A Bayesian State-Space Approach to Improve Biomass Projections for Managing New England Groundfish

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Acknowledgements

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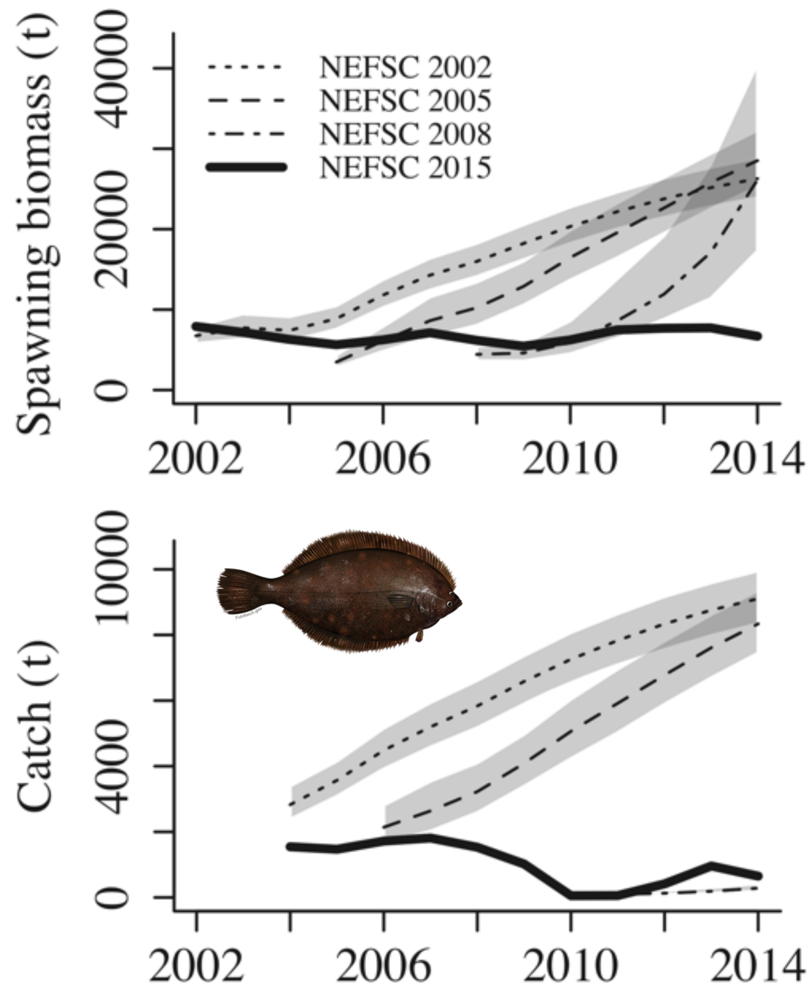
Motivation

Stock biomass forecast errors have led to:
- Unintentional overfishing
- Sharp quota reductions
- Decreased stakeholder confidence in the management process

Lack of consensus on index-based approaches

Can we improve biomass predictions?
- Can we shorten prediction windows?



Wiedenmann & Jensen (2017)

Roadmap

I. Dynamic Linear Models (DLMs)

II. Index-Based Approach

III. Index-Based Model Stress Tests

IV. Index-Based Methods Working Group Results

V. Extended DLM approaches

VI. Future Work

What is a dynamic linear model (DLM)?

SI: survey index
q: catchability
ν: observation error
ω: evolutions
V: observation error variance
W: evolution variance

$$SI_t = qSSB_t + \nu_t \qquad \nu_t \sim N(0, V)$$

$$SSB_t = SSB_{t-1} + \omega_t \qquad \omega_t \sim N(0, W)$$

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Observation Equation

$$y_t = F_t\theta_t + \nu_t \qquad \nu_t \sim N(0, V_t)$$

State Equation

$$\theta_t = G_t\theta_{t-1} + \omega_t \qquad \omega_t \sim N(0, W_t)$$

y: response variable
θ: state variables
F: observation matrix
G: evolution matrix

Fit by MCMC (Gibbs Sampler)

Why DLMs?

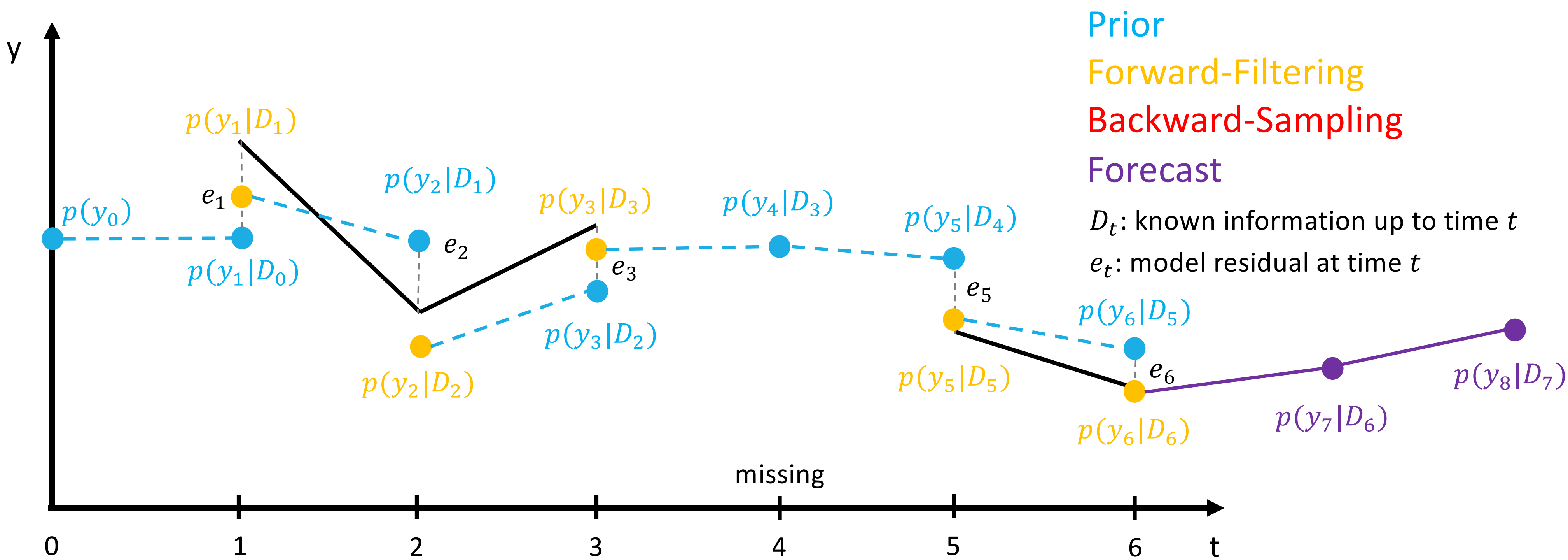
Flexible!

- Can handle dynamic coefficients/errors, interventions, and autocorrelation
- Capture unobserved processes

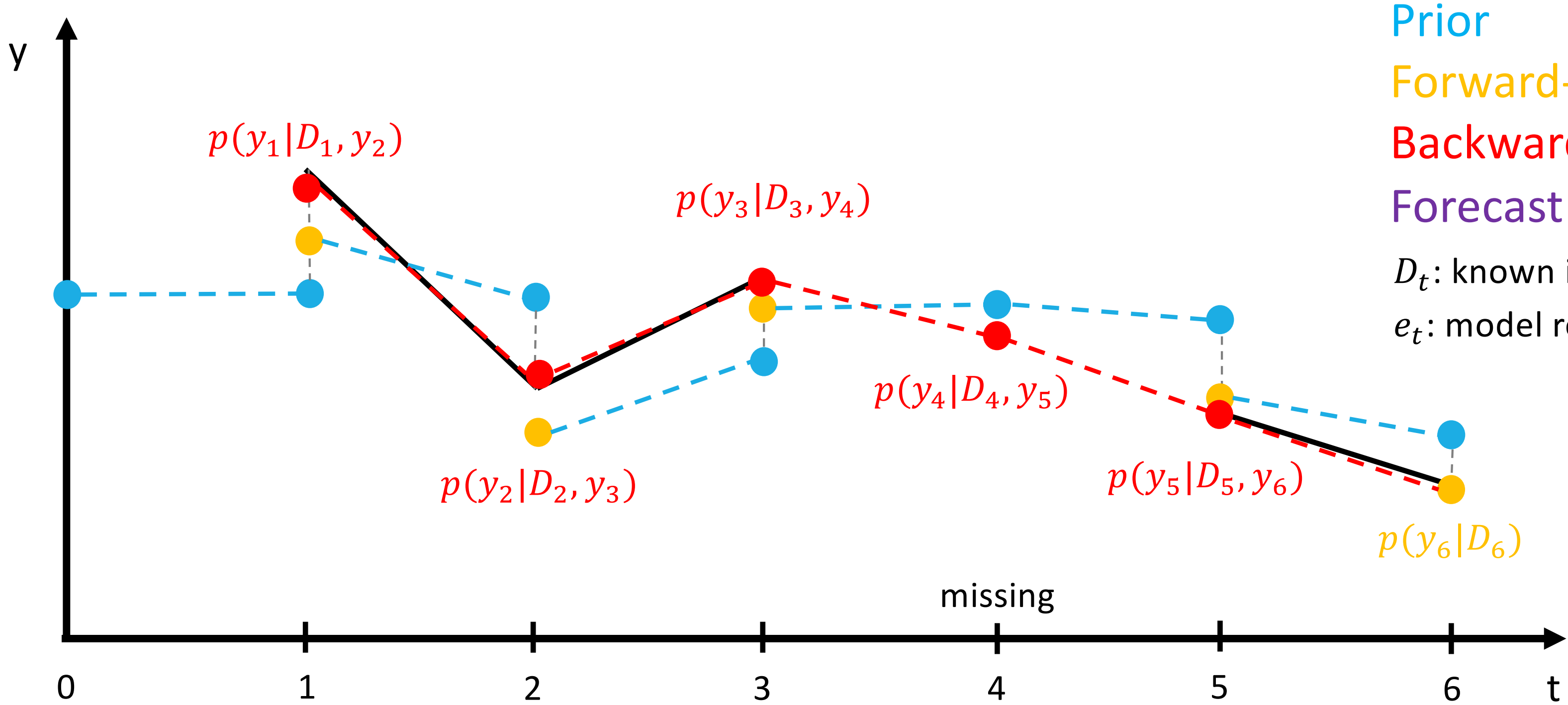
Missing data estimated from the predictive distribution

Fit and forecasts are easily updated

Fitting DLMs: Forward Filtering Backward Sampling



Fitting DLMs: Forward Filtering Backward Sampling



Prior

Forward-Filtering

Backward-Sampling

Forecast

D_t: known information up to time t

e_t: model residual at time t

Why DLMs?

Flexible!

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- Capture unobserved processes

Missing data estimated from the predictive distribution

Fit and forecasts are easily updated

Can incorporate environmental data, demographic information, multiple surveys, multispecies data

Imperfect catch data is ok

Basic Index-Based Approach

Survey Index = Trend + Catch Regression + Error

Trend options

- Random walk
- Dynamic trend

Catch Regression

- Use catch anomalies by differencing out the mean relative catch rate
- Catch $\sim \beta$survey index + intercept + anomalies

Basic Index-Based Approach

Survey Index = Trend + Catch Regression + Error

Example model: Dynamic trend + Catch Anomaly Regression

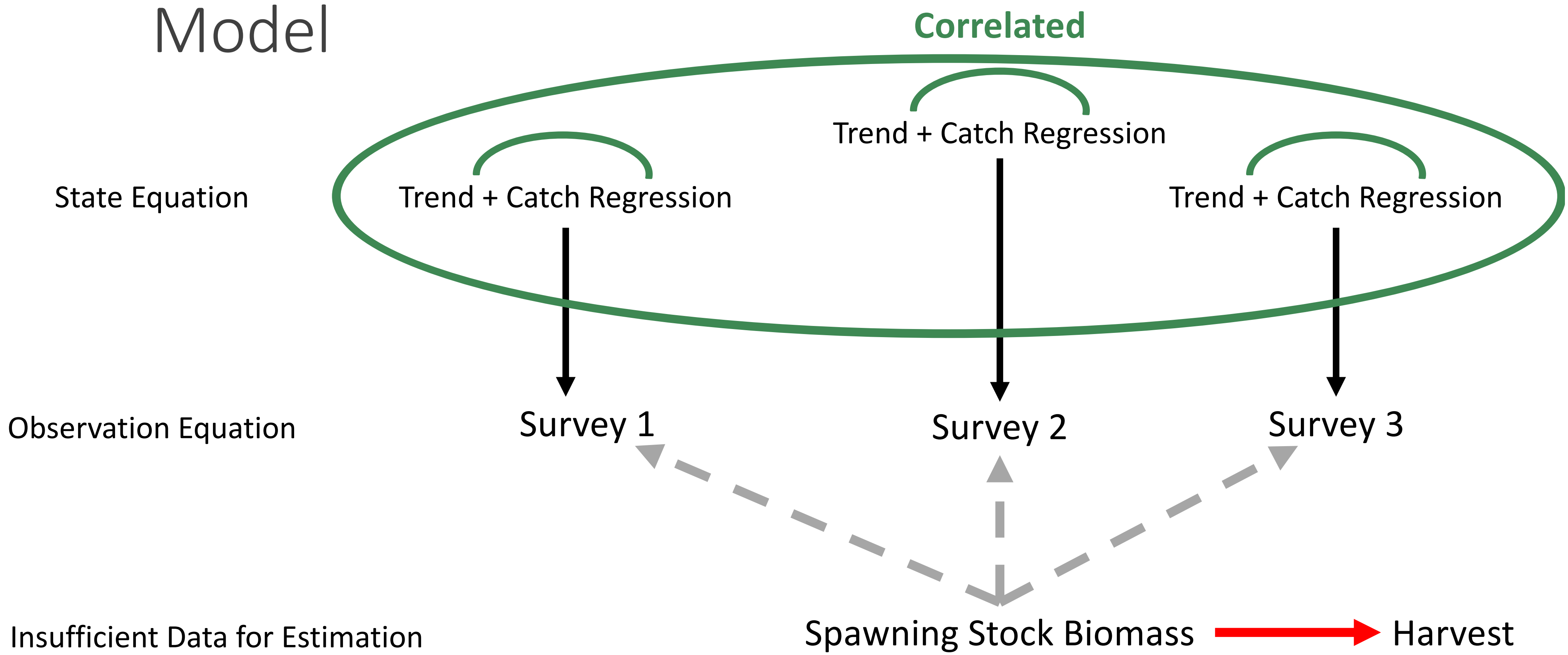
SI: survey index
θ_{int}: intercept of dynamic trend
θ_{trend}: slope of dynamic trend
β_{CA}: Regression coefficient on catch anomalies
ν: observation error
ω: evolutions
V: observation error variance
W: evolution variance

$$SI_t = \overset{\boldsymbol{F}}{[0 \quad 1 \quad 1]}\,[\theta_{int,t} \quad \theta_{trend,t} \quad \beta_{CA,t}]' + \nu_t \qquad \nu_t \sim N(0, V),\ V \sim IG(a, b)$$

$$\begin{bmatrix} \theta_{int,t} \\ \theta_{trend,t} \\ \beta_{CA,t} \end{bmatrix} = \overset{\boldsymbol{G}}{\begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}} \begin{bmatrix} \theta_{int,t-1} \\ \theta_{trend,t-1} \\ \beta_{CA,t-1} \end{bmatrix} + \omega_t \qquad \omega_t \sim N(\boldsymbol{0}, \boldsymbol{W}),\ \boldsymbol{W} \sim IW(\boldsymbol{\Psi}, v)$$

<u>Priors</u>
State Variables: approximate guesses with large variance
Variances: split total data variance between observation errors and evolutions

Multivariate Model



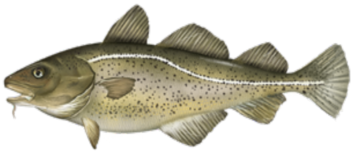
Example: GB Cod

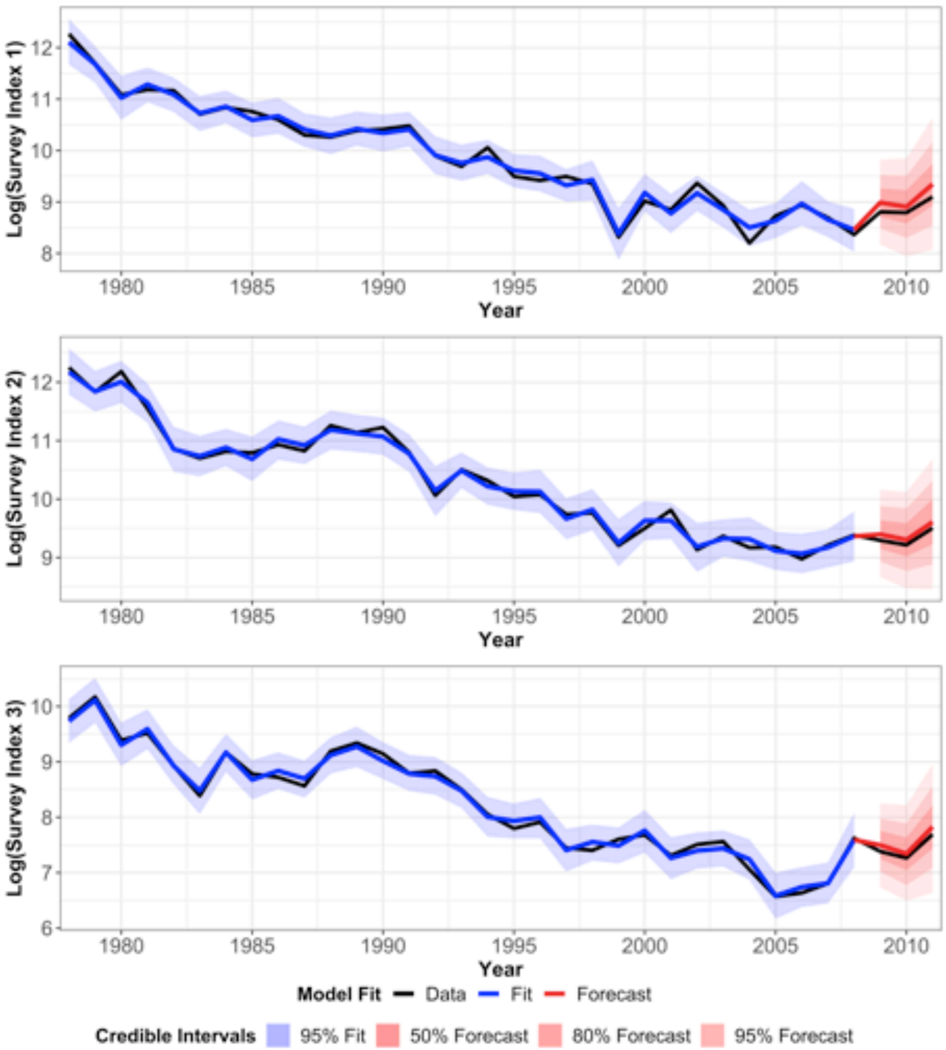
3 simulated surveys

Constant M = 0.2

Random Walk + Regression on Catch Anomalies

Retrospective forecasts



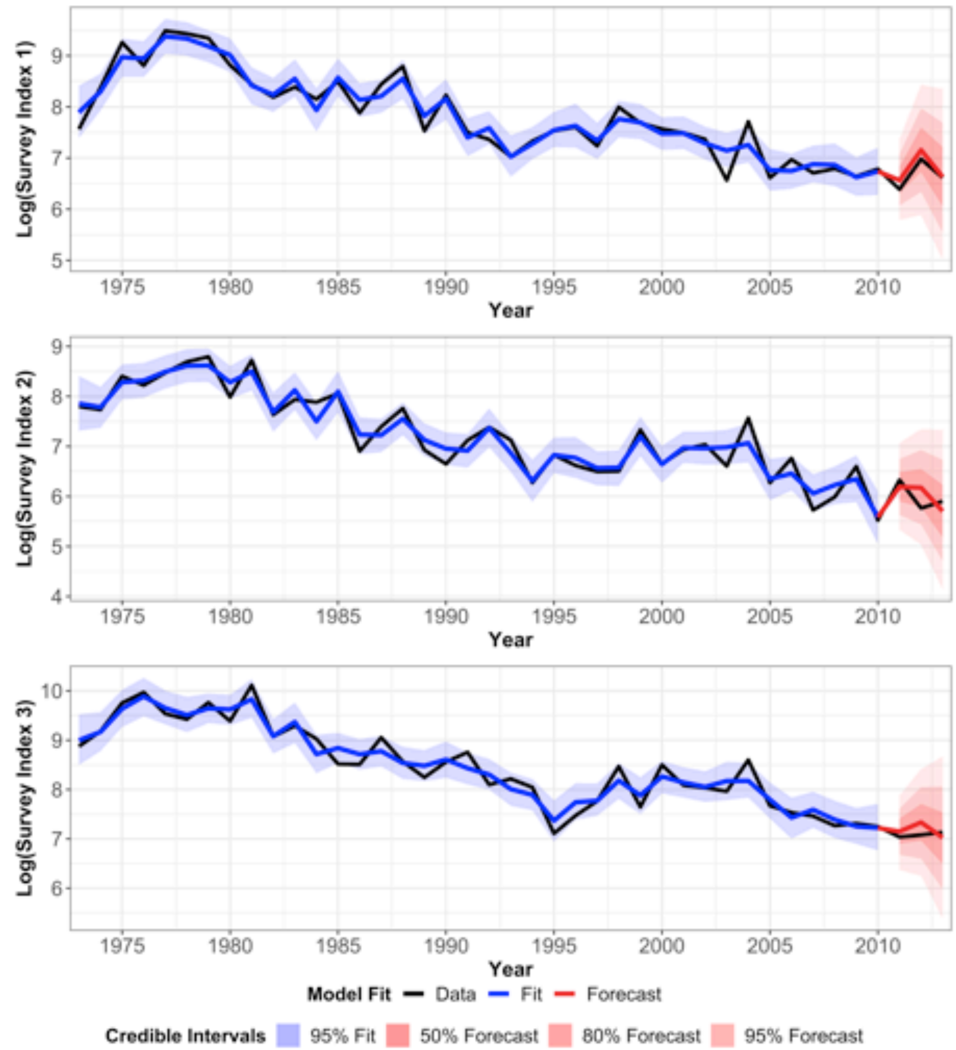


Example:
GB Yellowtail

3 simulated surveys

M ramp from 0.2 to 0.4

Dynamic trend + Regression on Catch Anomalies

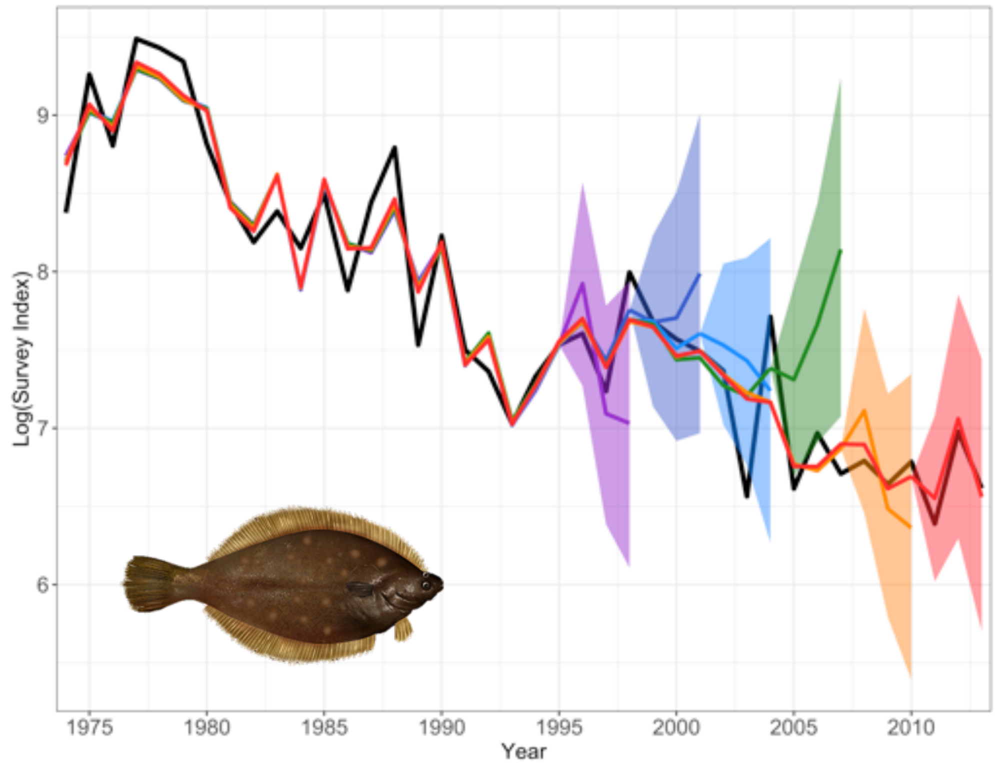


GB Yellowtail Retrospective Peels

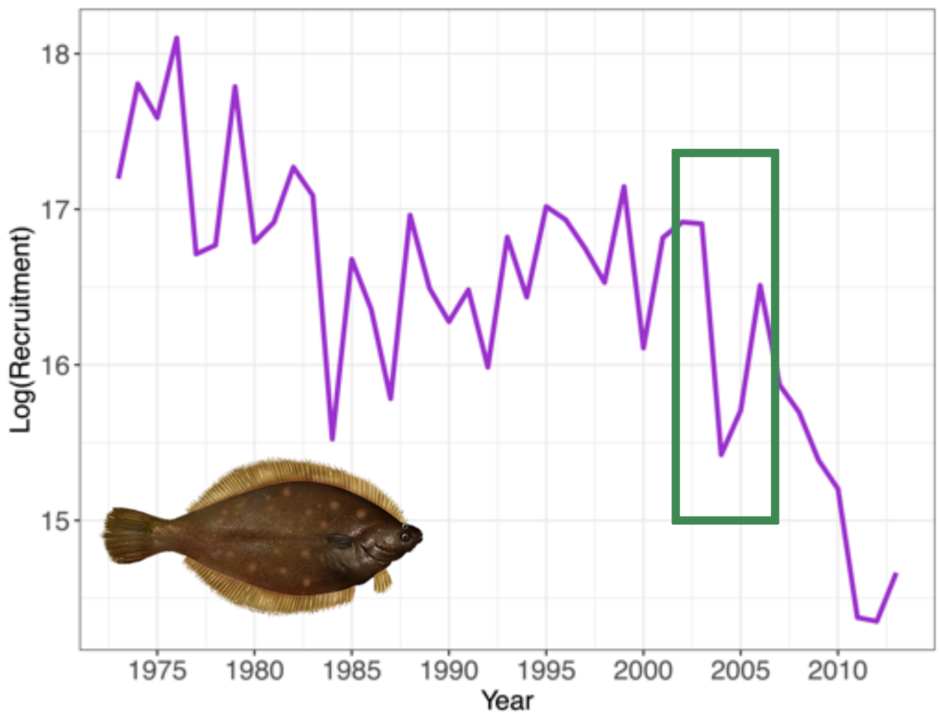
Sequential model fits every 3 years in colors

Forecasts shown with 80% credible interval

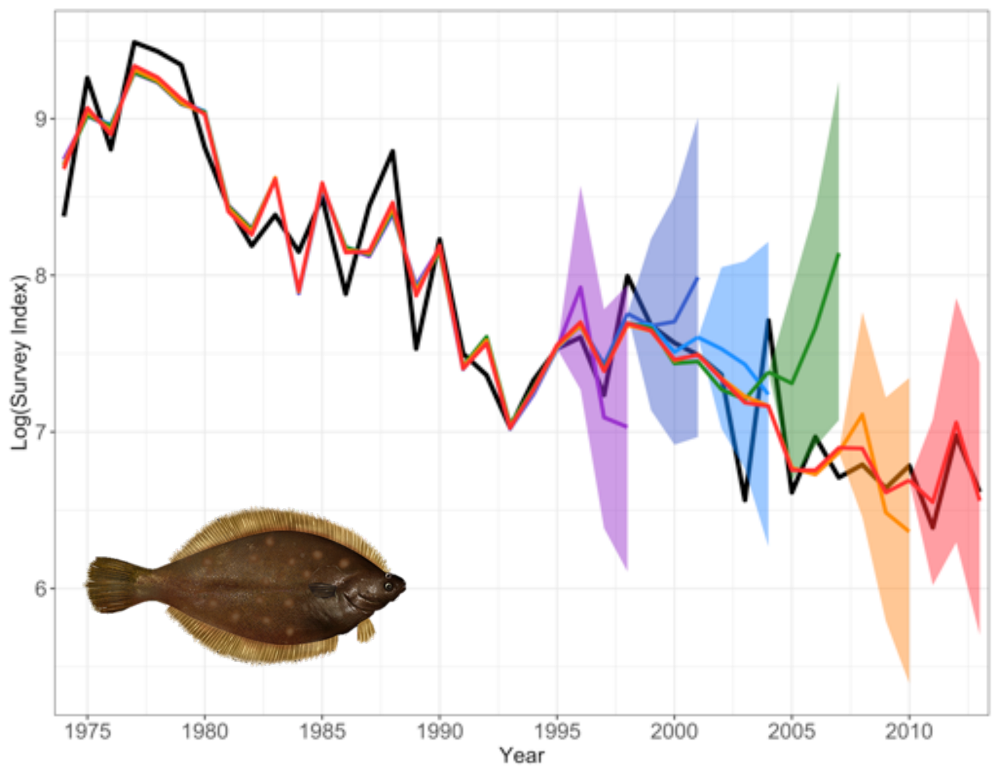
Green forecast?



GB Yellowtail Retrospective Peels



GB Yellowtail Retrospective Peels



Preliminary Conclusions

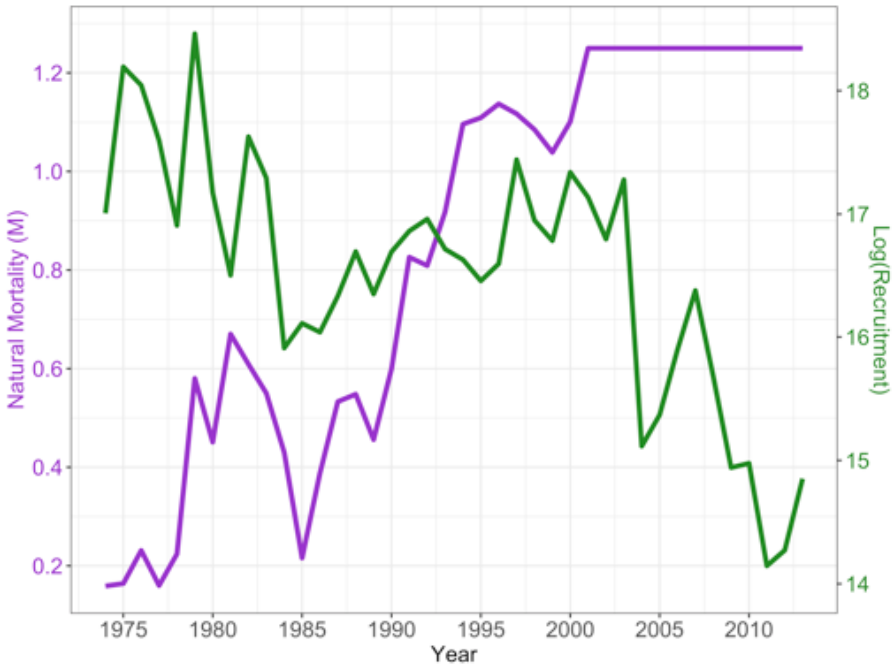
<u>Advantages</u>

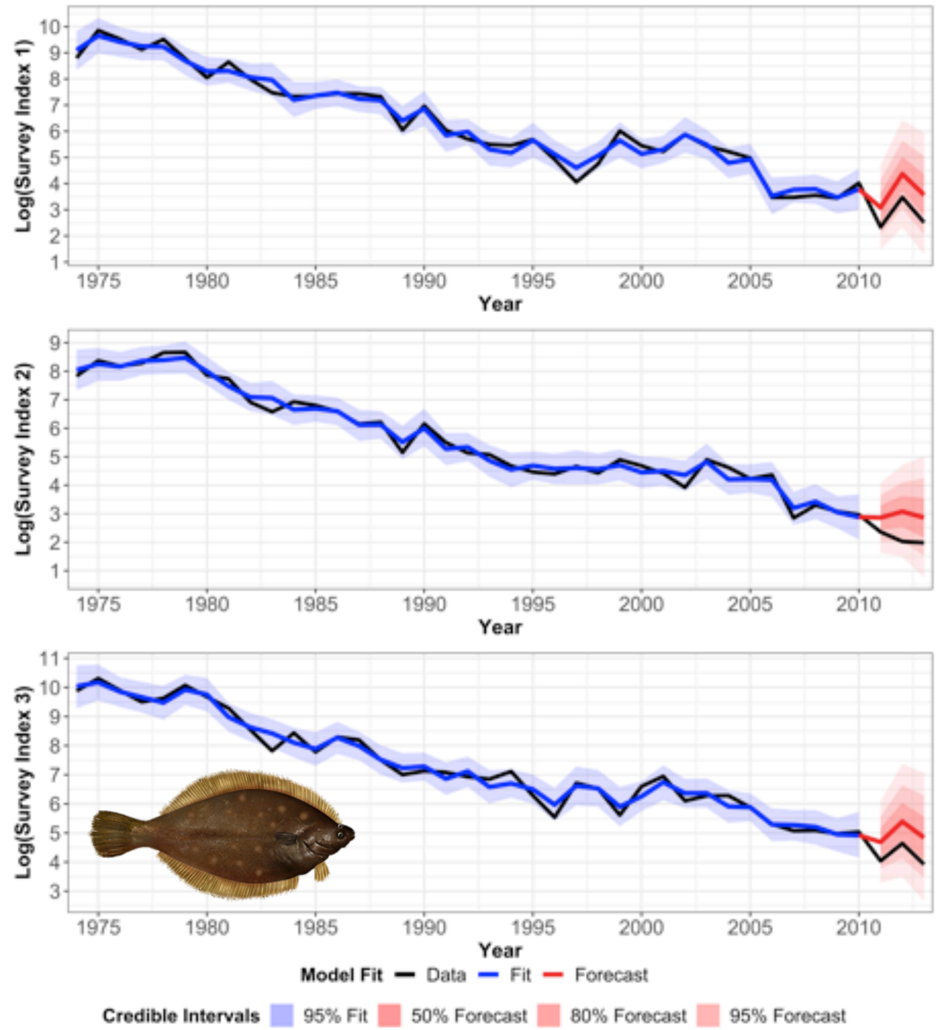
- Flexible model structure that can be tailored to a target stock
- Makes no assumptions about population dynamics or catch data
- Can leverage multiple abundance indices to improve fit
- Provides probabilistic forecasts to develop catch advice and assess risk
- Promising forecast performance in simulation

<u>Challenges</u>

- Allocation of variance between observation errors and evolutions
  - More data (longer time series, more abundance indices) helps
- Basic model formulation cannot "see" changes coming in the population

Large Change in Natural Mortality





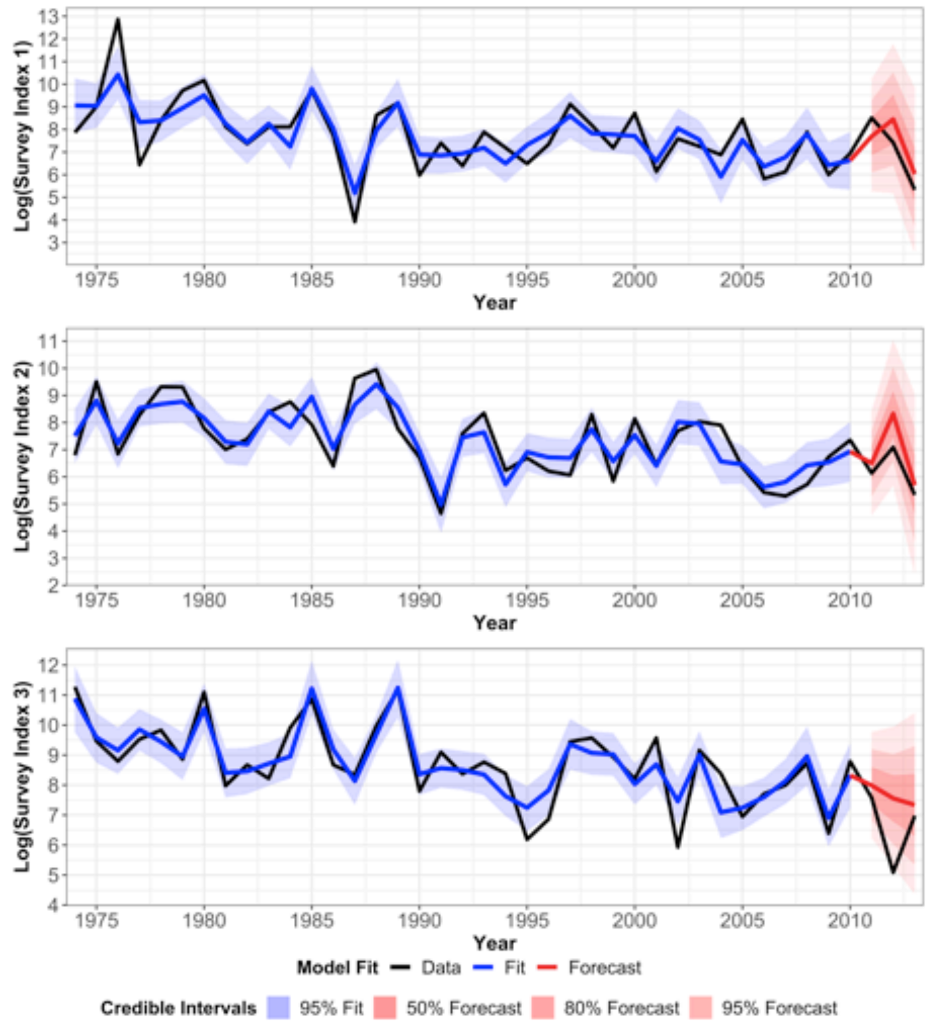
High Measurement Error

Survey CVs: 1.5-2.0

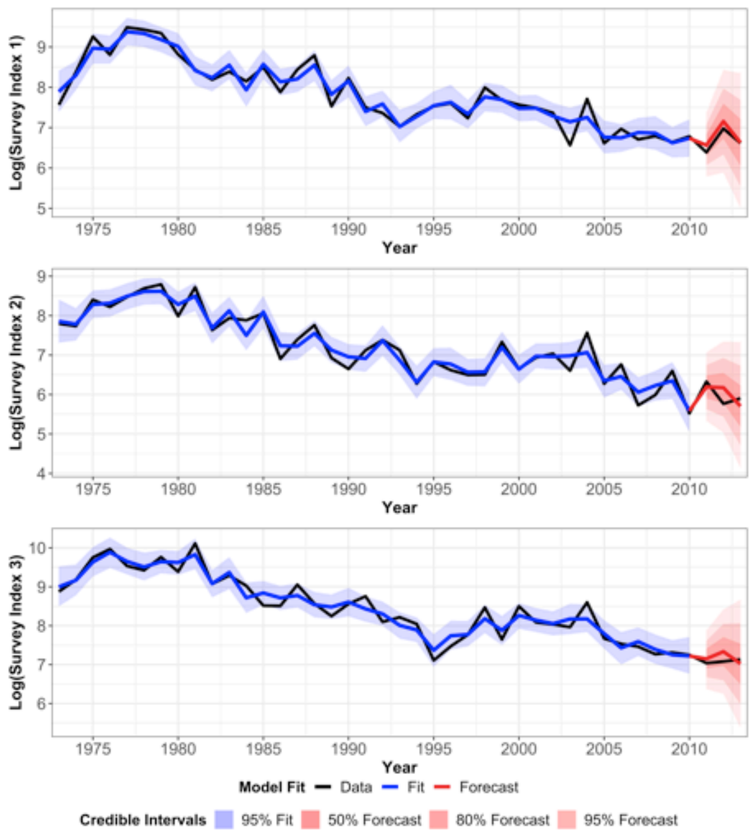
- Actual: 0.3-0.4

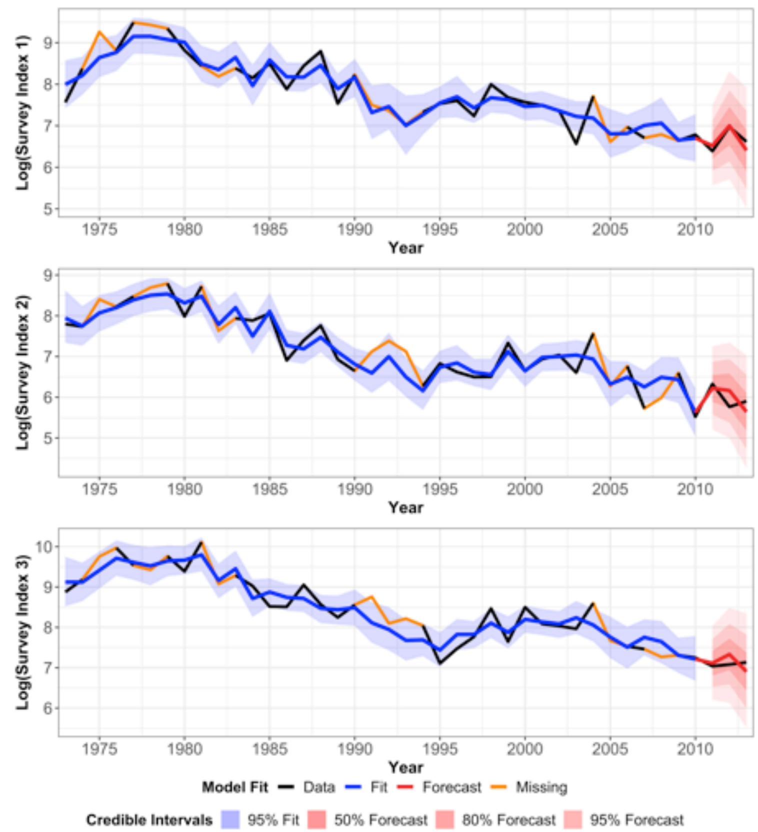
DLM has difficulty allocating variance

Solution: alter prior weights



Frequent Missing Data (20%)





Index-Based Methods Working Group

Simulation experiment based on WHAM operating model

- Base period of 50 years, two survey indices
- Fit IBM to "observed" data from WHAM, develop catch advice for 2 years ahead
- WHAM updates population based on catch advice for 40 years

Variety of scenarios

- Overfishing for half or all of base period
- Shifts in fishery selectivity
- Retrospective errors due to changing M or unaccounted catch
- Take catch advice from IBM or multiply catch advice by 75%

Simulate each scenario with each IBM up to 1000 times

DLM Set-up For Simulation Experiment

Model: Dynamic trend + regression on catch anomalies

- No ability to test model structures or priors
- “Hands off” experiment

Catch advice: set harvest such that trajectory of mean forecast will get population to reference level in ~10 years

- No use of uncertainty
- Reference level: 75th percentile of observed data

IBMWG DLM Performance

DLM was one of the top performing methods (long-term)

- Exact ranking varied by category of performance metrics

DLM had similar performance regardless of retrospective error source

DLM produced fairly stable catch advice over the long-term

Chosen catch advice decision rule was not optimal

- 75th percentile was poor estimate of B_{MSY}, particularly when overfishing occurred throughout base period
- Because 75th percentile was recalculated every time new "survey" data was available, reference level was a moving target

The DLM framework showed great promise!

Can we include more information?

"Stage-Based" Hierarchical Model

Gibbs Sampler

Recruits

$$\theta_t = G\theta_{t-1} + \omega_t$$

$$y_t = F\theta_t + \nu_t$$

Sample measurement and evolution error variances

Post-Recruits

$$\theta_t = G\theta_{t-1} + \omega_t$$

$$y_t = F\theta_t + \nu_t$$

Sample measurement and evolution error variances

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Sample measurement and evolution error variances

Covariate

Post-Recruits

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"Age-Based" Hierarchical Model

Gibbs Sampler

Age-1

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$$y_t = F\theta_t + \nu_t$$

Sample measurement and evolution error variances

Age-2

$$\theta_t = G\theta_{t-1} + \omega_t$$

$$y_t = F\theta_t + \nu_t$$

Sample measurement and evolution error variances

…

Age-6+

$$\theta_t = G\theta_{t-1} + \omega_t$$

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Sample measurement and evolution error variances

Age-6+

$$\theta_t = G\theta_{t-1} + \omega_t$$

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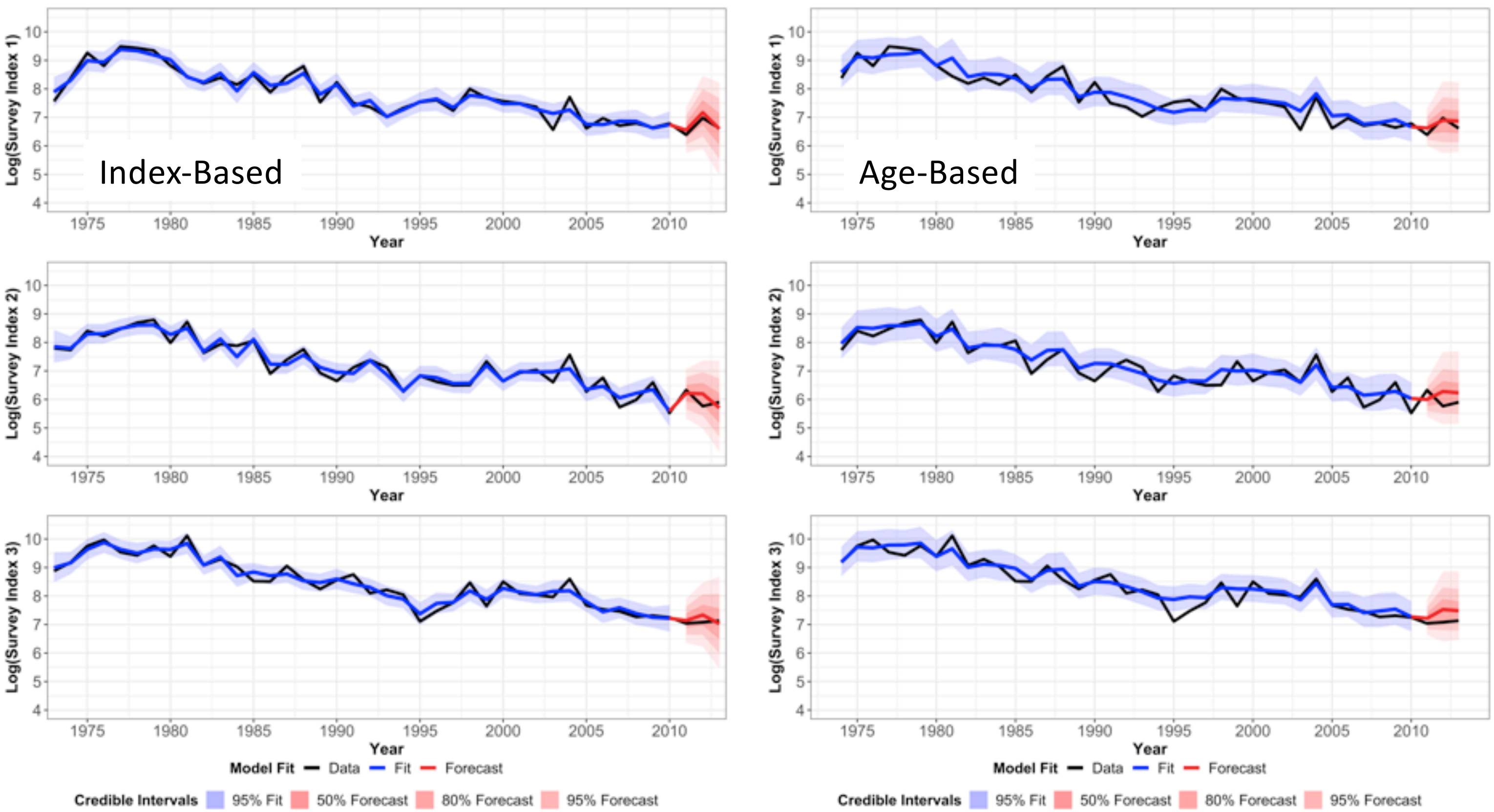
Sample measurement and evolution error variances

SSB (Survey Scale)

Dynamic Stock Recruit Relationship

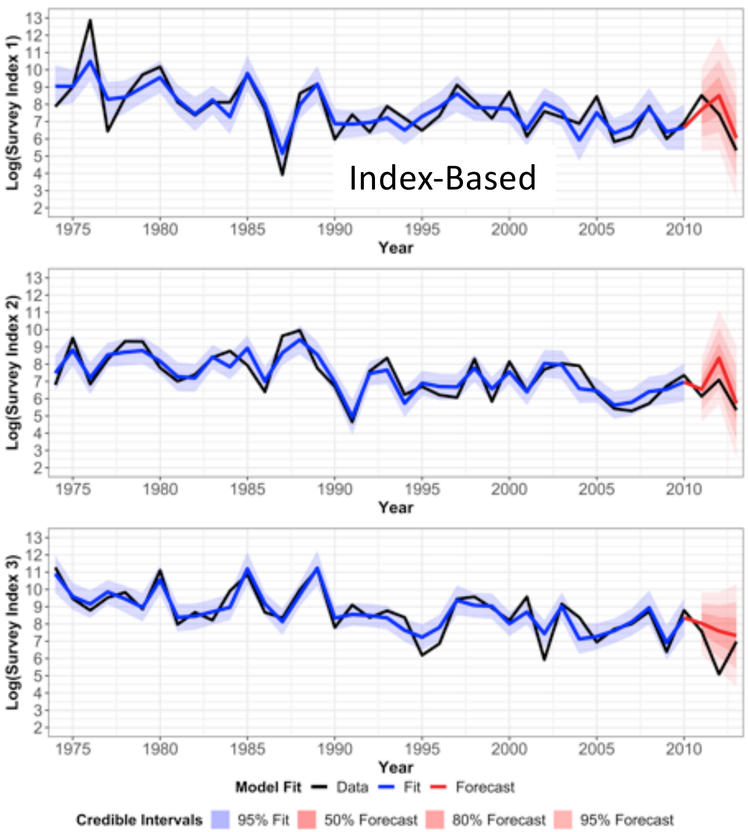
Example: GB Yellowtail

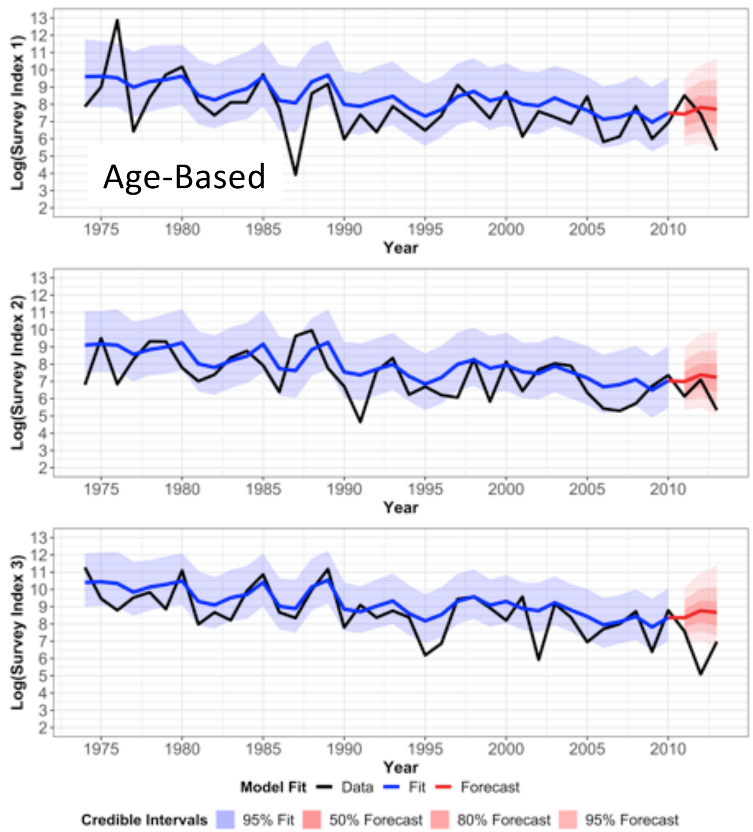


Data	Correlation With SSB
Observed	0.8618
IB Fit	0.9143
AB Fit	0.9337

Age-based model yields 1.5x improvement over Index-based model

Example: GB Yellowtail, High Measurement Error





Data	Correlation With SSB
Observed	0.1969
IB Fit	0.2653
AB Fit	0.4922

Age-based model yields 3.6x improvement over Index-based model

Multispecies Hierarchical Model

Gibbs Sampler

Prey

$$\theta_t = G\theta_{t-1} + \omega_t$$

$$y_t = F\theta_t + \nu_t$$

Sample measurement and evolution error variances

Covariate

Predator

$$\theta_t = G\theta_{t-1} + \omega_t$$

$$y_t = F\theta_t + \nu_t$$

Sample measurement and evolution error variances

Conclusions

DLM framework provides a spectrum of customizable models

- Single survey index to multispecies, multi-survey model with environmental covariates

Index-Based DLM has shown very promising performance in simulation

DLMs are robust to common causes of forecast errors and other challenges

- Changing M
- Unaccounted catch
- Missing data

Including size or age-information appears to improve forecasting

Easily updated as new data becomes available

Future Work

Explore model structures in extended models

Evaluate extended model performance

Construct model that estimates the true SSB

Multispecies models?

Questions?

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- Single survey index to multispecies, multi-survey model with environmental covariates

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