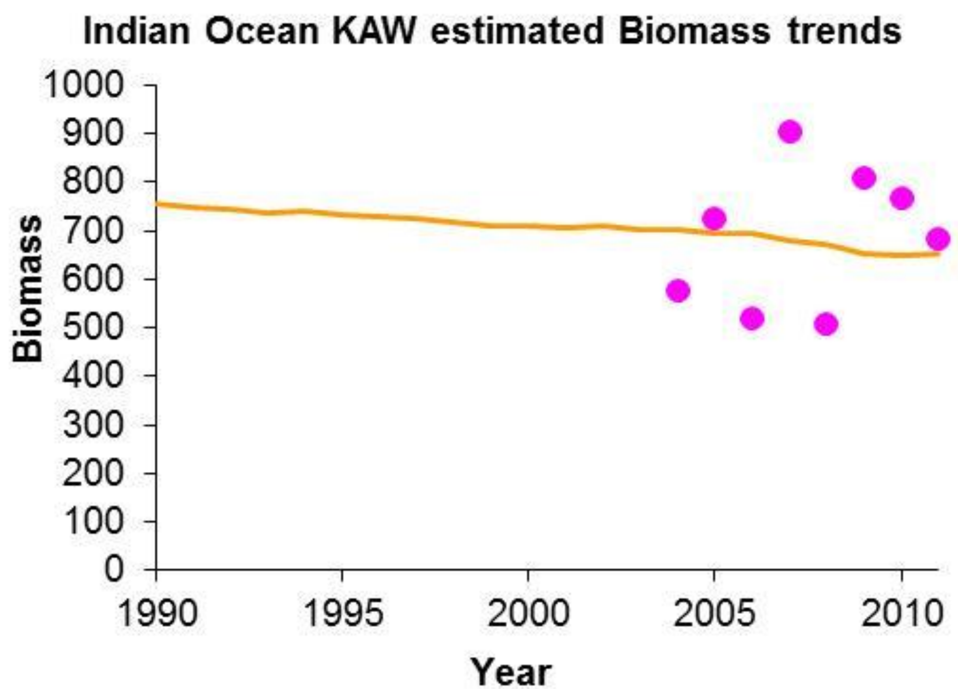
Data Quality and type of Information

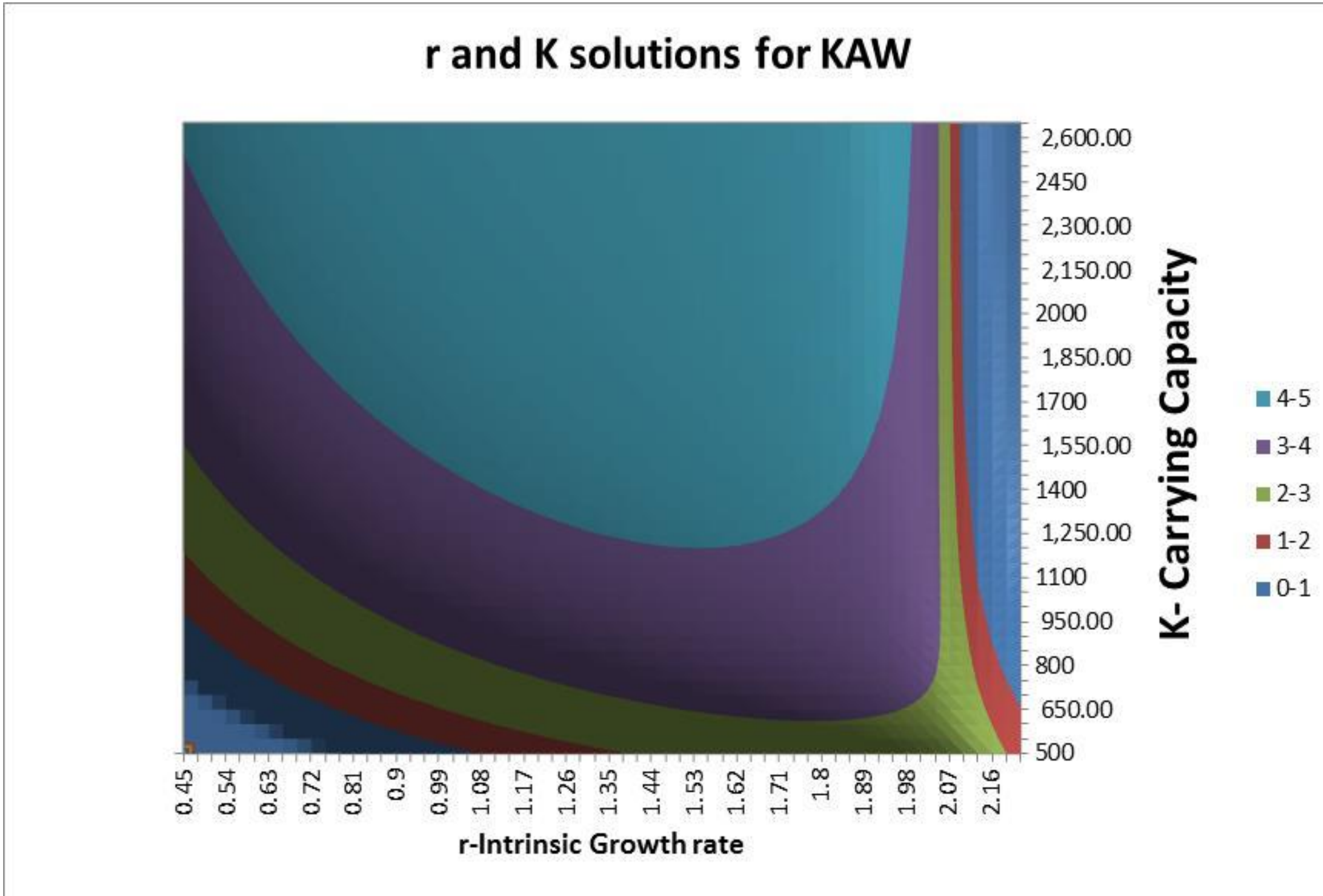
- Catch Data from 1950's.
- Standardized Index of Abundance data from 2004-2011 (Maldives).
- Assumed one stock for the entire Indian Ocean.

Results Kawakawa-Indian Ocean



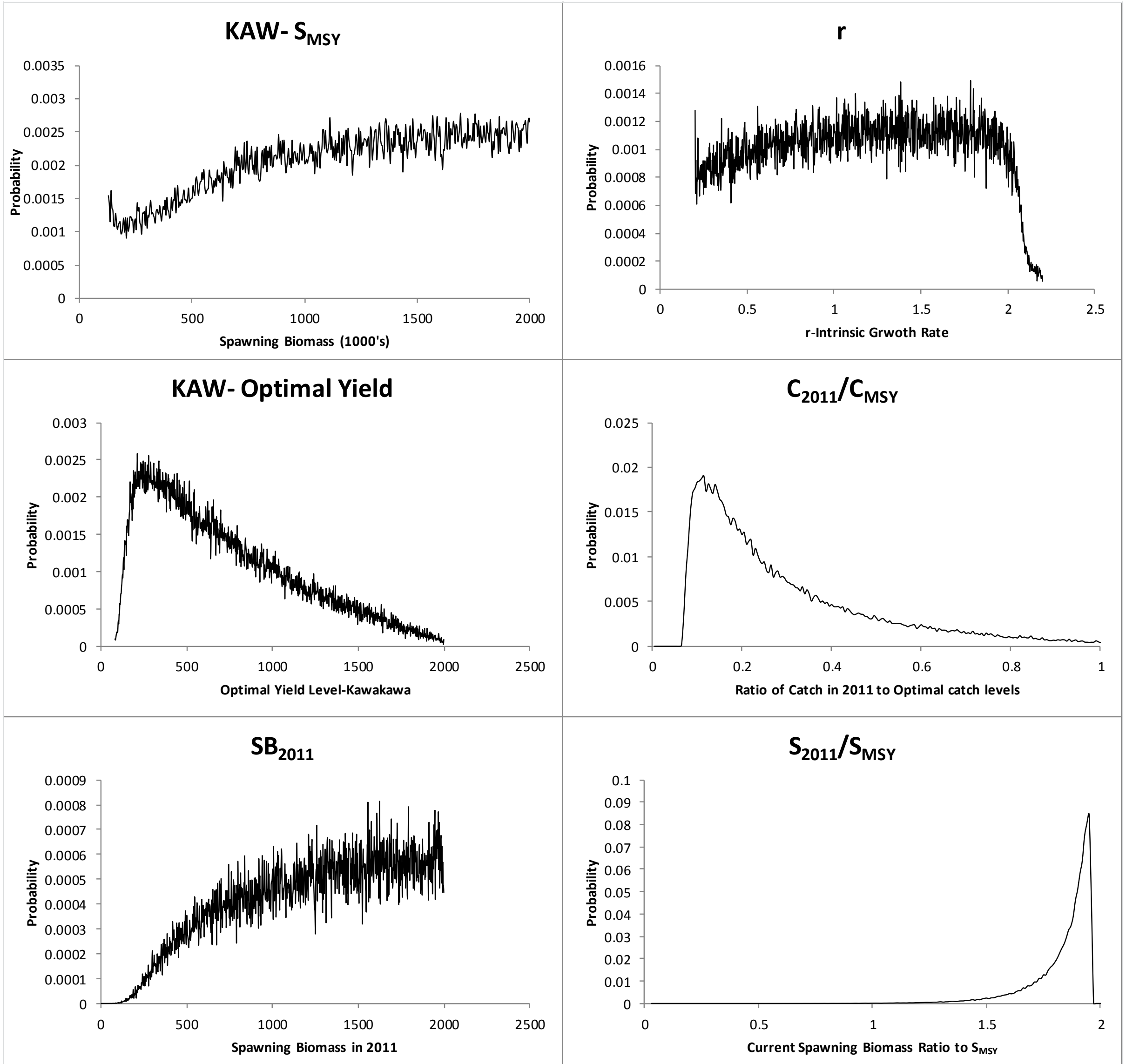
Pars	Model 1 (low productivity)	Model 2 (Medium productivity)	Model 3 (High productivity)
r	0.250	0.650	1.100
k	1,600	1,200	800
Likelihood	1.39	3.01	2.97
SMSY	800	600	400
Yield	100.0	195	220
ratioS	1.16	1.58	1.63
ratioF	1.26	0.42	0.31
Prob	19%	41%	40%





r and K solutions for KAW
2,600.00
2450
2,300.00
2,150.00
2000
1,850.00
1700
1,550.00
1400
1,250.00
1100
950.00
800
650.00
500
K- Carrying Capacity
4-5
3-4
2-3
1-2
0-1
0.45
0.54
0.63
0.72
0.81
0.9
0.99
1.08
1.17
1.26
1.35
1.44
1.53
1.62
1.71
1.8
1.89
1.98
2.07
2.16
r-Intrinsic Growth rate

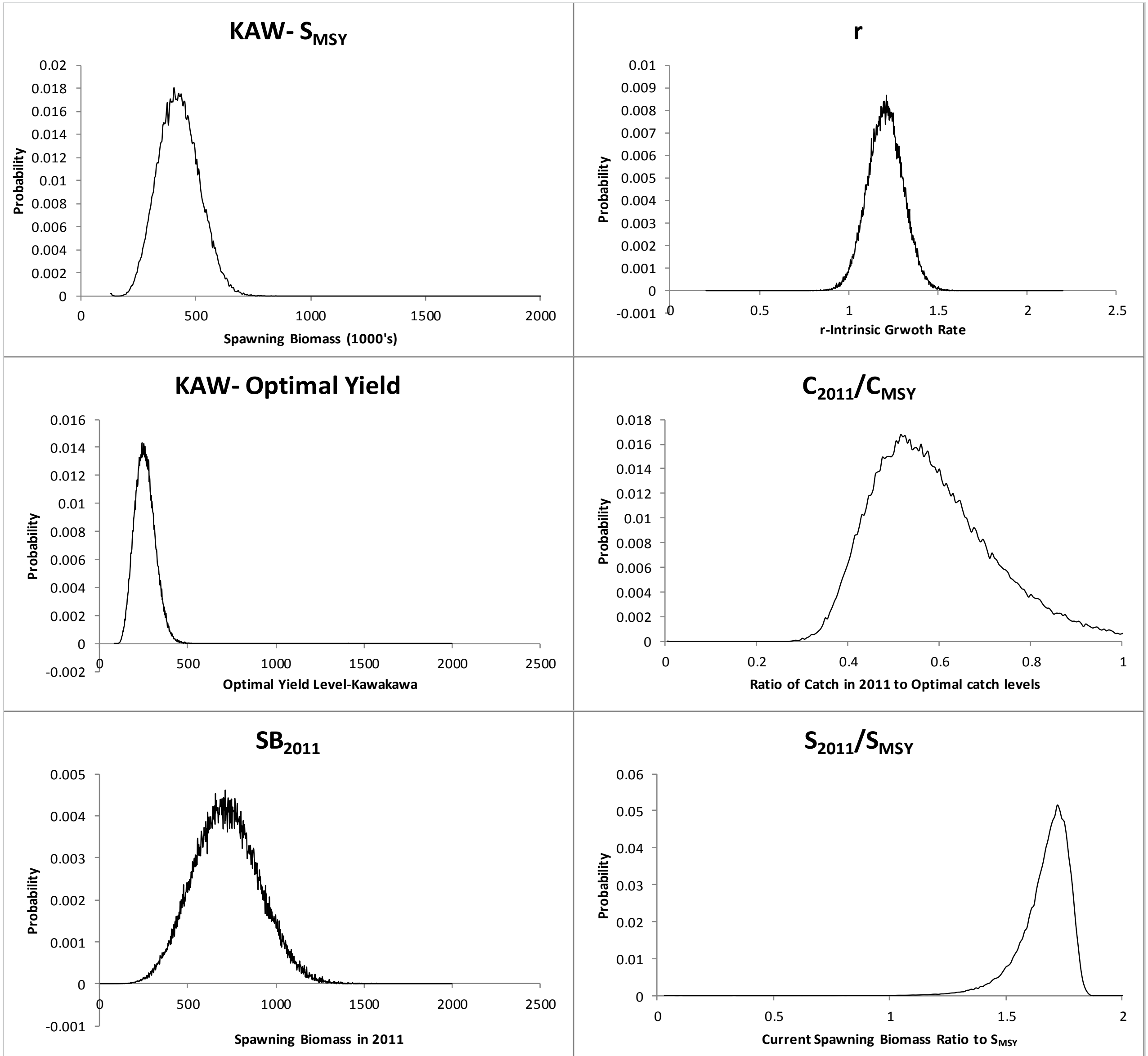
Non_informative Priors



Parameters	5%	50%	90%
SMSY	296	1236	1900
MSY	178	622	1386
r	0.31	1.18	1.88
SB 2011	632	>2000	>2000
S2011/SMSY	1.55	1.88	1.95
C2011/CMSY	0.09	0.245	0.795

Posterior Mode MSY
~ 210K

Informative Priors



Parameters	5%	50%	90%
S_{MSY}	284	420	584
MSY	164	252	354
r	1.04	1.2	1.37
SB_{2011}	416	712	1030
S_{2011}/S_{MSY}	1.45	1.69	1.79
C_{2011}/C_{MSY}	0.4	0.57	0.87

Posterior Mode MSY
~ 230K

Summary/Conclusions on Traditional Approaches

- CPUE data non-informative
- Anchored FAD can be expected to cause hyper-stability in CPUE indices .
- Maldives CPUE series representing Indian Ocean.
- Further research needed.
- Age/length data organized by fishery.

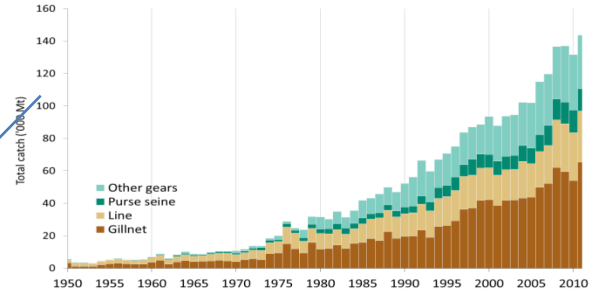
Alternatives : Stock Reduction Analysis and Data Poor Approaches

- Used Walters et. al. (2006) approach adapted by Martell and Froese for ICES stocks (2012).
- Key in this approach is assumptions about depletion levels at various time periods in the trajectory and then finding a set of r and K values that fit these
- Using that set of r and K values, we make projections on the health of the stock.

SRA and Posterior Catch Based SRA

r

K



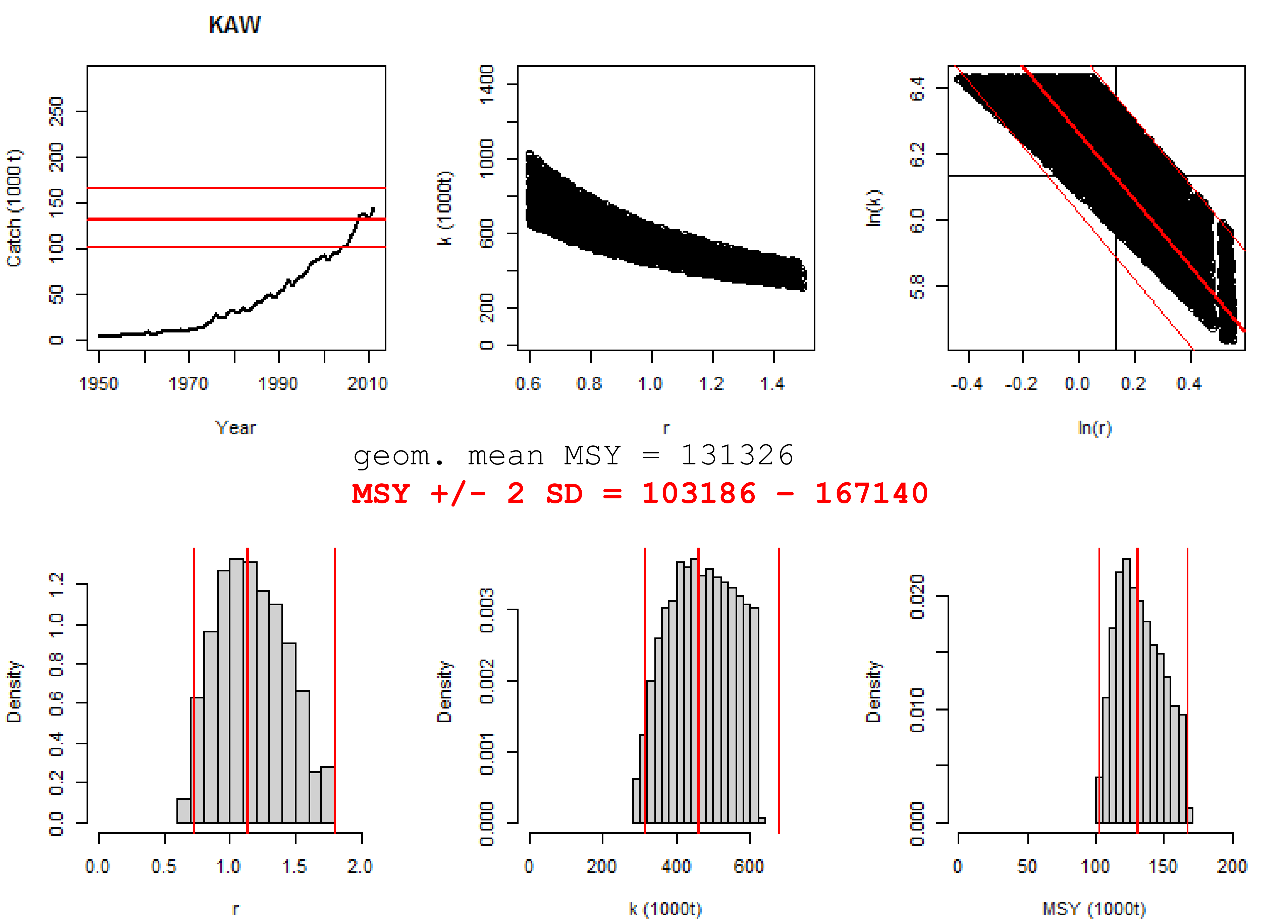
$$B_{t+1} = B_t + f(B_t) - C_t, t = 0, 1, \ldots,$$

Assumed initial biomass (B/k) = 0.5 - 0.9 k
Assumed intermediate biomass (B/k) in 1981 = 0 - 1 k
Assumed final biomass (B/k) = 0.3 - 0.7 k

r constrained by species resilience. K constrained 100 * max catch

Assumed depletion level in 2011(0.1-0.9 K)
r constrained by species resilience.

Find solution that meets threshold depletion level within specified precision (i.e. r and K solutions):Optimize


KAW
Catch (1000 t)
Year
k (1000t)
r
ln(k)
ln(r)
geom. mean MSY = 131326
MSY +/- 2 SD = 103186 - 167140
Density
r
Density
k (1000t)
Density
MSY (1000t)

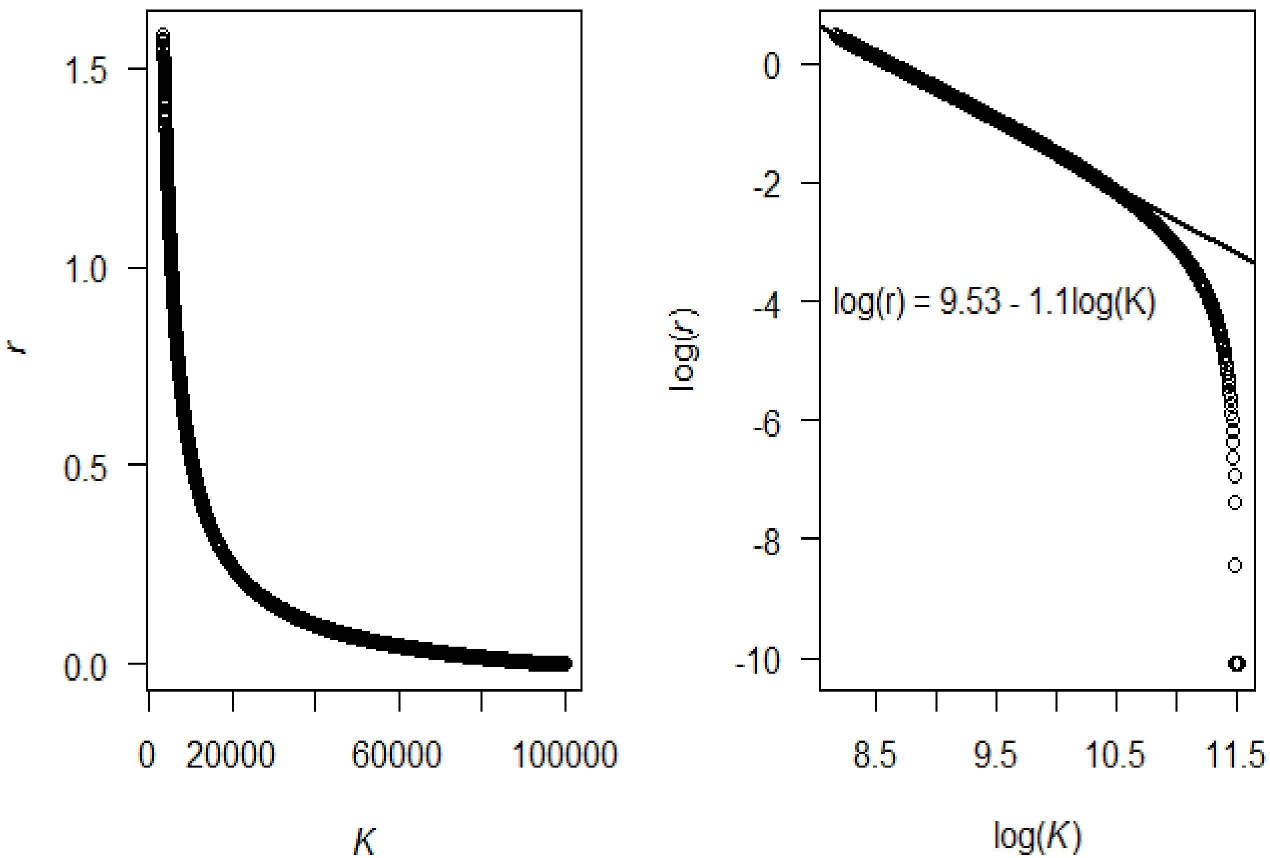
Posterior-focused catch-based assessment

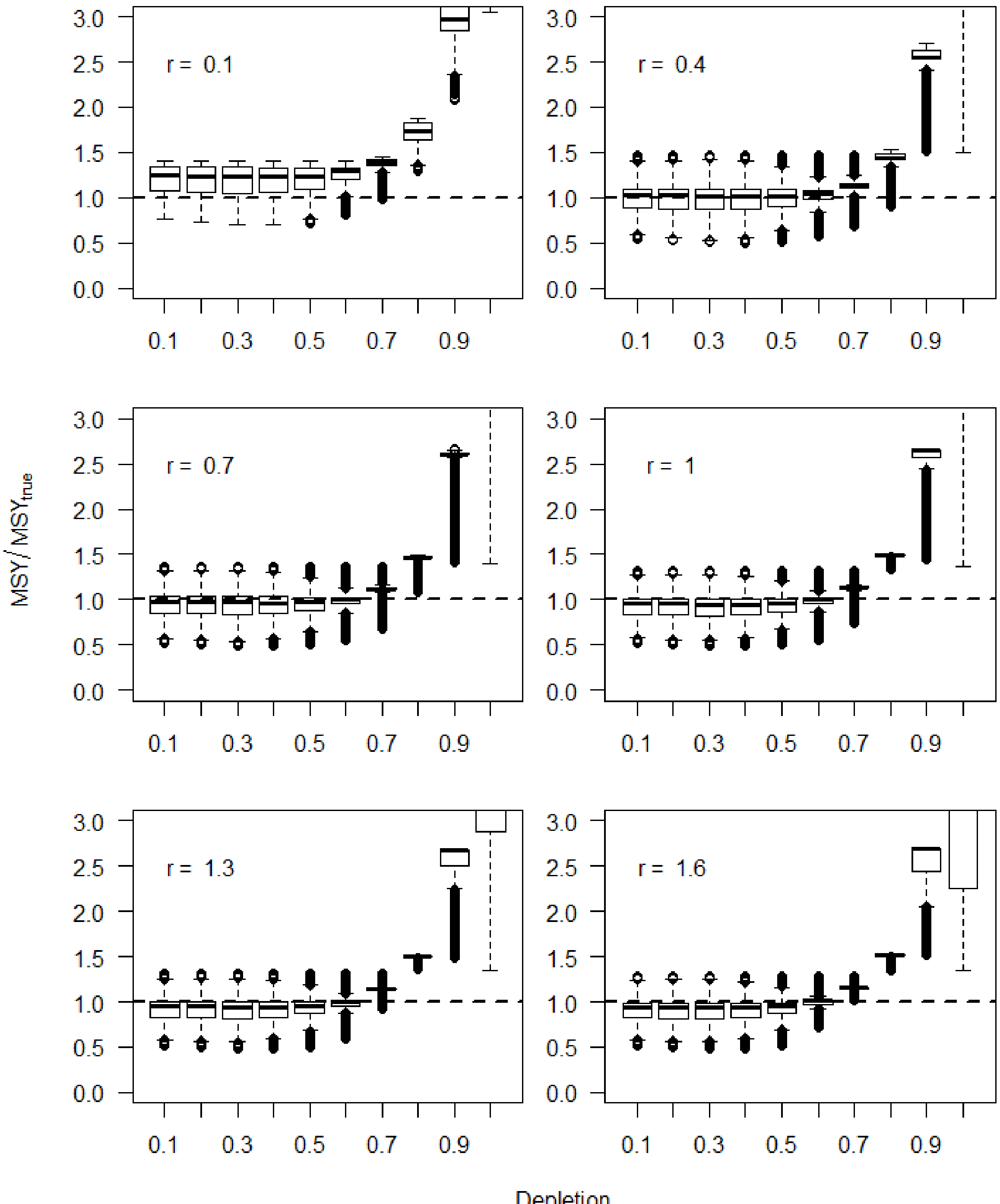
- Modification of the SRA Method presented.
- Method requires fewer priors.
- Using a prior range in r improves the outcome.
- Use optimisation instead of simulating biomass trajectories.
- Perform management strategic evaluation by forward simulation.

Focus on posterior

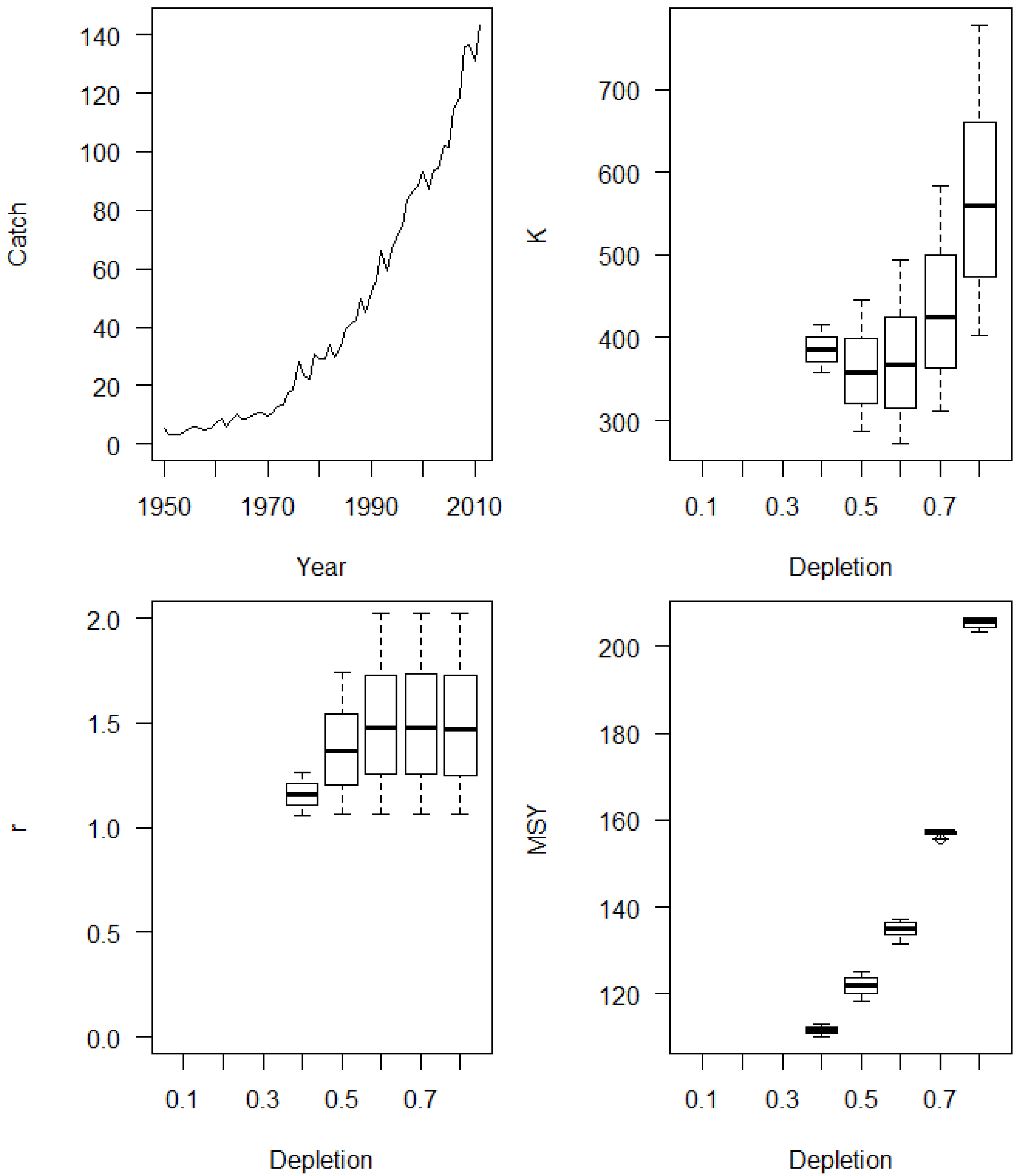
- Use unconstrained priors for K and r, that is $0 < K < \infty$ and $0 < r < \infty$.
- Use control rules to retain all viable iterations, e.g.,
  - $B_t > C_t$,
  - $B_t > 0$,
  - $B_t <= K$
  - $|(B_{end} - B_{true})/B_{true}| < \alpha$

Typical posterior r and K





r = 0.1
r = 0.4
r = 0.7
r = 1
r = 1.3
r = 1.6
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.1
0.3
0.5
0.7
0.9
MSY/MSY_true
Depletion

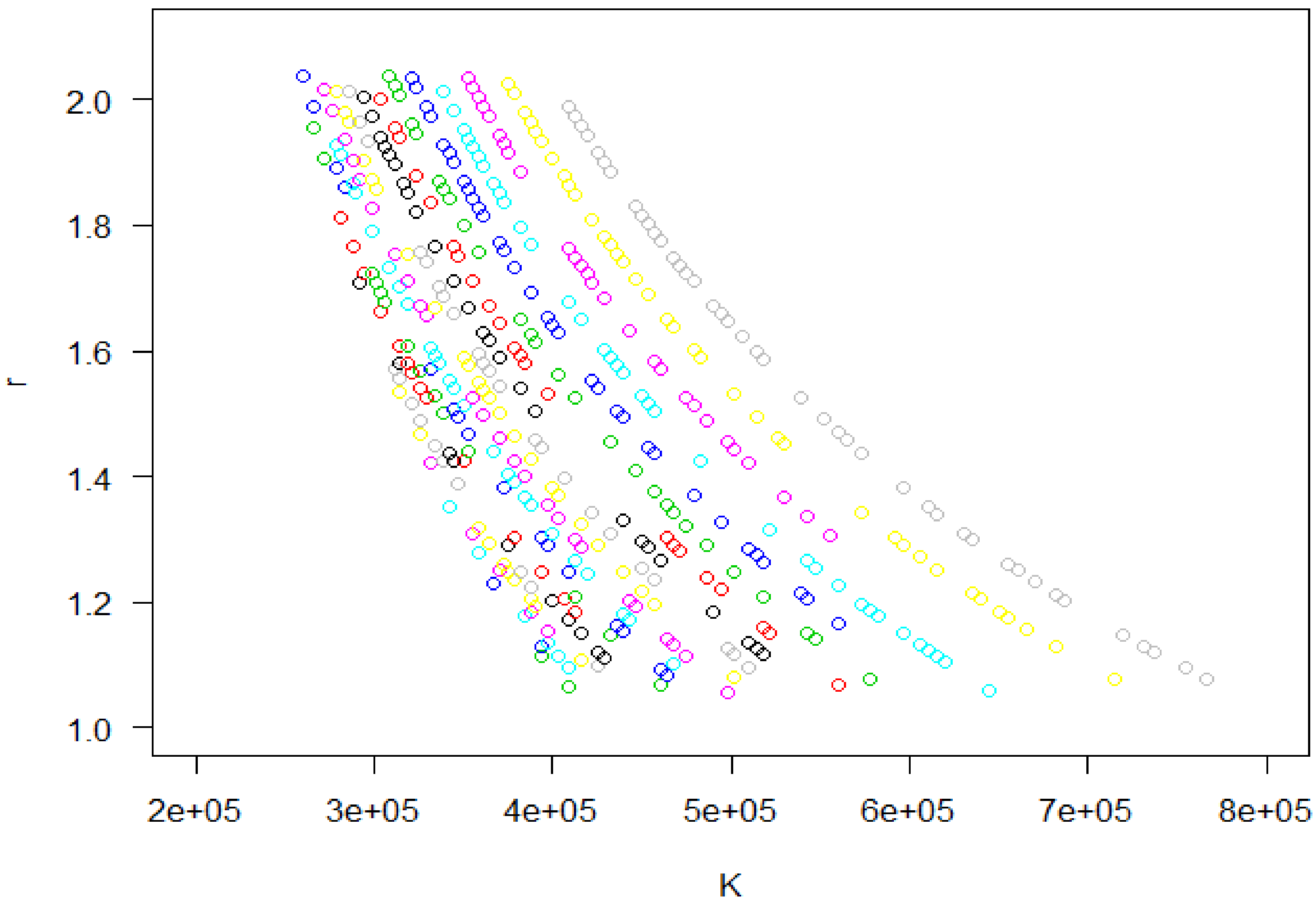


Assuming depletion level from 0.1 to 0.8, and r between 1.06 and 2.04.

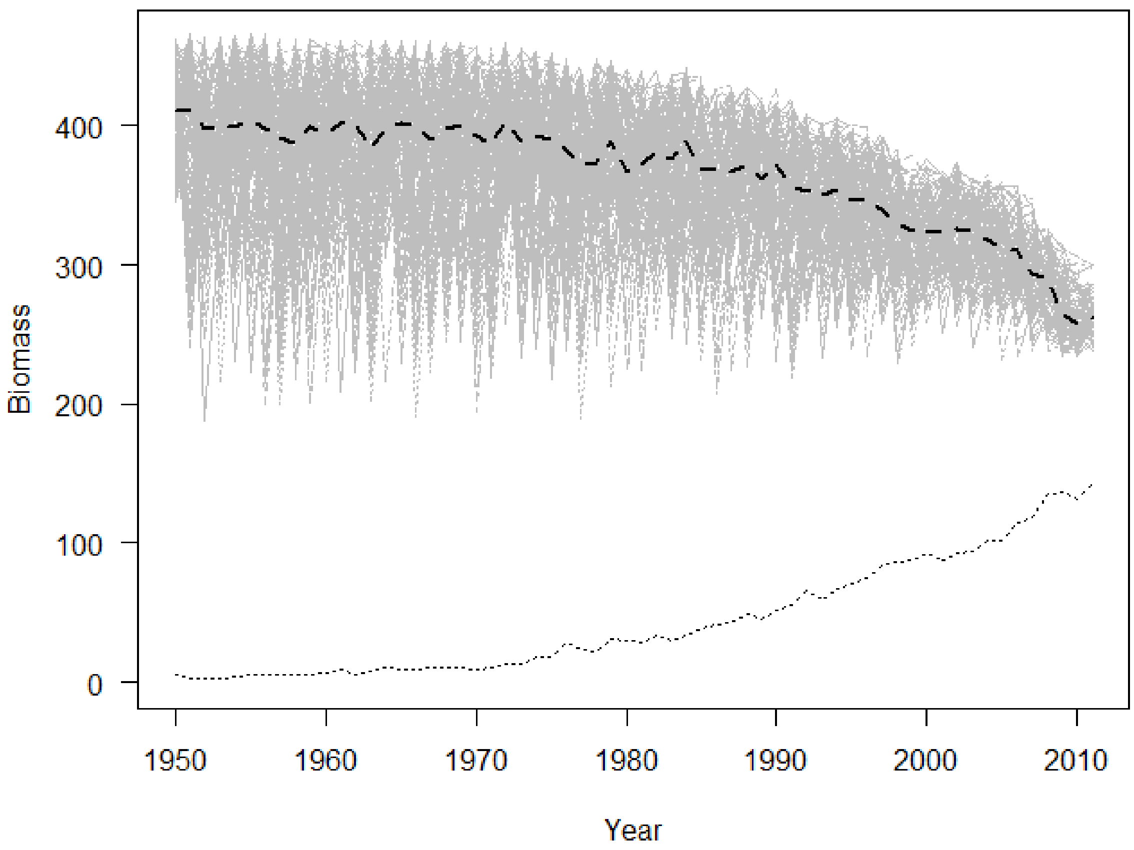
There is no feasible solution when the depletion is assumed to be below 0.4.

The unit is thousand tonnes (except for r).

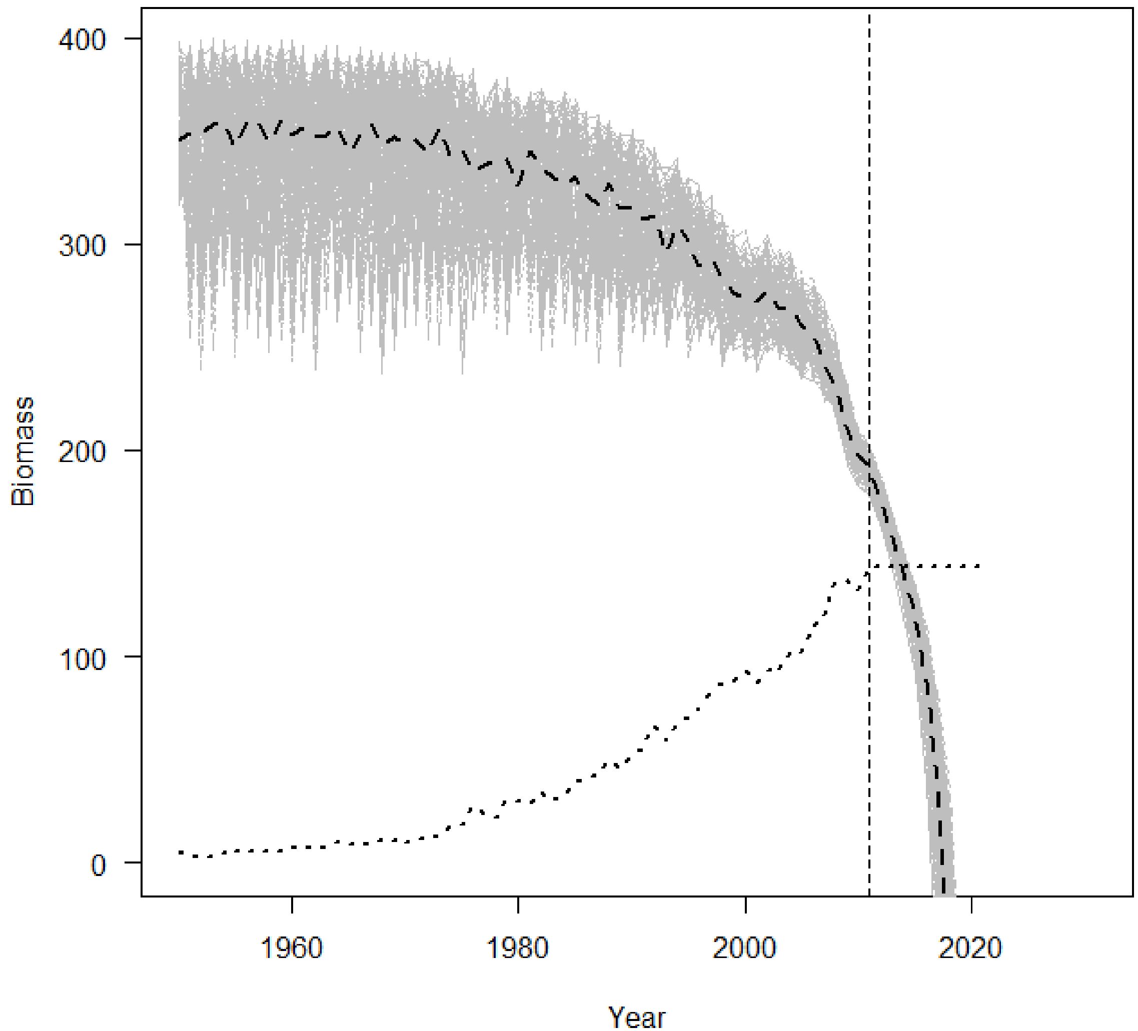
Possible [r, k] combinations for depletion between 0.38 and 0.8



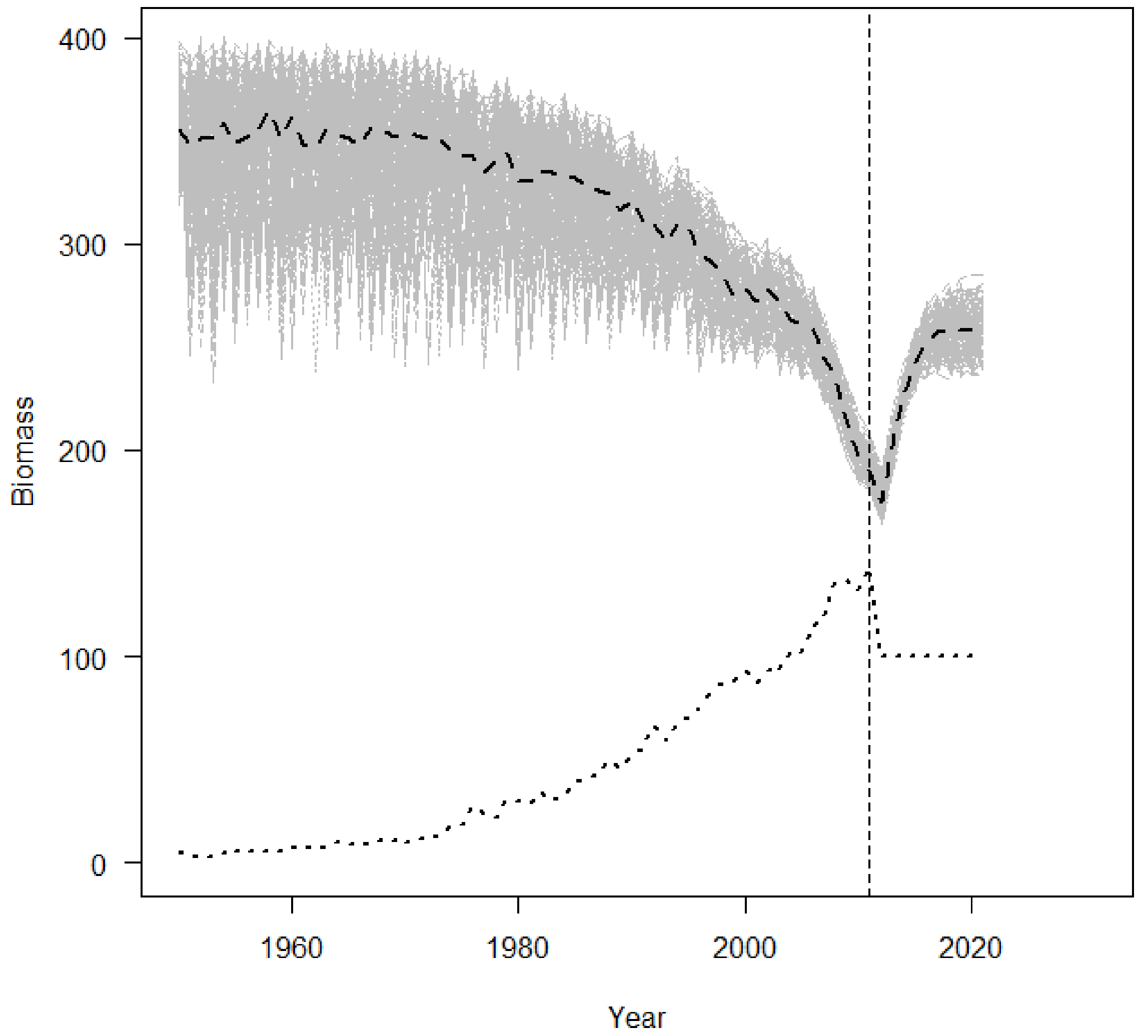
Kawakawa biomass trajectories from 100 simulations



Kawakawa biomass projection assuming catch maintains at 2011 level

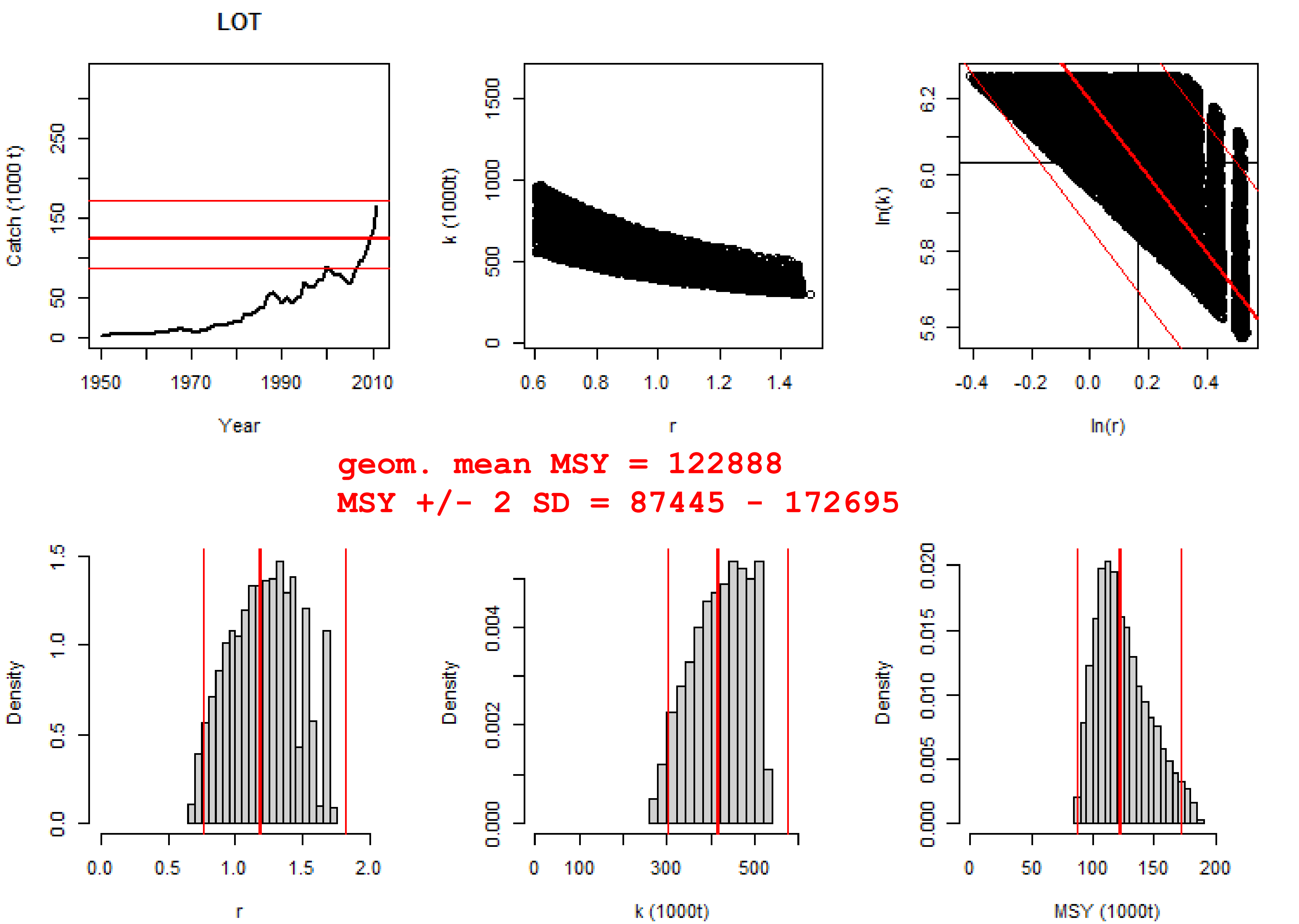


Kawakawa biomass projection assuming catch = 100 thousand tonnes

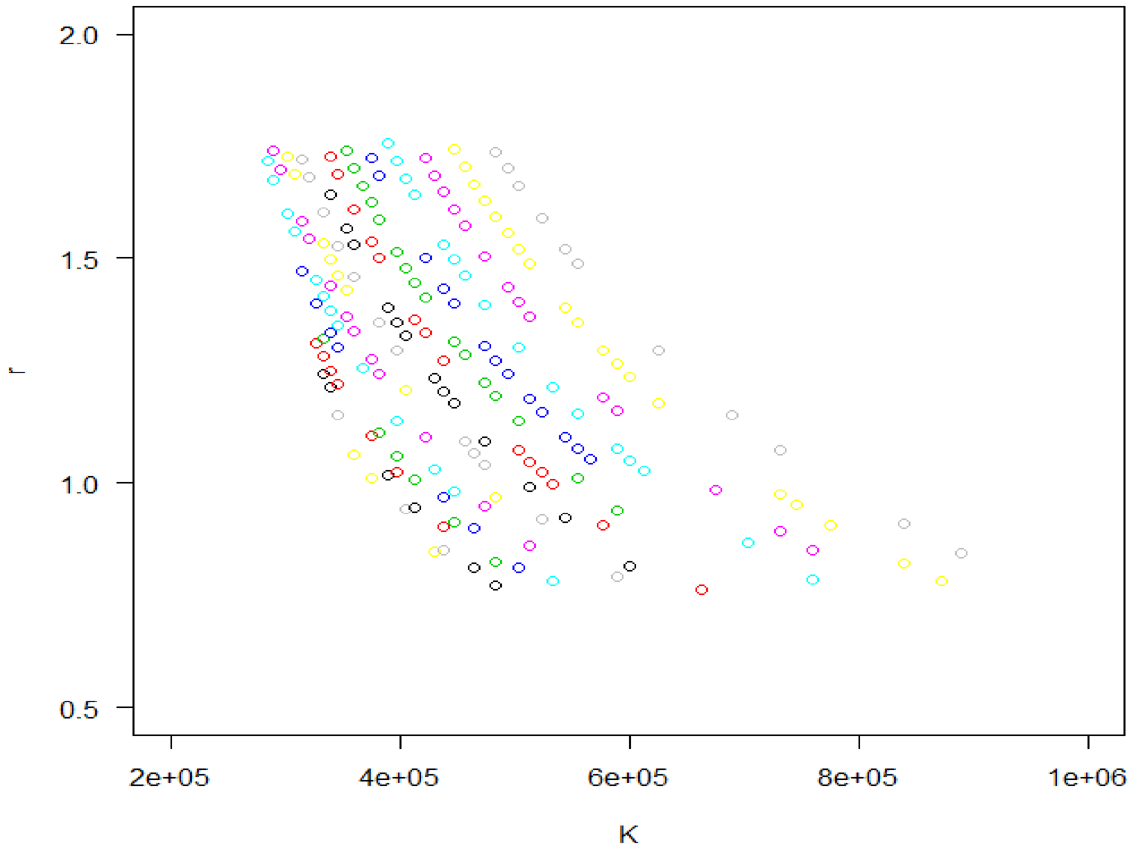


Kawakawa results
- catch-based method

Upper D	Pars	Mean	5%	25%	50%	75%	95%
0.6	K	358	322	337	358	378	395
0.6	r	1.43	1.29	1.35	1.43	1.51	1.58
0.6	MSY	126	113	120	128	132	136
0.6	B_{2011}	192	181	187	193	197	204
0.6	D_{2011}	0.54	0.48	0.51	0.54	0.57	0.6


LOT
Catch (1000 t)
Year
k (1000t)
r
ln(k)
ln(r)
geom. mean MSY = 122888
MSY +/- 2 SD = 87445 - 172695
Density
r
Density
k (1000t)
Density
MSY (1000t)

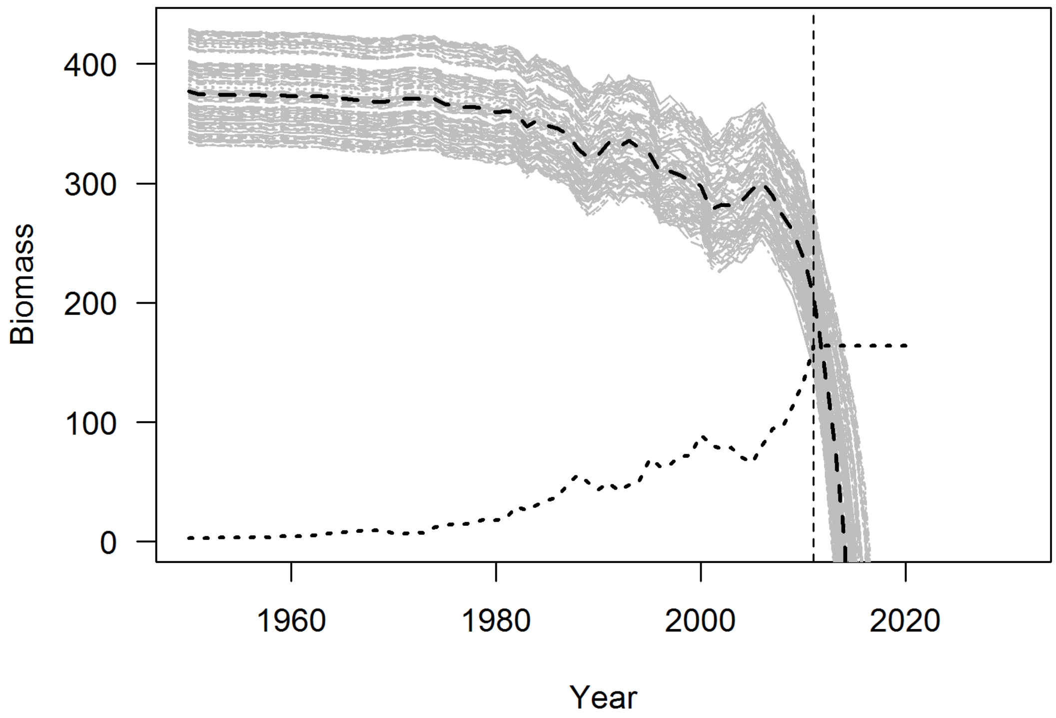
Possible [r, K] combinations



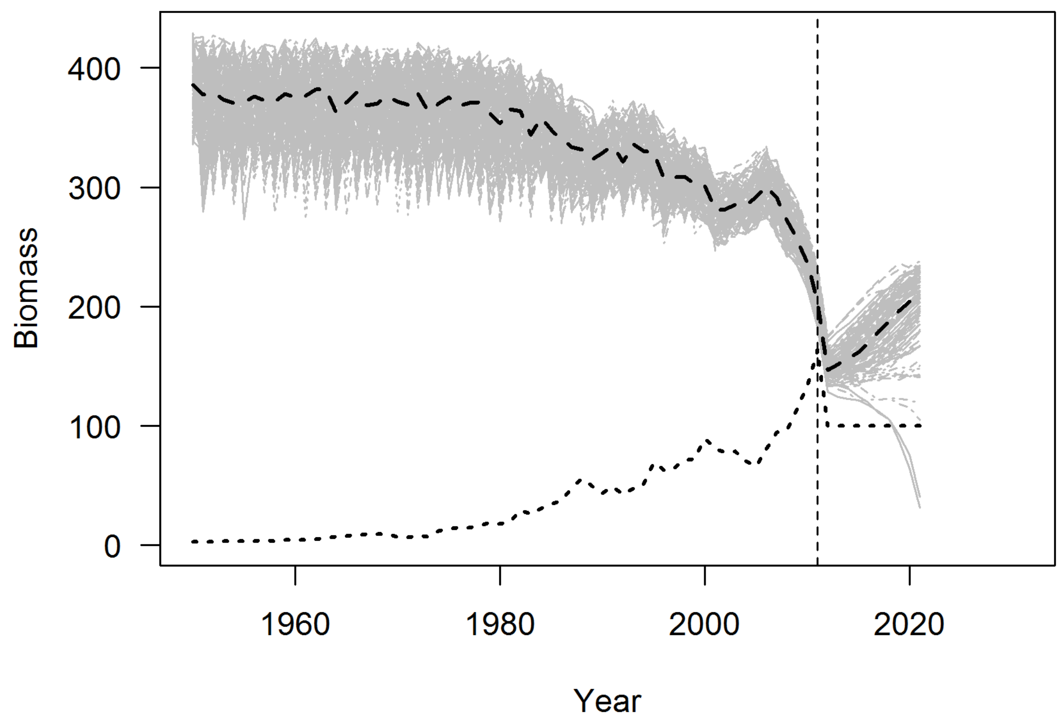
r [0.75, 1.76]

D[0.46, 0.80]

Longtail biomass projection assuming catch maintains at 2011 level



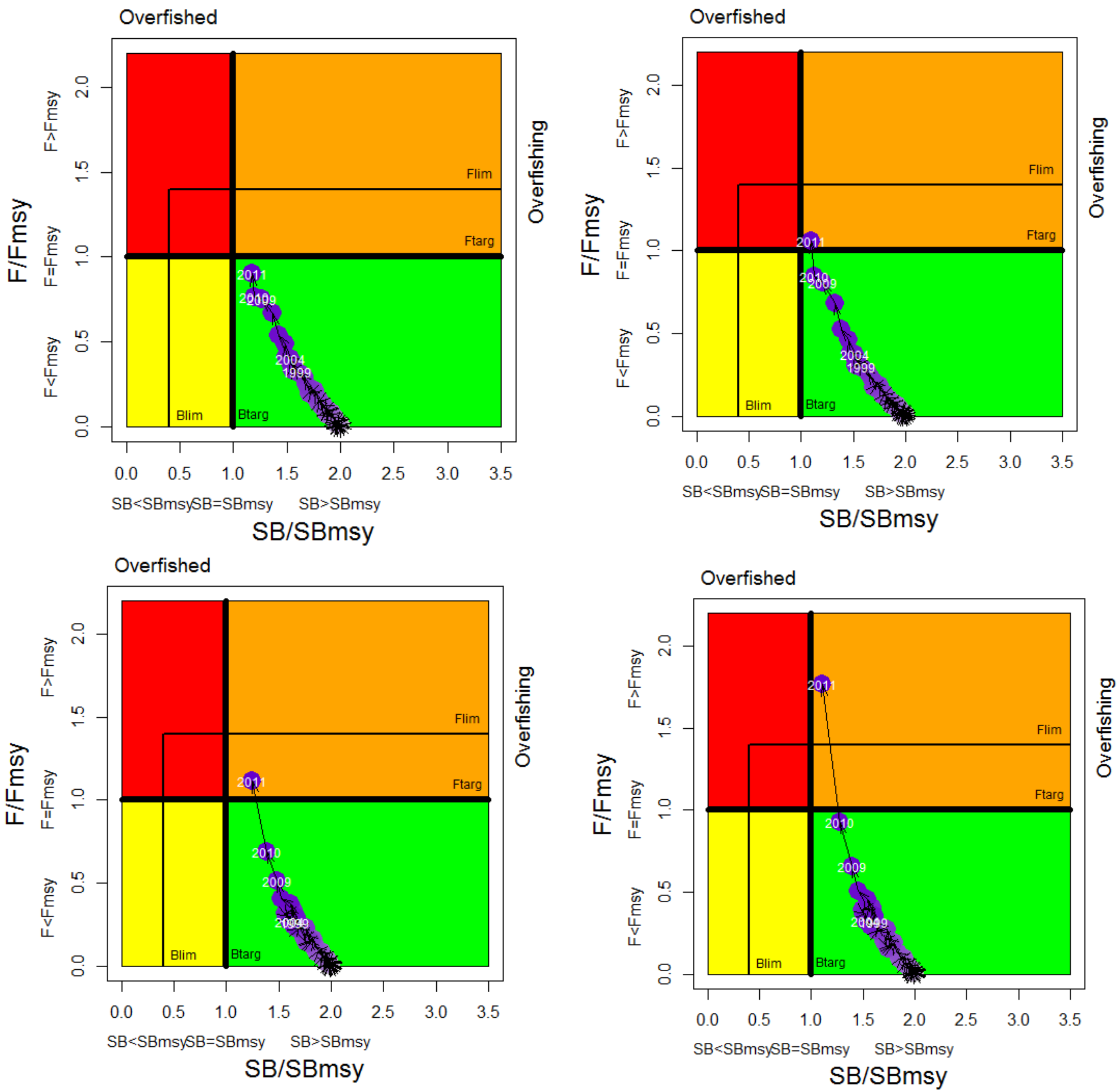
Longtail biomass projection assuming catch =100 thousand tonnes



Longtail results - catch-based method

Upper D	Pars	Mean	5%	25%	50%	75%	95%
0.6	K	381	338	357	381	405	425
0.6	r	1.16	1.03	1.08	1.15	1.23	1.3
0.6	MSY	109	94	102	110	118	124
0.6	B_{2011}	211	152	183	212	242	268
0.6	D_{2011}	0.55	0.44	0.51	0.56	0.6	0.64

Stock Status



KAW

LOT

Overall Conclusions

- Both KAW and LOT appear susceptible in recent years.
- Total catch in recent year (2011) appears to exceed MSY based on both the SRA and the Posterior based SRA Methods.
- Catch levels probably unsustainable at these levels.
- Assessments would be improved if Iran and Indonesia can develop CPUE indices for LOT and India can for KAW.
- Stock Structure (accounting for this in assessments).
- Results comparable to simpler LH Based methods.

Acknowledgements

- Steve Martell, IPHC.
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Thank You

Battle of the Methods: Which Empirical Predictor of Natural Mortality Rate Works Best?

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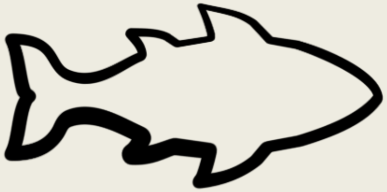
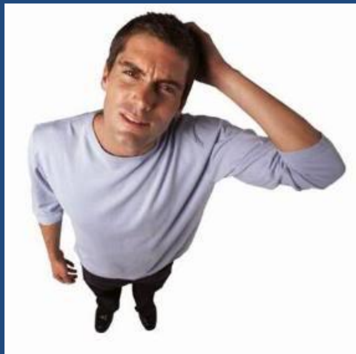
BOSTON
WCSAM
2013
WORLD CONFERENCE ON STOCK ASSESSMENT METHODS



Introduction

- Natural mortality *M*…*influential* parameter
- Difficult to estimate reliably by *any* means
- Data poor (& rich?) stocks: routinely use empirical *M* methods
- *Averaging* multiple *M* estimates - good practice
- Empirical *M* estimates –
  all *equally* good/ independent?



Questions of Interest

M prediction

Ranking

Updated

Improved combo

'Fair' comparison

Issues

Issues

1. *M* – variable & complex

   Useful to consider *constant M*

2. True *M* unknown

   Predict what *is* known

3. Available estimates of *varying quality*

   Users judge quality of data

4. *Non-random* sample of species from *ill-defined* population

   Test relationships on *subsets*

5. *Multiple* estimates for some taxa

   Hierarchical structure/ single estimates for species

Fair comparison

- *Historical*: performance of original methods?

  'New' dataset

- *Approach*: how do the methods compare to each other?

  'Common' dataset – good or bad

- *Updated*: performance of updated methods?

  'Full' dataset

  Update coefficients & evaluate

The 'battle'

Empirical estimators	Citations*
• Pauly (1980): *K, L_∞, Temp*	1866
• Hoenig (1983): t_{max}	836
• Jensen (1996): *K*	284
• Alverson & Carney (1975): K, t_{max}	203
• 1-parameter t_{max} ($M = \hat{c} / t_{max}$)	

* based on Google Scholar; last updated on July 11, 2013

Methods

- Compile direct *M* estimates
- M methods*: catch curve, length-based, *Z* vs *f*, tagging

  **statistical catch-at-age estimates not included*
- Find matching *K*, L_∞, *Temperature*, t_{max} *(spatially, temporally); no ‘borrowing’*
- Evaluation: approach & updated
- *Metrics of performance:* 10-fold cross-validation prediction error (RMSE)

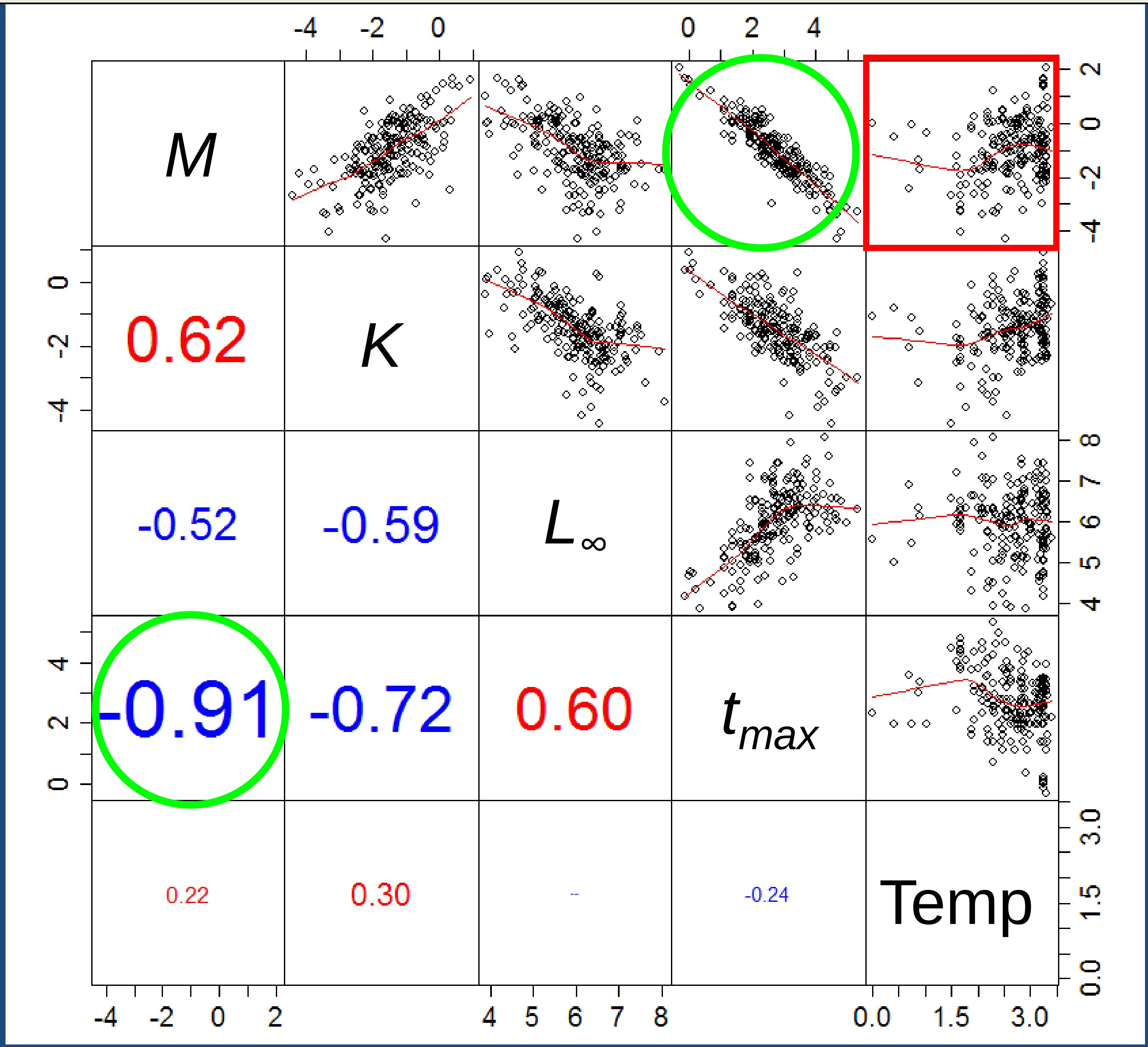
Results

Dataset

- ‘Common’: 201 unique species
- *M* range 0.014 - 7.92 yr^{-1}
- Dataset *will* be posted online, maintained & updated by a committee
- Contributions are welcome!

Results

r^2: *M* & Predictors (log)



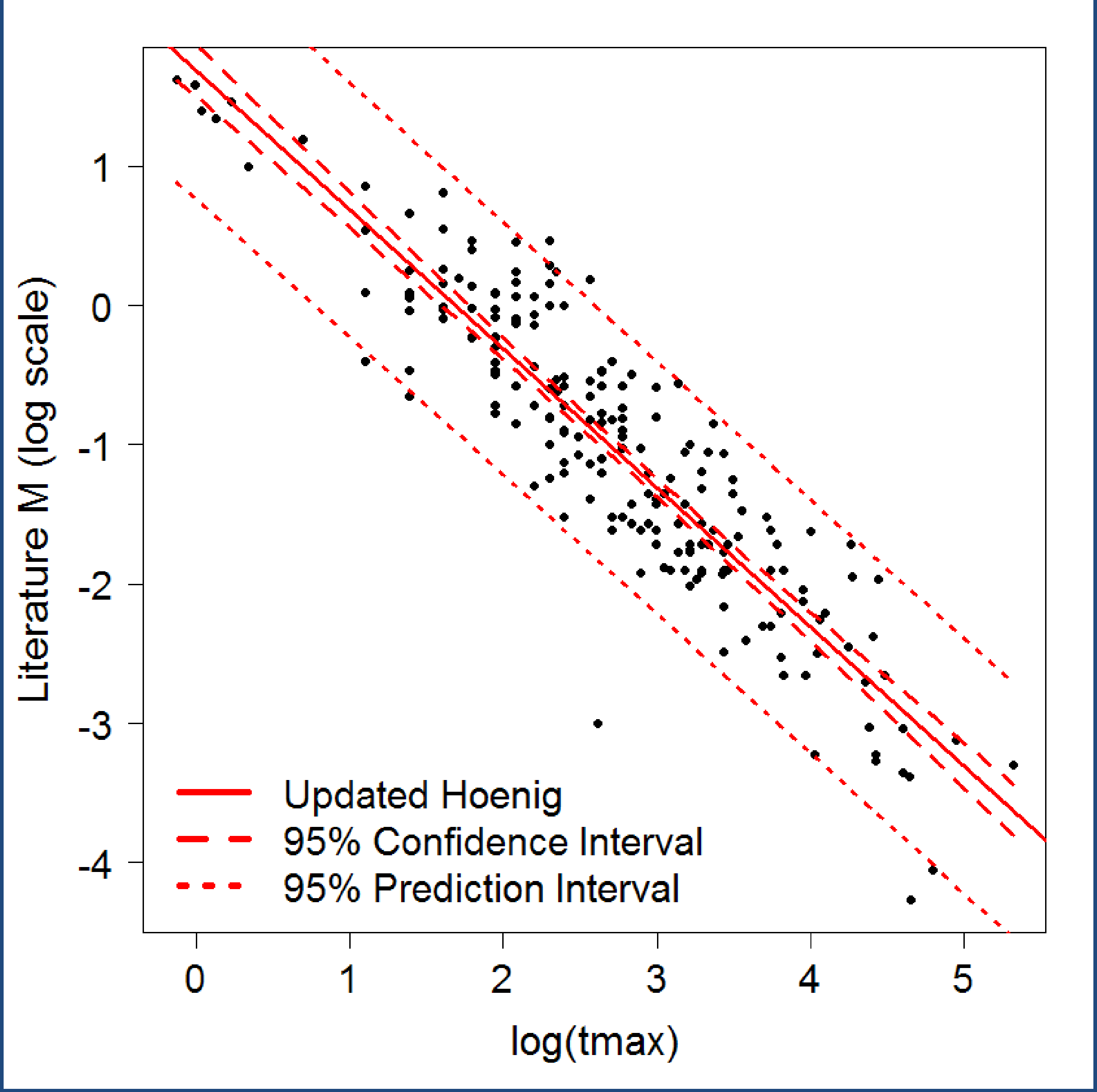
Results

Prediction error (RMSE)

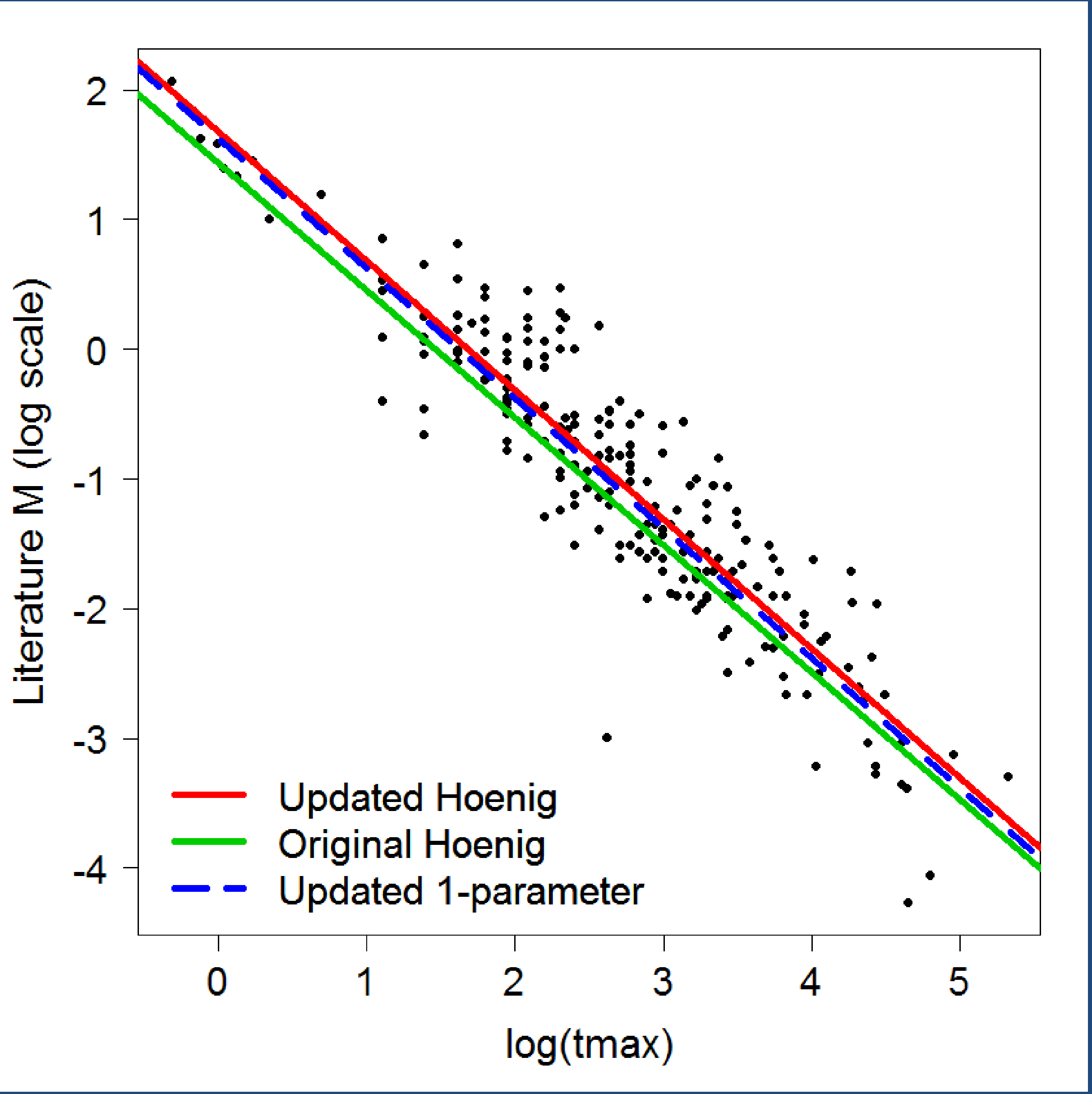
Updated estimators	Equal n (= 201)	Updated ('Full')		
	Error	r^2	Error	n
1-parameter tmax	0.31	0.90	0.31	214
Hoenig	0.32	0.90	0.32	214
Jensen	0.59	0.46	0.61	205
Pauly	0.62	0.53	0.62	201
Alverson & Carney	1.17	0.85	1.20	202
Hoenig - Pauly Combo	-	0.86	**0.30**	201

Results

Updated Hoenig

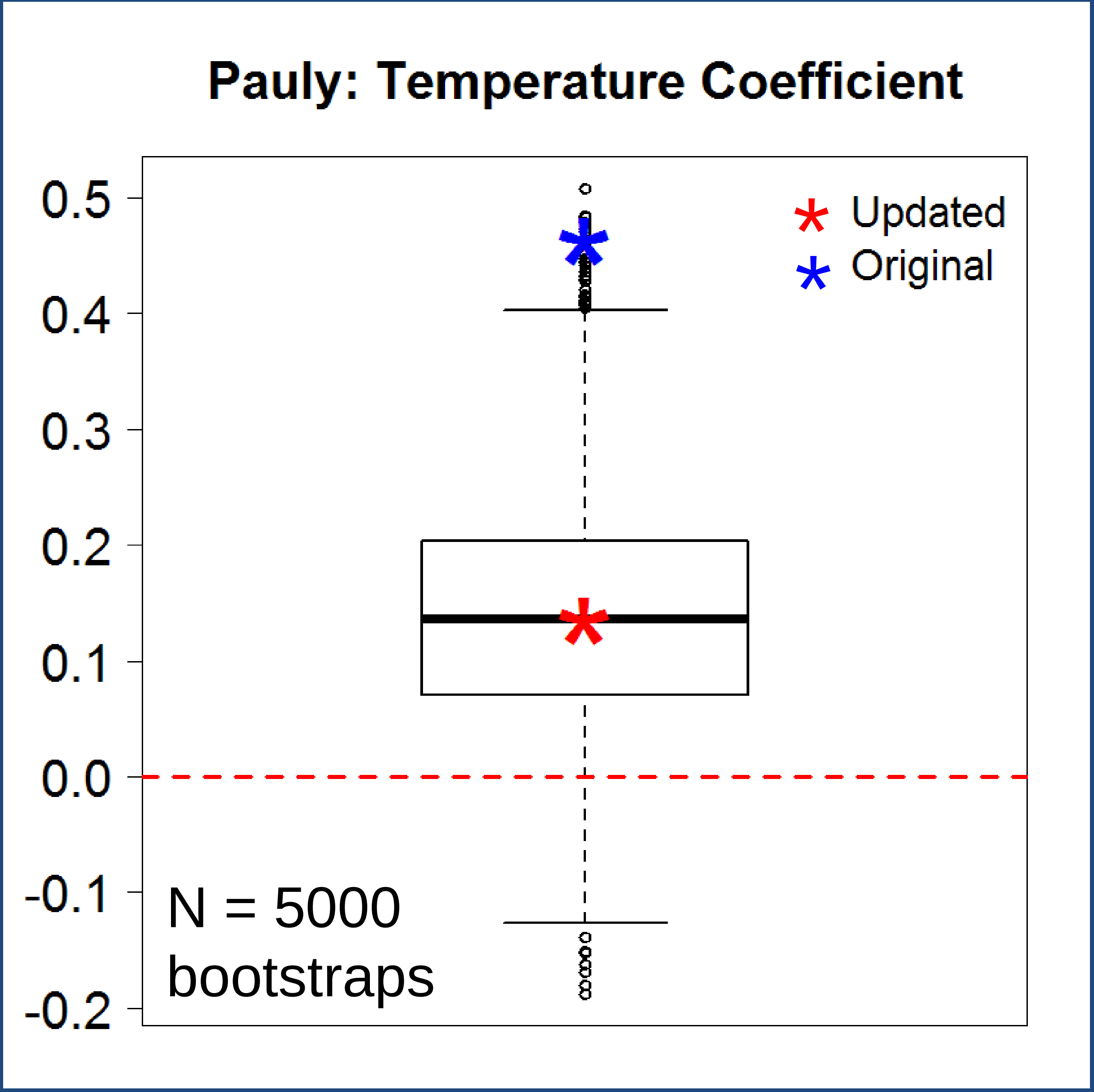


Updated t_{max}-based

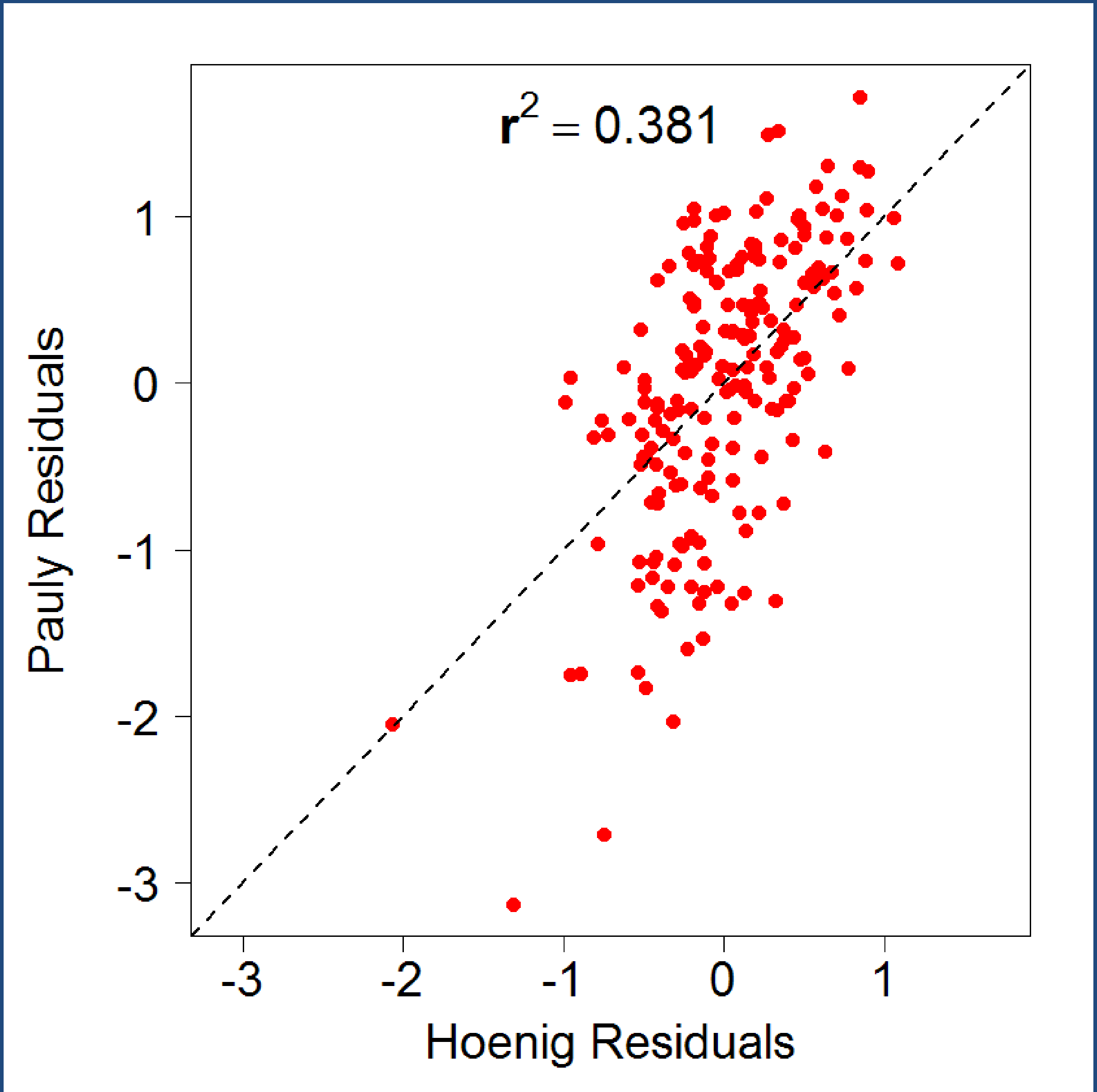


Results

Updated Pauly

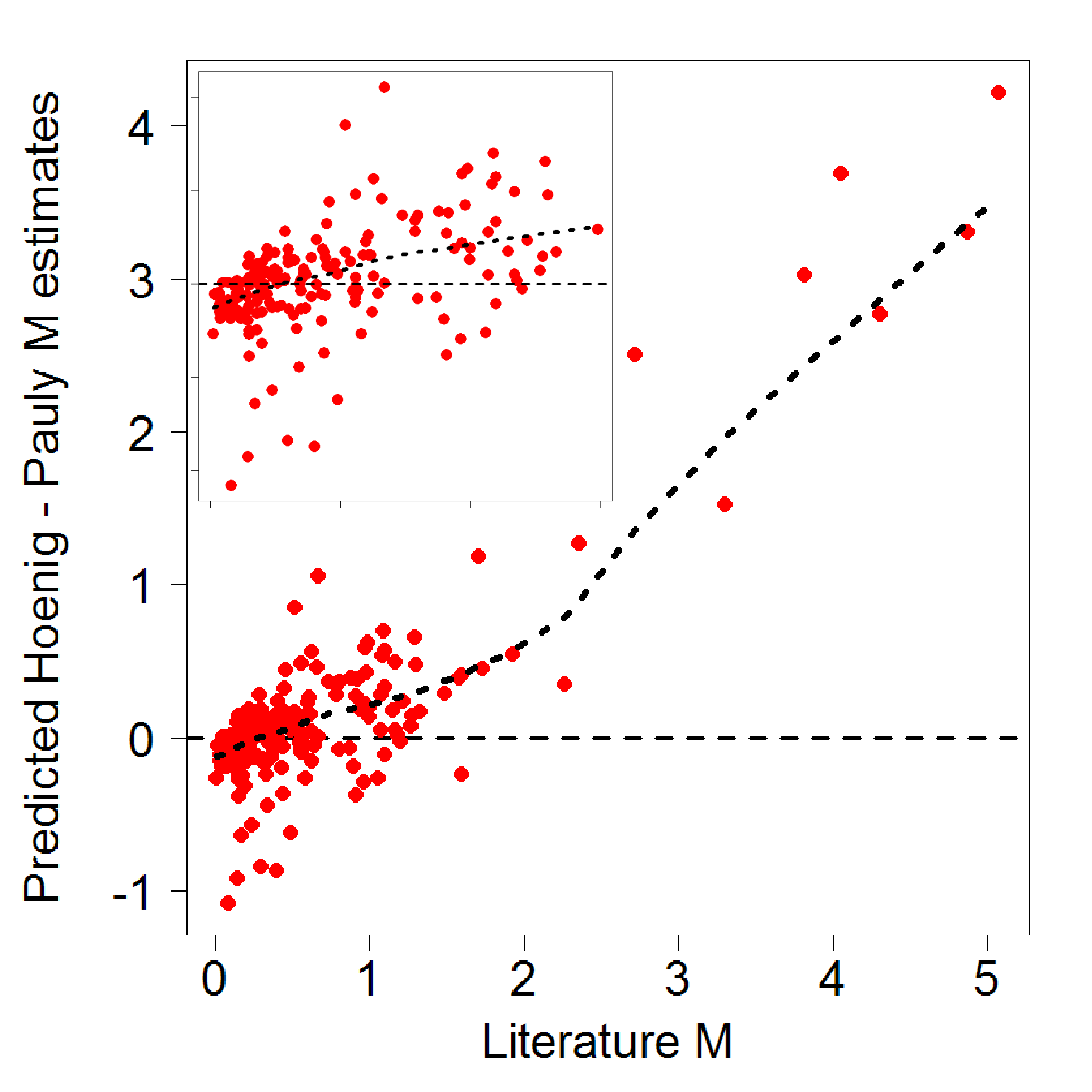


Independence?



Hoenig - Pauly

Results



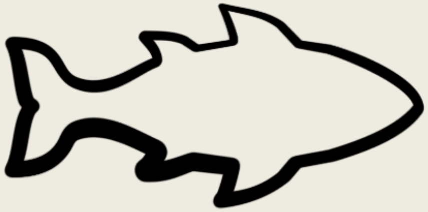
Results

Highlights

- Rank:
  1-parameter t_{max} ~ Hoenig >>
  Jensen ~ Pauly >>
  Alverson & Carney

- Updated Pauly (+Temp) ~
  Updated Pauly (-Temp)

- *Best*: *Hoenig - Pauly combo*
  (79% weight to M_{Hoenig}, 21% to M_{Pauly})
  → *only slightly* better than t_{max}-based



Conclusions & Recommendations

- Updated *1-parameter t_{max}* or Hoenig preferred
- Use updated Jensen or Pauly (- Temp) when t_{max} not available
- Alverson & Carney *not* recommended
- Other variants (e.g. Hoenig geometric regression, Pauly & Binohlan) *not* recommended
- Support for *continual maintenance* of ‘database’

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- Todd Gedamke, Clay Porch

Myctophidae Callionymidae Ammodytidae Gasterosteidae Percidae

Scaridae Macrouridae Pomacentridae

Oreosomatidae Nemipteridae Serranidae

Cichlidae Cepolidae

Thank you!

Acipenseridae Polyodontidae Syngnathidae Malacanthidae Carangidae Apogonidae

Emmelichthyidae

Merlucciidae Poeciliidae Sparidae Sphyrnidae

Triakidae

Lutjanidae Arripidae Cyprinidae Engraulidae