## Informative Data and Uncertainty in Stock Assessment

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## Outline

### Introduction

Uncertainty in stock assessment, research questions

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### Papers 1 & 2 (simulation studies)

Informative data, stock status, key parameters Delta method, bootstrap, MCMC

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### Paper 3 (synthesis and case study)

Broader overview, application of methods to Icelandic saithe Profile likelihood, retro, bivariate confidence region, HCR

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#### Conclusions

Summary of findings, general recommendations

Uncertainty in stock assessment

Fisheries management relies on stock assessment

Stock status, harvest rate, reference points, key parameters

Not just the most likely value, but a range of plausible values

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Fisheries management relies on stock assessment

Stock status, harvest rate, reference points, key parameters

Not just the most likely value, but a range of plausible values

Give advice that is robust to violated assumptions

Failure to incorporate uncertainty into the management advice  $\rightarrow$  suboptimal yields, fishery collapse

## Research questions

### What makes some datasets more informative than others?

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### How reliable are statistical methods to measure uncertainty?

What are good practices for confronting uncertainty?

## Study design

### Simulation studies 1-2

Generate random datasets where the true values are known Evaluate the performance of statistical methods Typical groundfish data and age-structured model

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Generate random datasets where the true values are known Evaluate the performance of statistical methods Typical groundfish data and age-structured model

### Review & case study 3

Review findings from simulation studies Apply same methods to Icelandic saithe, interpret results Demonstrate additional methods to confront uncertainty

Fishing history Key parameters

### Paper 1

FISH and FISHERIES, 2007, 8, 337-358

### What makes fisheries data informative?

Arni Magnusson<sup>1,2</sup> & Ray Hilborn<sup>1</sup>

Fishing history Key parameters

### Paper 1

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### What makes fisheries data informative?

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Fishing history Key parameters

## Informative fishing history?



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1 Informative data

2 Uncertainty methods 3 Confronting uncertainty Key parameters

## Key parameters: h, M, r



*h* : stock-recruitment steepness

3 Confronting uncertainty

Fishing history Key parameters

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*h* : stock-recruitment steepness only if data include very low *SSB* 

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*h* : stock-recruitment steepness only if data include very low *SSB* 

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r : right-hand selectivity

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Fishing history Key parameters

## Key parameters: h, M, r



*h* : stock-recruitment steepness only if data include very low *SSB* 

M : natural mortality rate only if data include high & low F

*r* : right-hand selectivity confounded with *M* 

Methods Performance

### Paper 2

FISH and FISHERIES, 2013, 14, 325-342

# Measuring uncertainty in fisheries stock assessment: the delta method, bootstrap, and MCMC

Arni Magnusson<sup>1,2</sup>, André E Punt<sup>1</sup> & Ray Hilborn<sup>1</sup>

Methods Performance

### Paper 2

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Methods Performance

## Uncertainty methods: delta, boot, mcmc

	Procedure	Interval
Delta method	$\widehat{\mathrm{SE}}_{\hat{\theta}} = \sqrt{\sum_{i} \sum_{j} \widehat{\mathrm{Cov}} \left( \hat{\theta}_{i}, \hat{\theta}_{j} \right) \left( \frac{\partial g}{\partial \theta_{i}} \right) \left( \frac{\partial g}{\partial \theta_{j}} \right)}$	$\left[\hat{g} - z_{1-\alpha/2}\widehat{\mathrm{SE}}_{\hat{g}}, \ \hat{g} + z_{1-\alpha/2}\widehat{\mathrm{SE}}_{\hat{g}}\right]$
Bootstrap	simulate datasets y*	$\left[\frac{\alpha}{2} \text{ quantile from }_{\mathrm{BC}}\vec{\vec{\theta}}^{*},  \left(1-\frac{\alpha}{2}\right) \text{ quantile from }_{\mathrm{BC}}\vec{\vec{\theta}}^{*}\right]$
МСМС	simulate parameter values	$\left[\frac{\alpha}{2} \text{ quantile from } \vec{\theta},  \left(1 - \frac{\alpha}{2}\right) \text{ quantile from } \vec{\theta}\right]$

Methods Performance

## Uncertainty methods: delta, boot, mcmc



Confidence level

Methods Performance

## Uncertainty methods: delta, boot, mcmc

### Performance



1 Informative dataData, model estim2 Uncertainty methodsFishing history3 Confronting uncertaintyDiagnostics, uncertainty

### Paper 3

## Confronting Uncertainty in Stock Assessment

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### Paper 3

## Confronting Uncertainty in Stock Assessment



Data, model estimates Fishing history Diagnostics, uncertainty

## Icelandic saithe







Data, model estimates Fishing history Diagnostics, uncertainty

### Biomass and harvest rate



Year

Data, model estimates Fishing history Diagnostics, uncertainty

### Biomass and harvest rate





Data, model estimates Fishing history Diagnostics, uncertainty

## Recruitment and surplus production



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## Retrospective analysis



Data, model estimates Fishing history Diagnostics, uncertainty

## Bivariate confidence region



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## Estimating M

Base model M = 0.2

Estimated M = 0.57





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## Estimating M

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1 0.3 0.3 0.1 0.3 0.1 0.3 0.1 0.3  $\sim$ 0.3 

#### Estimated M = 0.57



Data, model estimates Fishing history Diagnostics, uncertainty

## Estimating h and M

### Stock-recruitment steepness

- h = 0.90 in base model
- Point estimate is 0.99

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M = 0.20 in base model

Point estimate is 0.57

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## Summary of findings

### Fishing history

### One-way-trip proved no less informative than good contrast

'the more fish you catch, the better you know how many there were'

### Key parameters

- h : data must include years with very low SSB
- M : data must include high and low F
- r : confounded with M

### Uncertainty methods

MCMC, delta method, profile likelihood more reliable than bootstrap

## General recommendations

- 1 Use more than one method to evaluate uncertainty.
- 2 Keep in mind that the real uncertainty is greater than the analytical confidence intervals indicate.
- 3 Use more than one model and variations of models to evaluate how sensitive the main conclusions are to alternative assumptions.
- 4 Use retrospective analysis to evaluate uncertainty from an empirical viewpoint.

## General recommendations

- 5 Use simulation analysis to evaluate the performance of the estimation model, which parameters can be estimated reliably, and which uncertainty methods work best.
- 6 Examine the fishing history to evaluate whether the data are likely to be informative about the stock status and key parameters like *h* and *M*.
- 7 Consider ways to reduce uncertainty by generating informative data via management (e.g., applying different fishing mortalities between years) and research (e.g., design a dedicated survey for a given stock, sample age data).
- 8 Harvest control rules can be a practical way to incorporate uncertainty into management advice.



### Comprehensive overview and evaluation

of methods to analyze uncertainty



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of methods to analyze uncertainty

# Checklist of **recommendations** for stock assessment practitioners

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