Data Weighting in
Statistical Fisheries Stock Assessment Models

Chris Francis

- Widely acknowledged as important
- No consensus on best approach
- No objective method

This talk

Terminology

Some key data-weighting questions

Proposed approach to data weighting

Terminology 1

‘Statistical’ models = likelihood-based (*not* VPA)

Objective function = likelihoods + priors + penalties

Terminology 2: Data & Likelihoods

Data type	Likelihood example	Data	Weights
Abundance	$\log\left(c_{iy}E_{iy}\right)+0.5\left(\frac{O_{iy}-E_{iy}}{c_{iy}E_{iy}}\right)^2$	O_{iy}	c_{iy}
Composition	$-N_{jy}O_{jby}\log E_{jby}$	O_{jby}	N_y

(see Table 2 for more likelihoods)

Not data: information used outside the model to devise

- fixed parameters (e.g. von Bertalanffy)
- priors

Not a weight: σ_R (s.d. of recruitment variability)

Terminology 3: Two-stage weighting

1. Stage 1: set initial data weights based on sample sizes, sampling variabilty, etc
2. Run model using initial data weights
3. Stage 2: adjust weights using goodness-of-fit information

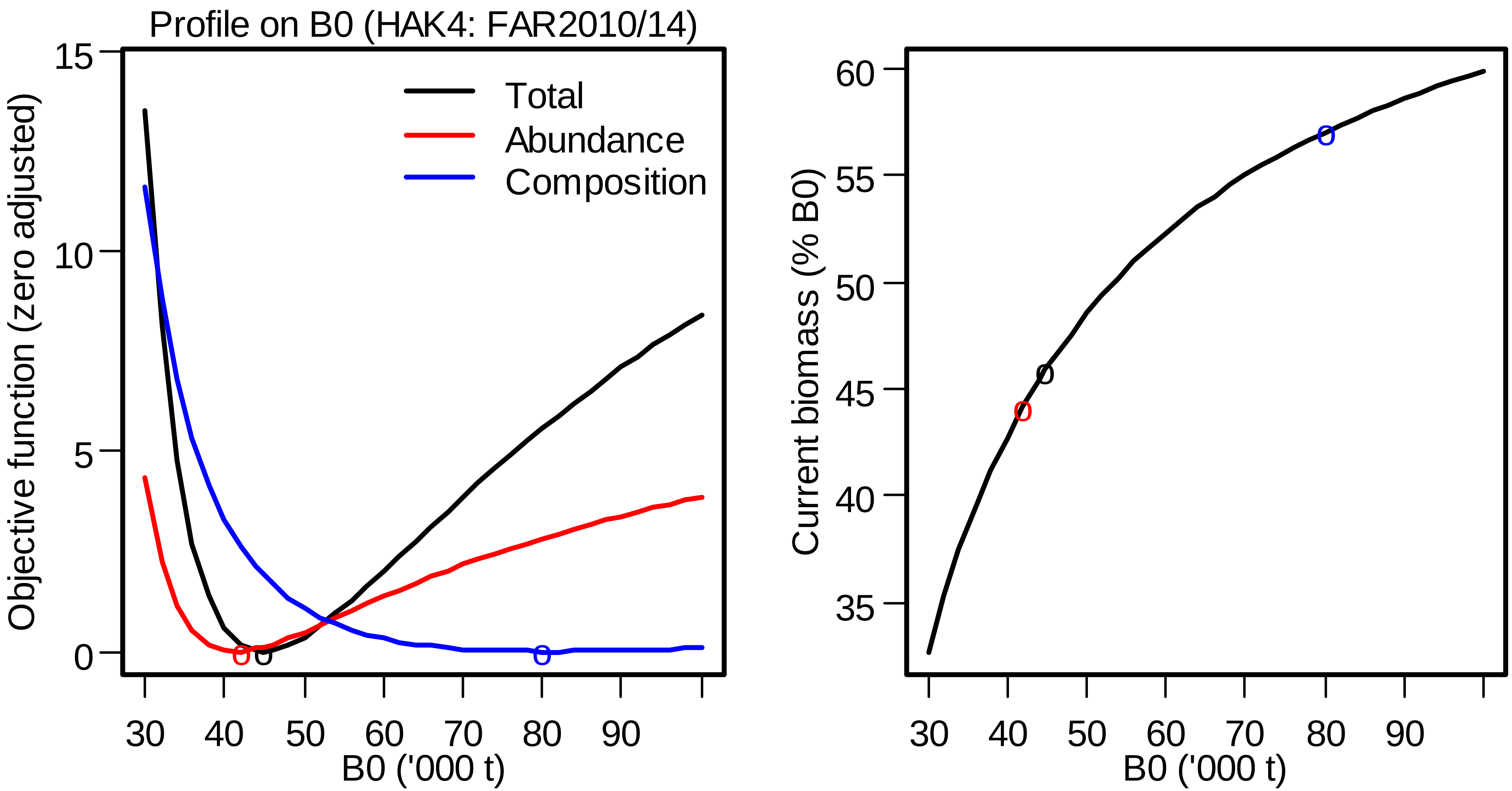
	Weights	
Adjusted weight	Stage 1	Stage 2
$c_{iy} = \sqrt{\tilde{c}_{iy}^2 + c_i^2}$	$\tilde{c}_{iy}$	c_i
$N_{jy} = \tilde{N}_{jy} w_j$	$\tilde{N}_{jy}$	w_j
$N_{jy} = 1 \big/ \left[\left(1 \big/ \tilde{N}_{jy} \right) + \left(1 \big/ N_j \right) \right]$	$\tilde{N}_{jy}$	N_j

(see Table 3)

Why is data weighting important?
(Fig. 1)

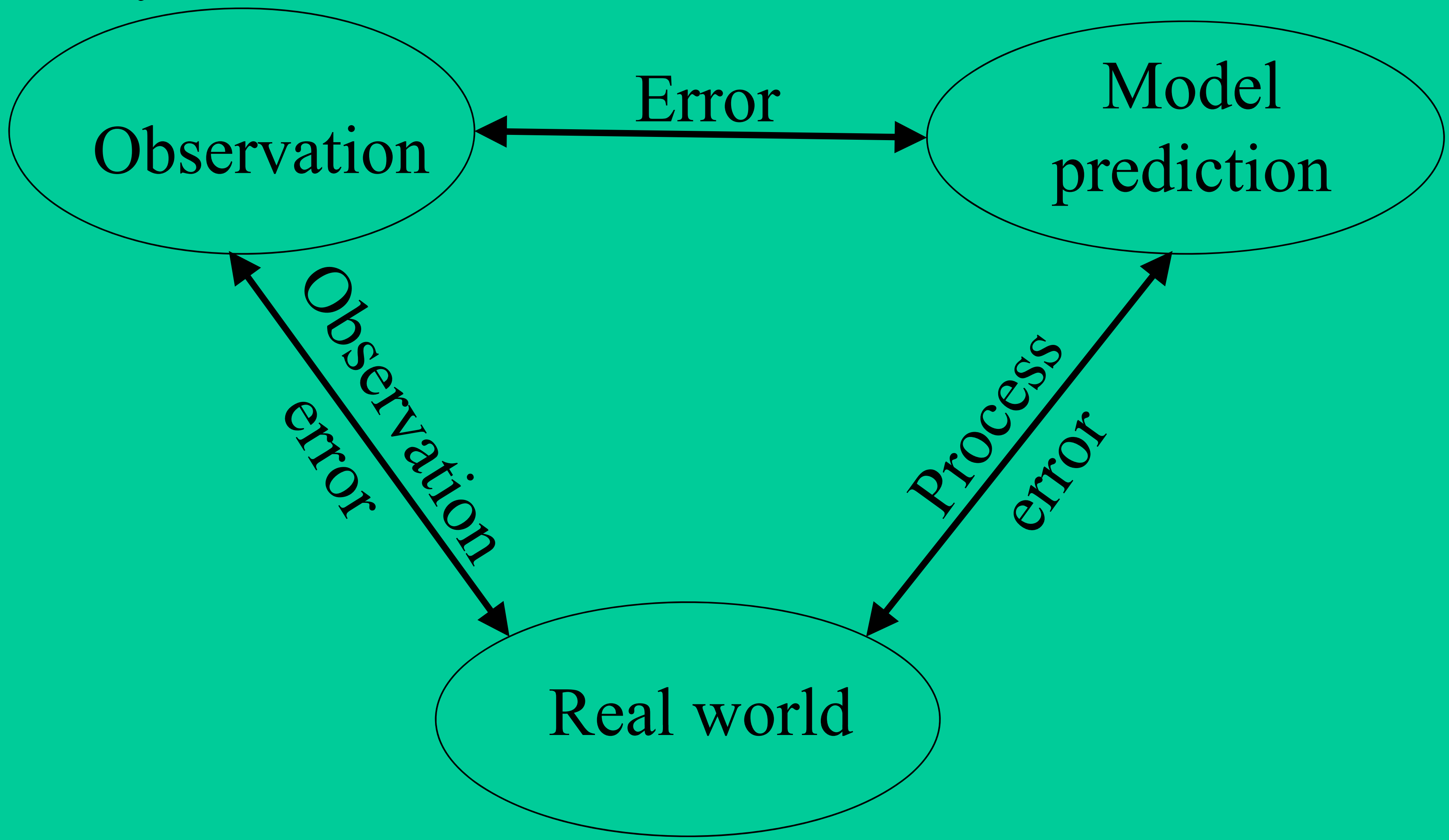
Can strongly affect stock status

Affects statistical inference (AIC, confidence intervals)



Why is stage 2 weighting necessary?

The weight given to each observation should describe the likely size of its error



Can we estimate process error outside the model?

For trawl survey biomass indices:

year-to-year variation in catchability; *c.v.* ≈ 0.2

(Pennington & Godø Fish. Res. 23: 301-310, 1995; Millar & Methot Can. J. Fish. Aquat. Sci. 59: 383-392, 2002; Francis et al, Fish. Bull. 101: 293-304, 2003)

For acoustic surveys

year-to-year variation in mean target strengths, abundance of non-target species, etc

(Rose et al. Aquat. Liv. Res. 13: 367-372; 2000 O'Driscoll, ICES J. Mar. Sci. 61: 84-97, 2004)

For composition data

year-to-year variation in selectivity and *M*; variation of *M* by age

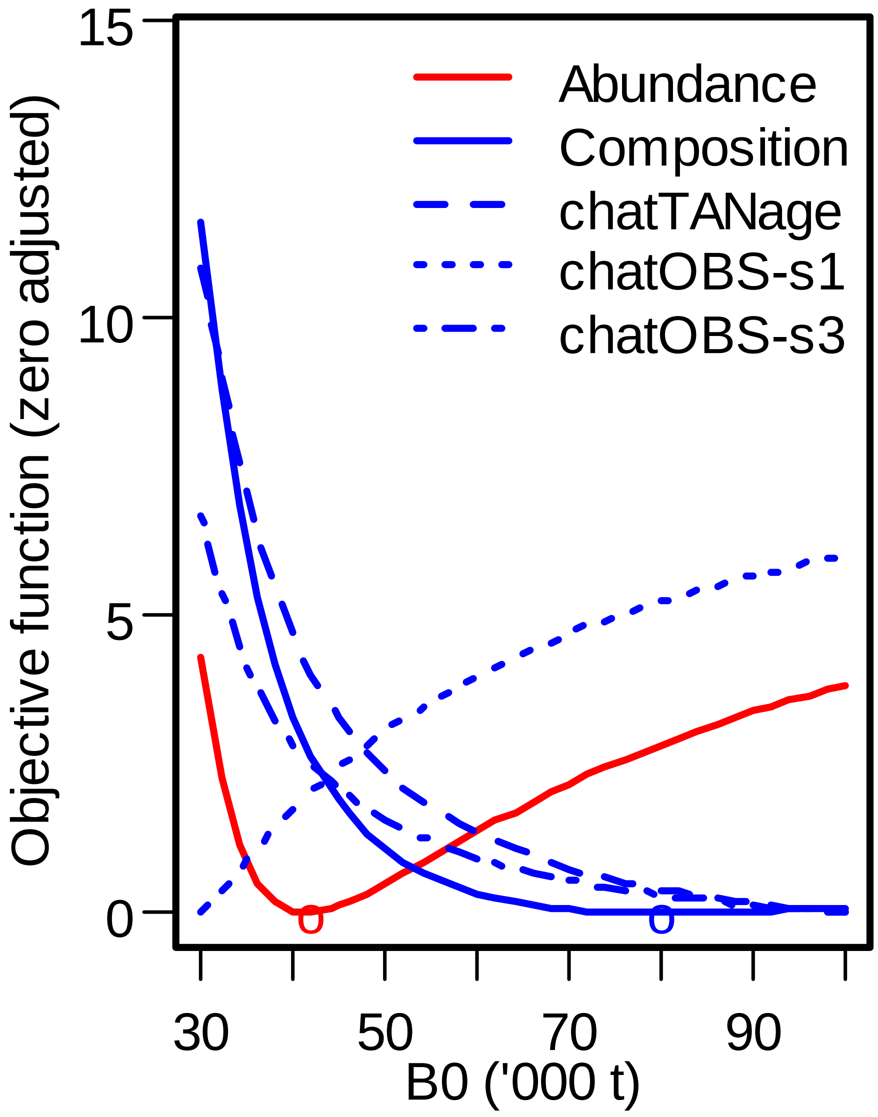
not possible to quantify outside the model

Why should abundance data have primacy?

Key stock assessment questions concern abundance

Composition data tell us
- lots about YCSs
- lots about selectivities
- little about abundance

Don't allow weighting on composition data to cause a poor fit to abundance data!



How to deal with abundance data that may be unrepresentative?

‘Unrepresentative’ = wrong trend

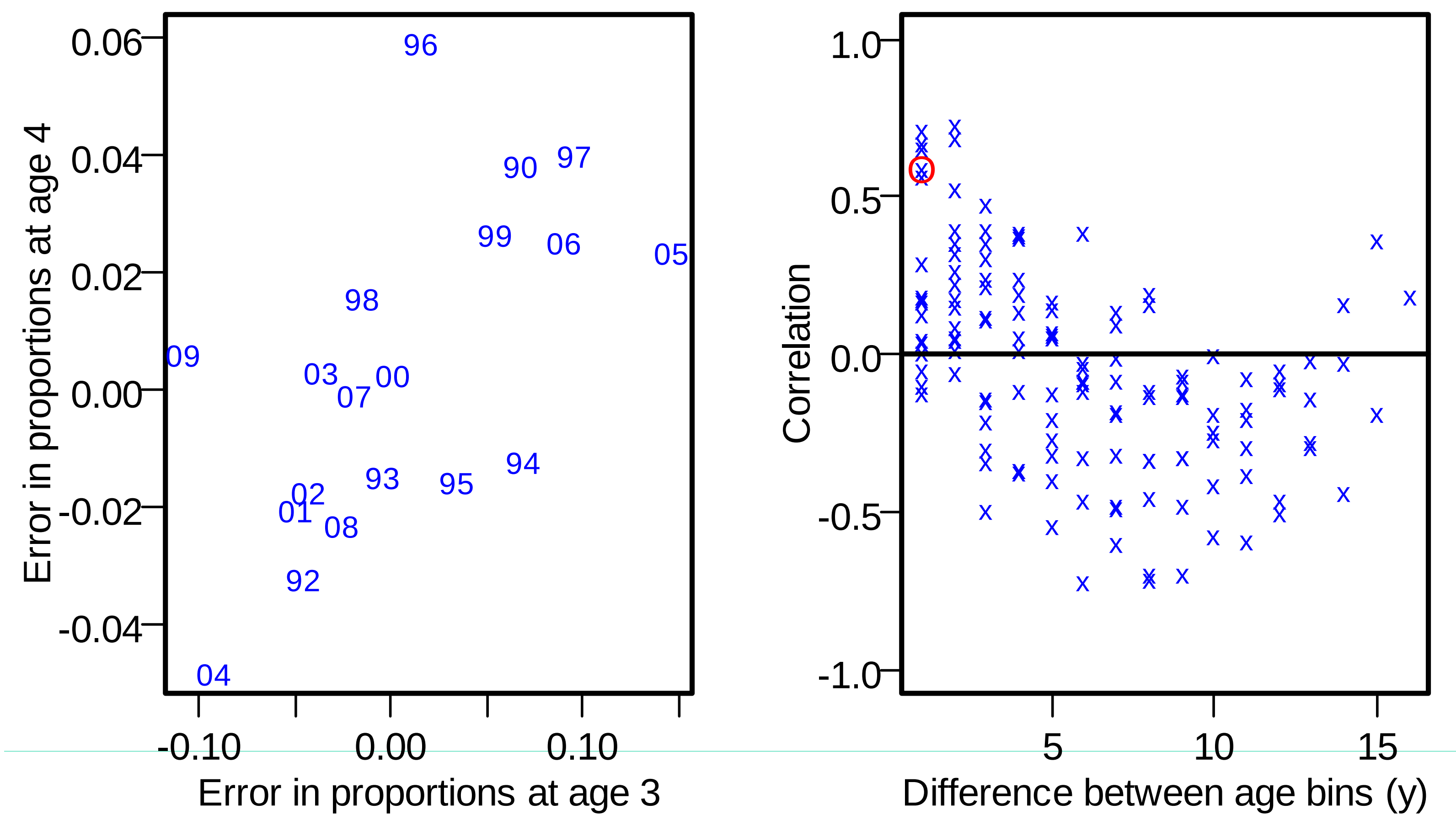
$\neq$ imprecise or noisy

Common response: down-weight the data

Better response: either fit well or discard

(cf problem of contradictory data sets [Richards 1991; Schnute & Hilborn 1993])

How should we deal with correlations in composition data?

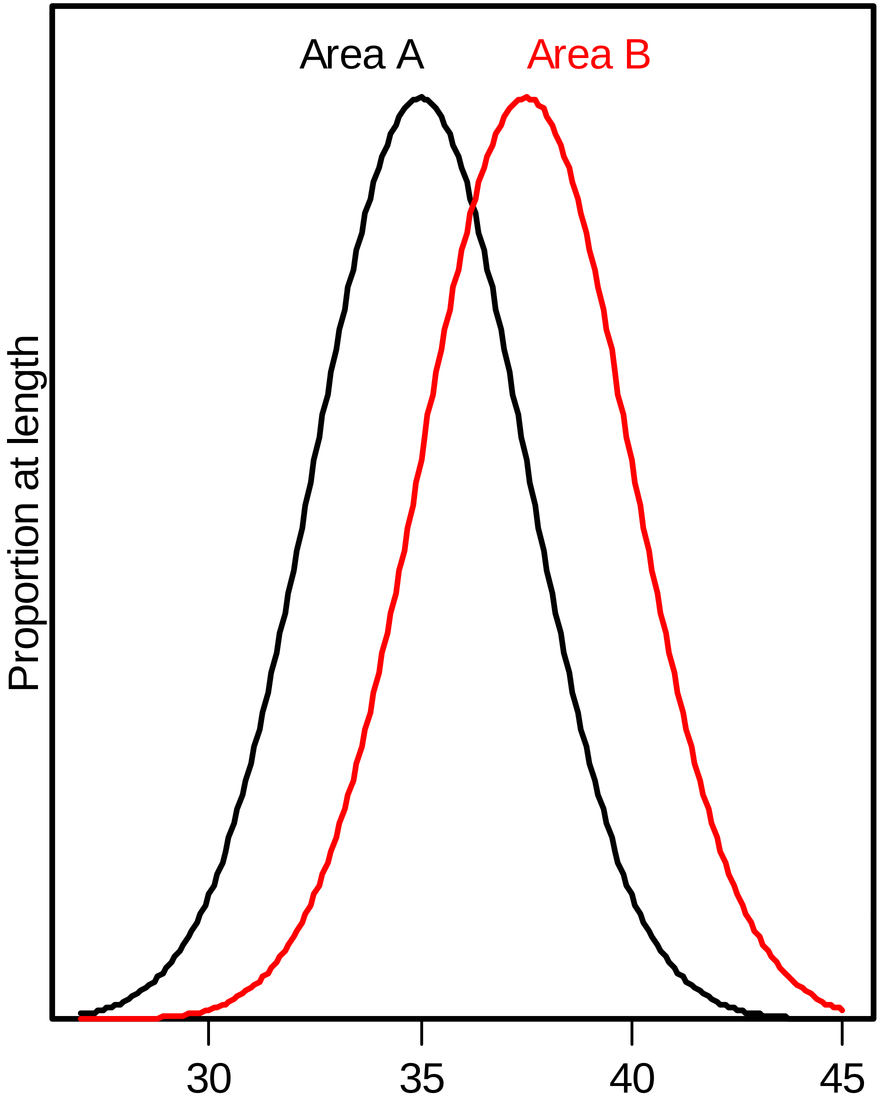


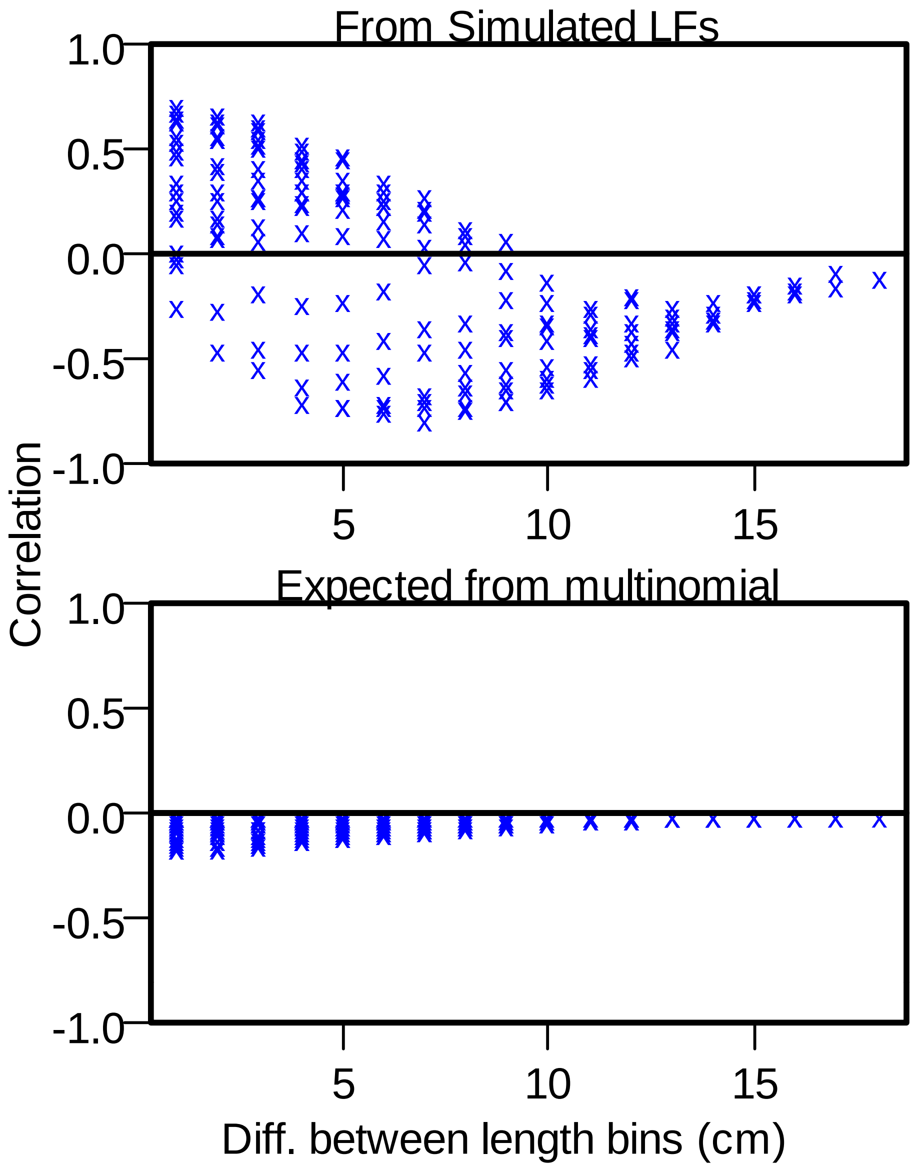
Two major sources of correlation:

observation error: intra-haul correlation (Pennington & Vølstad 2004)

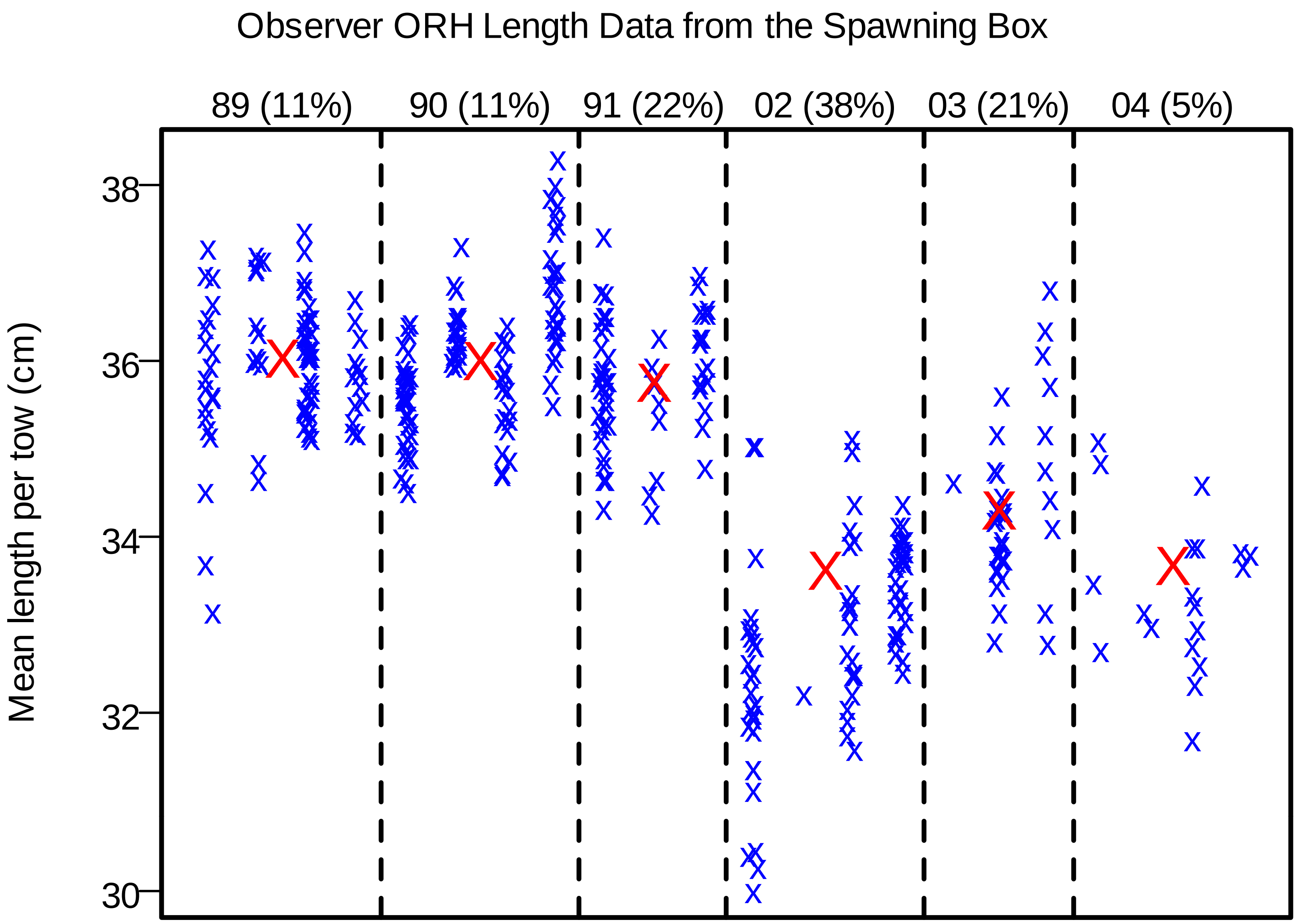
process error: selectivity mis-specification (see text associated with Fig. 3)

Simple intra-haul correlation example (from FAR 2006/43)





Example of intra-trip correlation
(fig. 10 from FAR 2006/45)



Dealing with correlations in composition data

Three alternative approaches

1. Include correlations in likelihood and stage-2 weighting
   - best approach theoretically
   - no satisfactory likelihoods
2. Ignore correlations, both in likelihood and stage-2 weighting
   - usual approach
   - over-weights composition data
3. Ignore correlations in likelihood, but allow for them in stage-2 weighting
   - ad hoc, poor theoretically
   - better weighting of composition data
   - best approach available

Chilean hake example
(Table 4)

Four composition data sets (proportions at age)

multinomial likelihoods with $N = 150$ (stage 1)

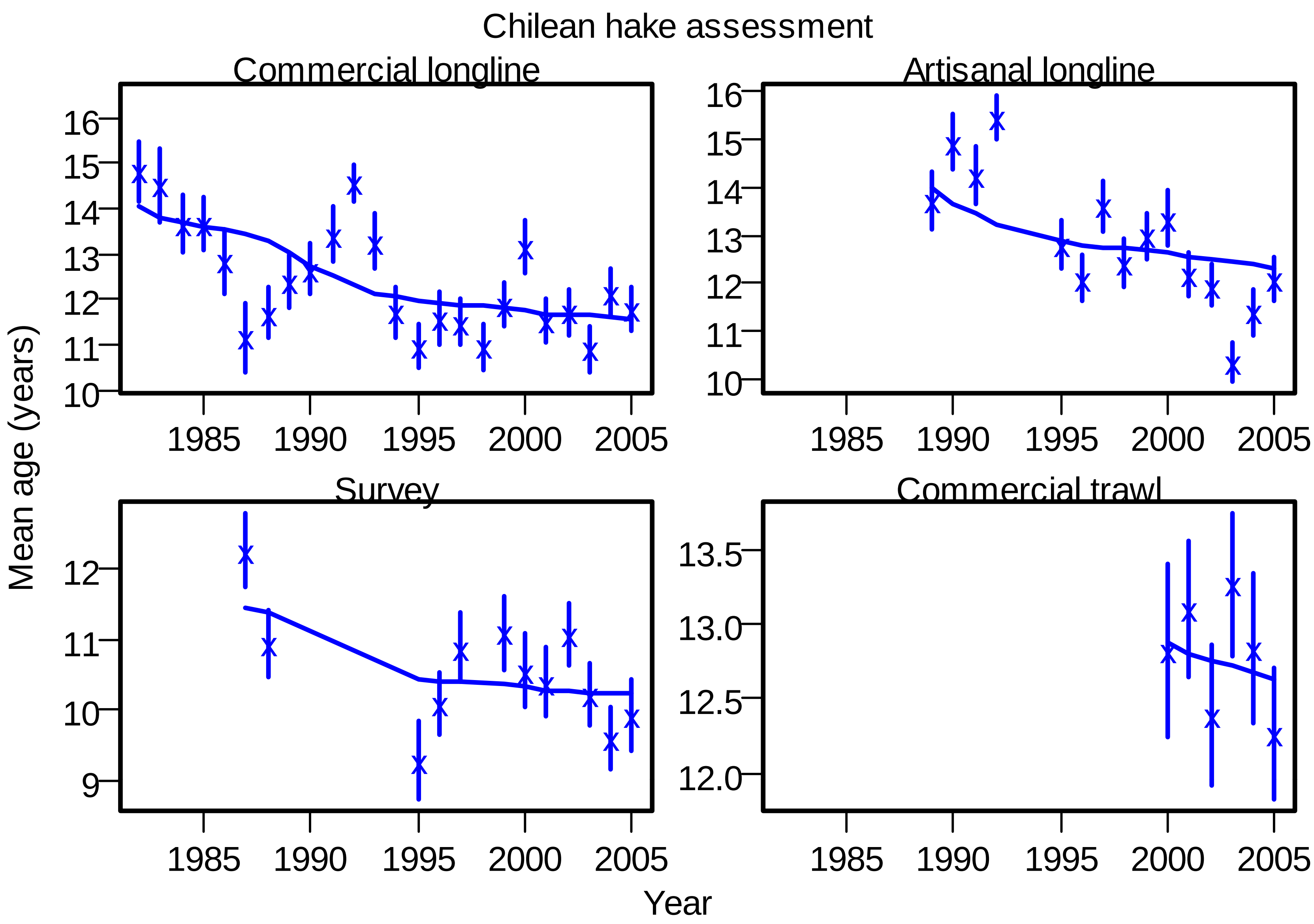
	Stage-2 sample sizes			
Composition data set	TA1.1[1]	TA1.2[3]	TA1.3[2]	TA1.8[3]
Trawl fishery	258	115	116	15
Commercial longline fishery	240	154	152	10
Artisanal longline fishery	557	251	248	25
Survey	338	232	233	69

[1]McAllister & Ianelli (Can. J. Fish. Aquat. Sci. 54: 284-300, 1997)

[2]Dunn & Hanchet (CCAMLR WG FSA 09/40, 2009)

[3]Francis (Can. J. Fish. Aquat. Sci., in press) – see Table A1

Mean age in Chilean hake example (Fig. 4)



How can robust likelihoods help?

Use with composition data

- reduce effect of occasional large outliers
- reduce possibility of interfering with fit to abundance data

Three data-weighting principles

1. Don't let other data stop the model fitting abundance data well

2. When weighting composition data, allow for correlations

3. Don't down-weight abundance data because they may be unrepresentative

End point to aim for

Ideally:

A single assessment model in which all abundance data sets are fitted well

If not possible:

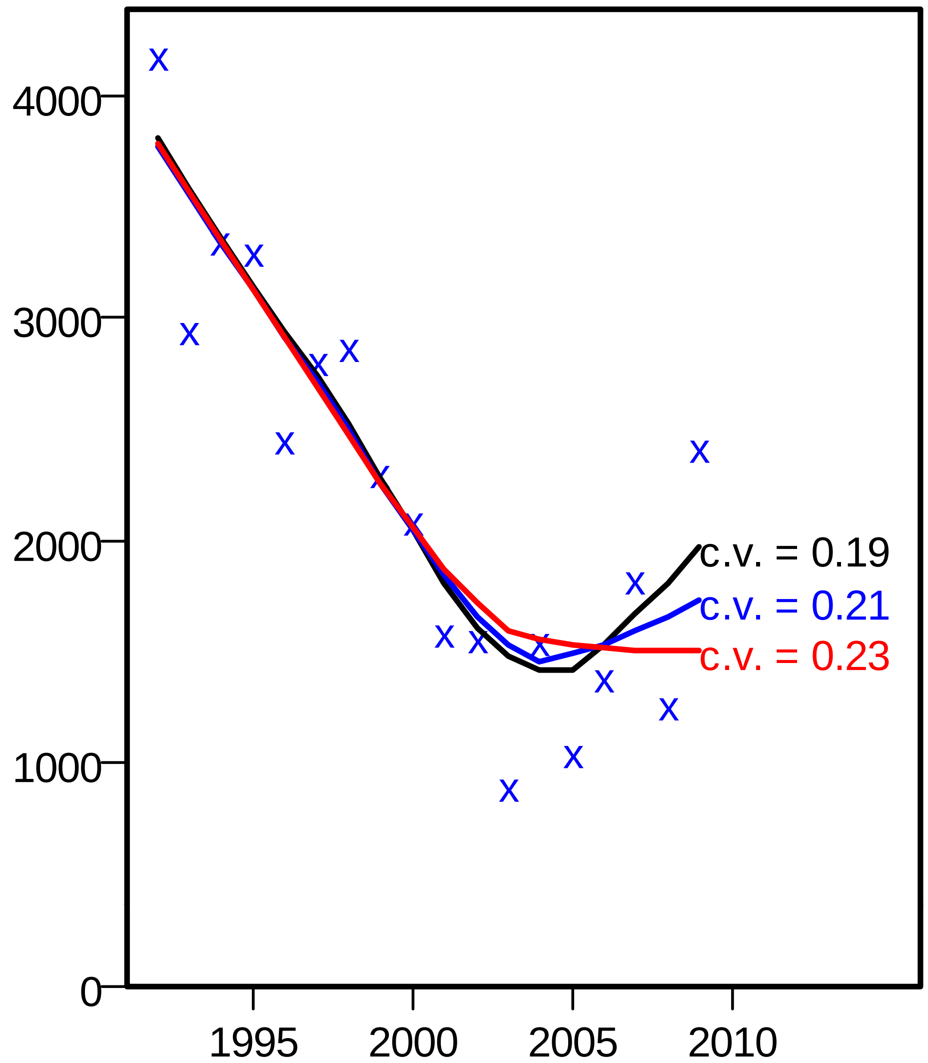
A set of alternative assessment models, in each of which one or more data sets has been omitted, but all remaining abundance data sets are fitted well.

Proposed approach:
1. Weighting abundance data

No stage-2 weighting

Where possible, pre-specify process error (e.g., trawl and acoustic surveys – see above)

Otherwise, use smoother to specify total error (Clark & Hare 2006)



Proposed approach:
2. Weighting other data types

Composition data

- stage-1 weighting based on observation errors, estimated by bootstrapping
- allow for correlations in stage-2 weighting

Other data

- apply Principle 1

Proposed approach:
3. Judging fit of abundance data

Calculate SDNR (standard deviation of normalised residuals - see Appendix B)

SDNR should be not much more than 1 $\left[< \left(\chi^2_{0.95,m-1} / (m-1) \right)^{0.5} \right]$

Don't worry if SDNR < 1

Plot fit to check for residual trends

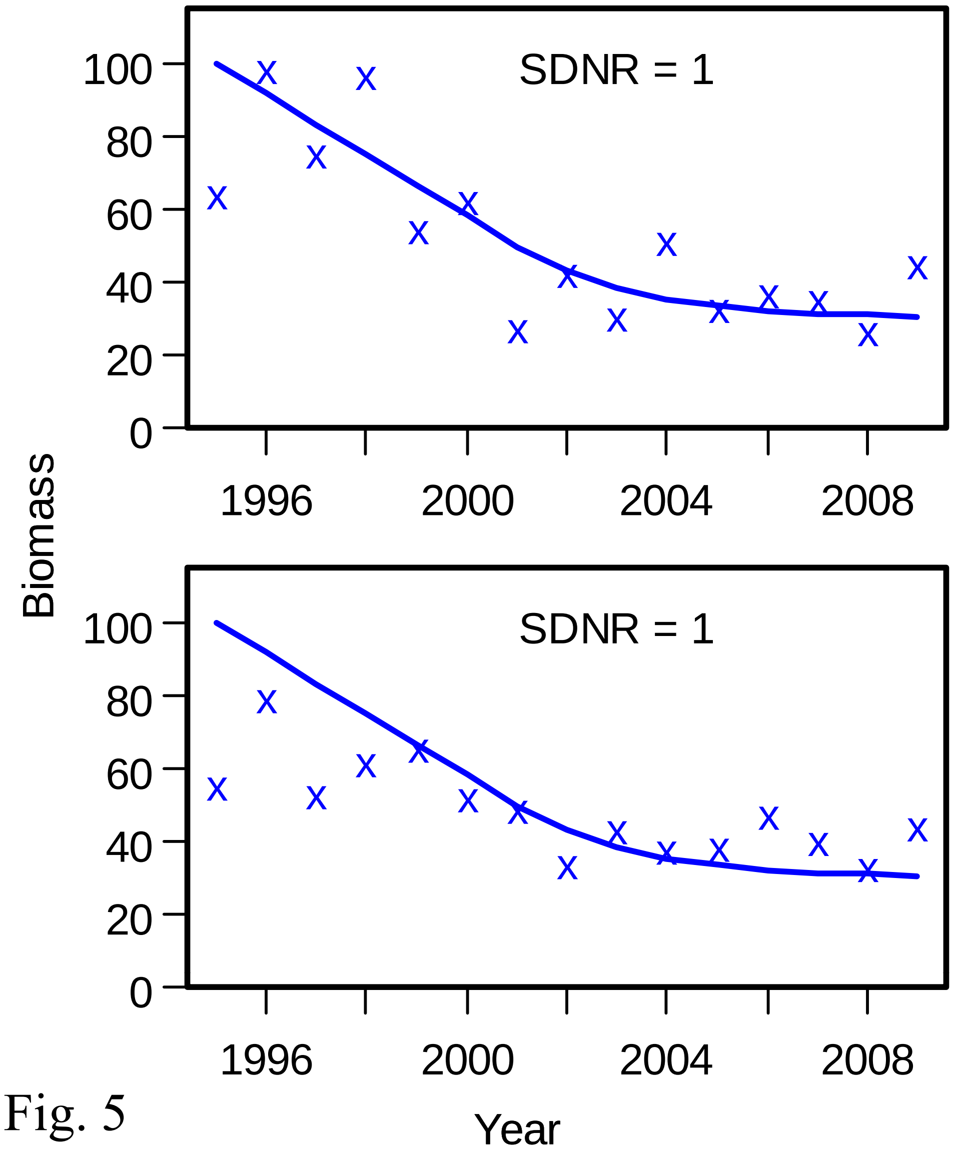


Fig. 5

Proposed approach:
4. When abundance data not well fitted

Check to see whether Principle 1 is violated (can we achieve adequate fit by down-weighting other data, or up-weighting abundance data?)

Investigate model modifications to achieve adequate fits

Otherwise, assume that at least one abundance data set is unrepresentative.

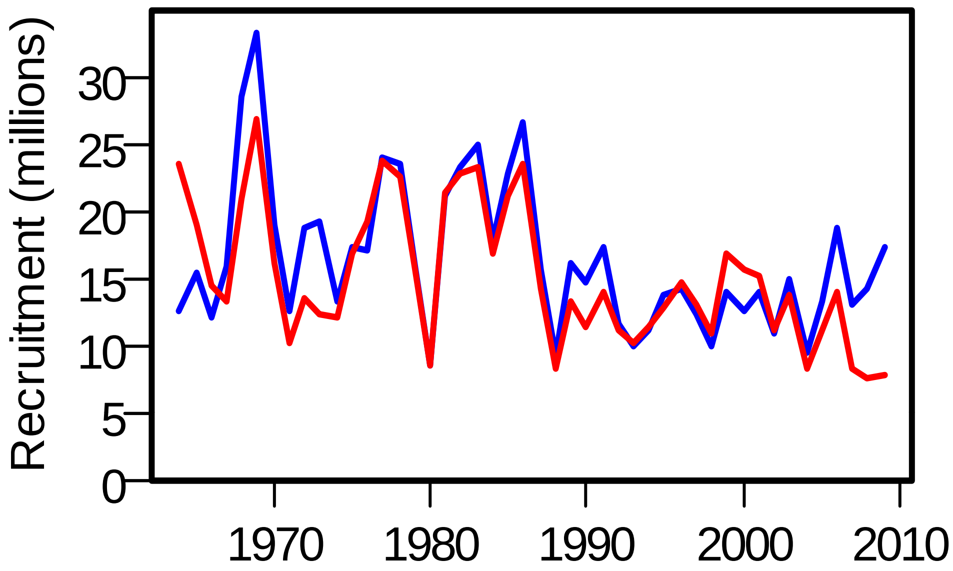
Create a set of alternative models, in each of which one or more abundance data sets is omitted and the remaining abundance data sets are all well fitted

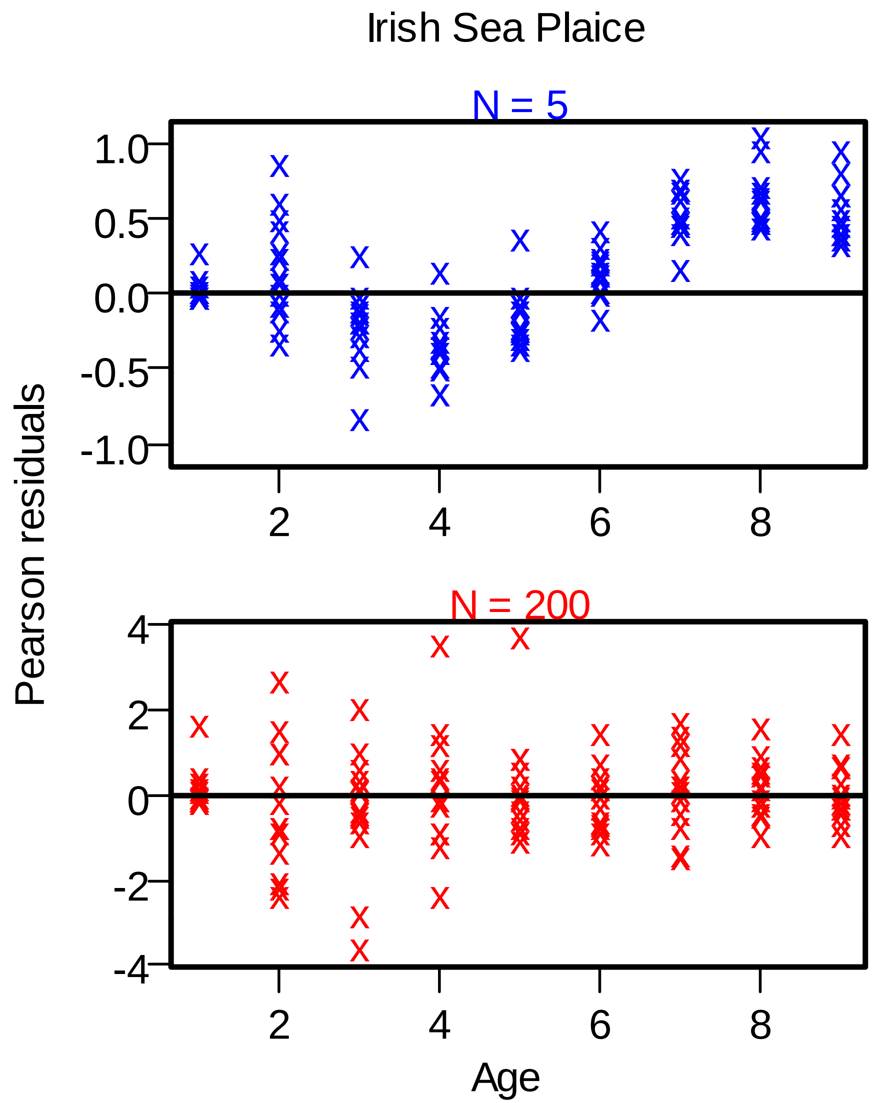
Proposed approach:
5. Goodness of fit to composition data

Don't use SDNR!

Poor fit often caused by model mis-specification, rather than wrong data weighting

Poor fit may not matter too much





Two final points

I have offered

- Three data-weighting principles
- An end point to aim for
- A proposed approach in five steps [least important]

Two major difficulties

- can’t avoid subjective decisions
- many unresolved technical problems