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# Moving through fisheries spacetime WCSAM 2013 

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## Some days fishing just feels like...

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## but next week...

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## Stating the observed and obvious

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■ Fish abundance changes with space and time
■ Sometimes a lot (frustrated fishermen around the globe)
■ Not all fish move in the same way

## What about everything else?

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■ Is abundance the only thing that changes?

- Assessment scientists care about and often need:

1 Growth dynamics
2 Reproductive dynamics
3 Stock-recruit relationship
4 Natural mortality

- How and when can these vary in space and time?


## General assumptions we make

- Population being assessed is spatially homogeneous
- Key parameters are time invariant:

1 Growth, natural mortality, maturity
2 Stock-recruit relationship
3 Catchability (for key abundance series), selectivity
■ Some processes non-stationary:
1 Recruitment
2 Surplus production
3 Fishing mortality

## Talk outline

■ Examples of where those assumptions don't apply
■ Inter-connectedness: knock-on effects of the changes
■ We can deal with change but does the cause matter?
■ If you look, you'll find it \& data collection implications
■ Is it space and time, or really more like spacetime?

## Growth

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■ All structured models (length/age/stage) need it
■ One of dominant determinants of sustainable yields
■ Temporal growth: Southern bluefin tuna
■ Spatial growth: Western Pacific swordfish

## SBT length-at-age over time

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■ Years: 1931-2012; Ages: 0-30+


## SBT length-at-age over time

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■ Generally, SBT now growing faster

- Not growing as long (smaller $L_{\infty}$ )
- Structural aspect to growth changes

■ In 1960s growth more von Bertalanffy
■ From 1980s definitively more two-stage (slow/fast/slow)
■ Cause: density-dependence, selective pressure, both?

## Western Pacific swordfish

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■ Genetic evidence that NW and SW Pacific separate stocks
■ Even in North there appears to be variation in growth
■ Up to 2008 Hawaiian growth curve used in SW Pacific

- SW Pacific length-at-age looks lower than Hawaiian

■ Until 2013 differences ascribed to ageing methodologies
■ SW Pacific tag returns just enough to check...

## Western Pacific swordfish

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## Western Pacific swordfish

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■ SW Pacific tag data not consistent with Hawaiian growth
■ Hawaiian growth rates significantly faster than SW Pacific
■ Hawaiian $L_{\infty}$ also lower
■ Bias? Both caught in pelagic long-line so...

- SW Pacific and Taiwanese growth more similar

■ Likely linked to notable variation in local productivity

## Growth isn't just how long you are...

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- Time-varying growth (SBT) we can (and do) deal with

■ Good evidence $M$ and maturity function of age and length
■ So in assessment with age-based $M$ and maturity...

- Reality is we probably have $M_{y, a}$ and $m_{y, a}$

■ Making sense of this in terms of key reference points...

## Is "why" important?

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- Returning to SBT growth example:

1 Selection: removal of slow growing juveniles?
2 D-D: over-fished $\left(\operatorname{cor}\left(\ln \widehat{N}_{t}, \bar{\ell}_{t}\right) \approx-0.8\right)$
■ D-D: will it change back again - any hysteresis?
■ Selection: permanent or transitory? timescales?

- What does either of these mean for defining $B_{0}$ or MSY?


## Natural mortality

■ Like growth, all age/length structured models need it
■ Unlike growth, very hard to estimate
■ Mostly assumed to be time and age/length independent
■ Mark-recapture, prey consumption data show age/length dependence

■ Hard to believe it is time-invariant...

## Time-varying $M$ : herring examples

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■ Central Baltic and North Sea herring as example cases
■ Baltic model (Mantyniemi et al., 2013, CJFAS):
1 Integrated Bayesian state-space model
2 Estimates recruitment, $F_{y, a}, M_{y, a}$, SSB etc.
3 Annual random effect structure for $M$
4 Catch and survey biomass/composition data
■ North Sea model (Hillary, 2011, CJFAS):
1 Integrated Bayesian state-space model
2 Estimates recruitment, $\pi_{y, a}^{s}$, SSB etc.
3 Bayes' factors used to estimate optimal $\pi_{y, a}^{s}$ structure
4 Uses survey data only (acoustic, trawl, larval)
5 Post hoc estimates of $M_{y, a}$ and $F_{y, a}$ from survival probabilities, catch and abundance

## Central Baltic herring $M$

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- $M_{y}$ for age 1 (bottom) and 5 (top)



## North Sea herring $M$

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■ $M_{y}$ for juveniles (0-1, Fig. a) and adults (2-6, Fig. b)



Year

## Time-varying $M$

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■ Different but "similar" stocks and qualitative observations:

1 Higher, more variable $M_{y}$ on younger/smaller fish
2 Lower, less variable $M_{y}$ for older/longer fish
3 Estimated $M$ quite different to assessment
4 Recruitment, survival/F, SSB differ to stock assessment
■ Conceptually different models estimate time-varying $M$
■ Commonalities:
1 "Good" survey biomass/composition data
2 Rigorous statistical estimation of model flexibility

## Reproductive potential

■ Status of reproductive population key management factor

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■ Be it SSB, total egg production key assessment output
■ Relative maturity ogive most common approach
■ Almost always assumed stationary and spatially isotropic
■ Maturity schedule strongly influential of sustainable yields

## South Pacific albacore

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■ Assessment: time/space invariant maturity-at-age
■ Recently completed project on albacore biology
■ One focus spatial patterns in female maturity-at-length
■ Does spatial and within-year grouping lead to bias?

## Sample areas

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■ From Farley et al. (2013, submitted)


## Model approach

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■ Generalised additive models for relative maturity:

$$
\mathbb{E}\left(p_{i, a, s, w}^{m}\right)=\operatorname{logit}^{-1}\left(s\left(F L_{i}\right)+\text { lat }_{a} * \text { season }_{s}+s e t_{w}\right)
$$

■ Use CPUE from ETBF areas as proxy for relative abundance

■ Calculate spatiotemporal maturity-at-length latitudinally

## Spatiotemporal albacore maturity

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Season 2


## Spatiotemporal albacore maturity

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## Season 1 <br>  <br> Season 2 <br> 

## Stock-recruit relationship

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■ Hugely important part of the puzzle
■ With growth, maturity, mortality, selectivity $\Rightarrow$ MSY
■ Often defined (Ricker, B-H) via steepness and $B_{0}$ (or $R_{0}$ )
■ Yes steepness hard to estimate, but is $B_{0}$ always $B_{0}$ ?
■ Sometimes over very long timeframes we assume so...

## Jackass morwong recruitment dynamics

■ Fairly long lived demersal species in SE Australia
■ Non-standard larval dynamics $\sim 9-12$ mth pelagic phase
■ Caught since 1915 mid-1980s onwards catch \& CPUE $\downarrow$
■ For assessment steepness of 0.7 (0.5-0.95 range) assumed
■ Declining recruitment seeming cause but declining why...

## Jackass morwong recruitment dynamics

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From Wayte (2013, Fish. Res):


## Jackass morwong recruitment dynamics

■ "New" $R_{0}$ from 1988 - better fits, removes residual trends
■ If steepness the cause, Morwong steepness $\approx 0.33 \ldots$
■ Correlation with westerly wind index lost around 1988
■ Climate change (I mentioned it!) strongly seen in region
■ Regime-shift in mean recruitment looks plausible...

## Keep looking and you'll keep finding...

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■ Over optimistic to assume these are rare exceptions
■ All these examples affect assessment and management

- Generally, seems to appear because:

1 Something in your model looks wrong
2 You go looking for it with alternative models
3 You actively collect/happen to have spatiotemporal data
■ Don't need climate change invocation $\Rightarrow$ see it more often

## What tools do we need?

■ Statistically we've got the necessary machinery:
1 Random-effect/hierarchical state-space models
2 Spatio-temporal smoothers (tensor product splines)
3 Non or semi-parametric approaches (GP, neural networks)
4 Spatial models \& the means to parameterise them

- Freedom being explored for selectivity and catchability

■ Often subjective: fixed variance REs or spline DFs
■ Future: more rigorous use of CV and REML for the above

## Fisheries relativity

■ A brazen attempted linkage with high-level physics...
■ Not replacing Baranov with Einstein field equations...
■ But are space and time really that distinct in our work?

- Changes in time often about space (selectivity, maturity)
- Thinking in a more spacetime frame of mind in the future


## Acknowledgements

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■ Conveners for inviting me and all the smart folks who let me steal their pictures for this talk

## Relative influence of assessment frequency and assessment model structure on fishery management performance



Quantitative Fisheries Center at Michigan State University

## Objectives

- For the current harvest policy of $65 \%$ total mortality on the maximally selected age [Lake whitefish in Great Lakes]:
-Compare fishery performance for alternative timings of the assessments
-Contrast the magnitude of these effects with effects of other assessment choices


## Basic approach (stochastic simulations)

- Model true system (operating model)
- Stochastic age-structured population
- Model observation and assessment process (feeds back to system)
- Need defined management strategy (includes assessment approach and harvest control rule: 65\% max total mortality)
- Evaluate with performance statistics


## Simulation methods

- 4 hypothetic populations
- with differing levels of productivity
- Mixing during the harvest season
- Spawning site fidelity
- 100 year simulations, 1000 simulations per scenario
- Performance based on last 25 years


Size large
All simulations done using ADMB
Quantitative Fisheries Center at Michigan State University

## Performance statistics

Based on the result of last 25 years of 100 year simulations

- Proportion of years SSB $\mathbf{~ 2 0 \%}$ unfished by area
- Average SSB by area
- The average total yield achieved across all areas and by area
- Inter-annual variation in yield across areas and by area
- Median relative error of estimating SSB
- Median absolute relative error in estimating SSB


## Experimental Design

- 8 options for timing of assessment
- 5 mixing scenarios
- 3 levels equal among populations
- Positive and negative correlations between movement and productivity
- 2 assessment models (separate and pooled(CPE))


## 8 options for timing of assessment

Assessment frequency

## Setting TACs for rotation years

- Annual
- With lag
- Without lag
- 3 year cycle
- 5 year cycle
- constant
- Target F
- adjusted by yield information


## 8 options for timing of assessment

Assessment frequency

- Annual
- With lag
- Without lag
- 3 year cycle
- 5 year cycle

Setting TACs for rotation years

- Constant
- Target F
- Adjusted by yield information

Low Productivity Population Results Proportion of years SSB < 20\% of Unfished


Annual assessment : LO (without lag) VS. L1(with lag)

## Low Productivity Population Results Proportion of years SSB < 20\% of Unfished



Quantitative Fisheries Center at Michigan State University

## Conclusions

$\checkmark$ The influence of lag was generally small.
$\checkmark$ Target F method for multi-year assessments has much to recommend it.
$\checkmark$ Conservative rule
$\checkmark$ Can be calculated for all years at time of assessment
$\checkmark$ The effect of less frequent assessments is modest.
$\checkmark$ Differences due to assessment model or approach to rotation as large or larger than those due assessment frequency.

## Acknowledgements



## Spawning season



Spawning site of MLP population

Spawning site of MHP population

Without intermixing

| LP area | MLP area |
| :---: | :---: |
| Spawning site of LP population | $\leftarrow \left\lvert\, \begin{aligned} & \text { Spawning } \\ & \text { site of MLP } \\ & \text { population }\end{aligned}\right.$ |
| $\underset{\substack{\text { Spawning } \\ \text { site of HP } \\ \text { population }}}{\longrightarrow}$ | $\leftarrow\left\{\begin{array}{l}\text { Spawning } \\ \text { site of MHP } \\ \text { population }\end{array}\right.$ |
| HP area | MHP area |

With intermixing
Fishing season

Simulation length of 100 years

* Alternative assessment models; alternative assessment frequencies
* 1000 simulations for each model

Repeat the simulation loop 1000 times


## Perceived system

The simulation framework

# Daniel Goethel 

## Application of a Tag-Integrated Model to Three Interconnected Stocks of Yellowtail Flounder off New England



World Conference on Stock Assessment Methods
Spatial Complexity and Temporal Change Boston, MA, July I8, 20 I3

## Outline

- Yellowtail Flounder Background
- Tag-Integrated Modeling Framework
- Impacts of Connectivity
- Does Movement Resolve Closed Population Model Residual Patterns?
- Conclusions


## Yellow tail rionnder

- There are 3 stocks of yellowtail flounder off New England - The offshore Georges Bank stock is much larger than the other stocks
- 4 years of tagging data indicates that movement is limited between each stock
- Question to explore: Does connectivity lead to uncertainty in closed population assessments of each stock?



## Tag-Integratedronte

- Spatially-explicit population dynamics equations require the addition of movement parameters and tracking of 'unit'

$$
N_{j, y, a}=\sum_{k} T_{k, j, y} N_{k, y-1, a-1} e^{\left[-\left(v_{k, y-1, a-1} F_{k, y-1}+M\right)\right]}
$$

- The tag-integrated framework incorporates raw tagging data directly into the model using:
- A tagging sub-model
- A tag component in the objective function

Tagging Assessment Model Model

## Tag-Integratedroode

## - Modeled Dynamics



## Impacts of conncecirit

- Movement estimates and reporting rates ( $\beta$ ) are relatively low
- Southern New England acts as a source in the metapopulation



## Impacts of connectivi

- Interpretation of regional recruitment events differ



## Impacts of Connectivity

- Interpretation of regional recruitment events differ



## Impacts of Connectivity

- Regional population trajectories are only moderately impacted by connectivity

Cape Cod Spawning Stock Biomass


Georges Bank Spawning Stock Biomass


## Residual Compapisons

- Main uncertainty in currently accepted assessments are sudden increases in Georges Bank survey biomass
- Inconsistency in signals between survey and catch data have caused retrospective patterns

GB Fall Predicted and OBS Area Swept Survey Biomass


GB Fall Survey Biomass Standardized Residuals


## Residual Comparisons

- Connectivity does not resolve residual patterns


GB Fall Survey
Biomass Standardized Residuals


## Conclusions

- Limited tagging information, but available data agrees with historical studies
- Tag-integrated model results are consistent across sensitivity runs and indicate connectivity does not have a large impact on results
- Interpretation of recruitment does change
- There are likely implications for management
- Simulation analysis is required to test performance under longer tagging time-series
- Currently in progress

| Totals for <br> 2003-2006 | Cape <br> Cod | Georges <br> Bank | Southern <br> New <br> England |
| :---: | :---: | :---: | :---: |
| Cape Cod <br> Recoveries | 959 | 1211 | 28814 |
| Georges Bank <br> Recoveries | 23 | 2236 |  |
| Southern New <br> England | 4 | 3 | 32 |



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# To split or not to split? Assessment of Georges Bank sea scallops in the presence of MPAs 

## Deborah Hart, Larry Jacobson and Jiashen Tang NEFSC/NAFS/NOAA Woóds Hole MA 02543

Most stock assessment models assume that fishing mortality risks at size or age does not vary spatially

Fishery closed areas, often termed "Marine Protected Areas" (MPAs), explicitly violate this assumption

## What can be done in a stock assessment that contains MPAs?

Choice 1 (Aggregated model): Model aggregated stock with domed commercial selectivities for periods when the MPA was closed to fishing
Advantages: Simplicity, less parameters, does not require uncertain splitting of landings inside and outside MPAs

Choice 2 (Split model): Model MPAs and fished areas separately (two models, "Open model" and "Closed model")
Advantages: More accurate population dynamics, ability to evaluate responses inside and outside of MPA, potential to estimate M

# Three large areas on or near Georges Bank were closed to groundfish and scallop fishing in Dec 1994 

Strong responses to the closures seen in two stocks only: GB sea scallops, GB haddock
Some species showed weak or ambiguous responses, but many showed little or no response to the closures
Portions of the closed areas have been reopened to limited scallop fishing between June 1999-Jan 2001 and again since Nov 2004
Even with access, F in closed areas has been relatively low


## Georges Bank sea scallop assessment

Statistical catch at size model (CASA) with stochastic growth matrix based on shell ring increments, coded in ADMB

Tuned to survey and fishery catch at size

Compare aggregated model with split models


## Aggregated model

## Estimated fishery selectivity curves



## Closed Area "split" model

 Estimated fishery selectivity curves

## Open Area model

Fishery selectivity curves
fishery selectivity


## Comparison between aggregate and split models

 Good agreement except final few yearsExpanded survey trend more supportive of split model


## Split models

## Closed, open, total



## Estimation of natural mortality

Estimate from closed area model is $M=0.16$, with 95\% confidence interval ( $0.13,0.19$ )

Estimate from open area model is $M=0.11$, with $95 \%$ confidence interval $(0.05,0.25)$

Estimate in aggregate model is $M=0.20$, with $95 \%$ confidence interval $(0.16,0.24)$
"Current" estimate is $M=0.12$, based on Merrill and Posgay (1964) - estimate of $M=0.16$ is very plausible

## Model evaluation through simulations

1000 simulations, simulated by independently coded and more spatially complex SAMS model (Scallop Area Management Simulator) F uniform spatially and temporally increasing prior to closures, then decreasing in open areas after closures, zero in closed areas with low F after reopenings
Realistic levels of observation errors added

Simulated overall
biomass and
exploitation rates


## Simulation Results

The two approaches gave similar estimates when they converged, with a slight edge to the split approach. However, the split approach converged (i.e., both open and closed models converged) in 93\% of the cases compared to only $17 \%$ of the aggregate runs. Difficulty in estimating the domed selectivities was a major issue.


## To split or not to split?

- Both approaches possible, but split models are simpler to fit and may be more accurate
- Split models give information on closed/open dynamics and possibly accurate estimate of M from closed area model
- Domed selectivities due to closures are not temporally stable, which may cause problems fitting them
. Caveat: In more mobile stocks, there would be movement between open and closed areas, causing problems with the simple split approach - the aggregate model or a more complex model may be needed

Reference: Hart, Jacobson, Tang. 2013. Fish Res 144:74-83

## EVALUATING THE EFFECTS OF MIXING RATES BETWEEN ATLANTIC BLUEFIN TUNA STOCKS USING SIMULATION

Lisa A. Kerr¹, Steven X. Cadrin², David H. Secor ${ }^{3}$ and Nathan Taylor ${ }^{4}$
${ }^{1}$ Gulf of Maine Research Institute
${ }^{2}$ University of Massachusetts, Dartmouth
${ }^{3}$ University of Maryland Center for Environmental Science ${ }^{4}$ Pacific Biological Station, Fisheries and Oceans Canada

## Bluefin Tuna Stock Structure

- At least two spawning locations
- High degree of natal homing
- High degree of spatial overlap


## Bluefin Tuna Assessment and Management

Distribution of catch 2000-2009


Spawning Stock Biomass



## Objectives

- Develop an operating model for bluefin tuna that incorporates the leading hypotheses of bluefin tuna stock structure and mixing
- Use simulation to examine the impact of connectivity on productivity, yield, and rebuilding goals for bluefin tuna stocks.


## Model Basics

- Two stocks
- Stochastic and age-structured (age 1 to 30)
- Temporally (quarters) and spatially-explicit (7 zones)
- Overlap model
- Model Inputs:
- Life history: growth, maturity, natural mortality, recruitment
- Movement matrix (MAST model)
- Fishing mortality by fleet (MAST model)
- Model Outputs: SSBs,z,y,q and Yields,z,y,q


## Model Framework

Spatial strata are informed by distribution, life history, fishery, and management of bluefin tuna


Western stock

## 1

Western stock


Mixed stock $40^{\circ} \mathrm{W} \quad 30^{\circ} \mathrm{W}$

$\square$ Eastern stock
$20^{\circ} \mathrm{W} \quad 10^{\circ} \mathrm{W} \quad 0^{\circ} \quad 10^{\circ} \mathrm{E} \quad 20^{\circ} \mathrm{E}$
$30^{\circ} \mathrm{E}$

## Life History Parameters

|  | West | East |
| :---: | :---: | :---: |
| Growth | $\begin{aligned} & L_{\text {inf }}=315 \\ & \mathrm{k}=0.089 \\ & \mathrm{t}_{0}=-1.13 \end{aligned}$ | $\begin{aligned} & L_{\text {inf }}=319 \\ & \mathrm{k}=0.093 \\ & \mathrm{t}_{0}=-0.97 \end{aligned}$ |
| Length-weight | $\begin{gathered} a=2.86 \times 10^{-5} \\ b=2.93 \end{gathered}$ | $\begin{gathered} a=2.95 \times 10^{-5} \\ b=2.90 \end{gathered}$ |
| Maturity | $\begin{gathered} 50 \% \text { @ age } 12 \\ 100 \% \text { @ age } 16 \end{gathered}$ | 50\% @ age 4 <br> 100\% @ age 5 |
| Recruitment | $\begin{array}{lc} \text { Low: } & R_{\max }=84,363 \\ & S S B_{\text {hinge }}=12,236 \\ \text { High: } & \alpha=432,982 \\ & \beta=61,344 \end{array}$ | Med: $\begin{gathered} R_{\max }=1,889,896 \\ \mathrm{SSB}_{\text {hinge }}=215,584 \end{gathered}$ |
| Natural mortality | Age-specific vector informed by tagging experiments on southern bluefin tuna |  |

#  

Conventional Tags ( $n=47,439$ )
ICCAT database


Otolith chemistry Rooker et al. 2008


Archival ( $\mathrm{n}=122$ ) and PSAT Tag $(\mathrm{n}=\mathbf{2 2 0})$
Block et al. 2001, 2005, Sibert 2006


Quarter 1: Movement defined by maturity-at-age

Quarters 2,3,4: Movement estimated for juvenile/sub-adults and adults

## Simulation Scenarios

## Bulk Transfer Method

Direct estimation of movement

|  | Scenarios |  |
| :--- | :---: | :---: |
|  | $\mathbf{1}$ | $\mathbf{2}$ |
| Movement <br> Rates | Bulk <br> transfer | Gravity |
| Recruitment <br> Western Stock | Low | Low |
| Management | Status <br> quo F | Status |
| quo F |  |  |


|  | Zone 1 | Zone 2 | Zone 3 | $\ldots$ | Zone 7 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Zone 1 | $R_{1 \rightarrow 1}$ | $m_{1 \rightarrow 2}$ | $m_{1 \rightarrow 3}$ | $\ldots$ | $m_{1 \rightarrow 7}$ |
| Zone 2 | $m_{2 \rightarrow 1}$ | $R_{2 \rightarrow 2}$ | $m_{2 \rightarrow 3}$ | $\ldots$ | $m_{2 \rightarrow 7}$ |
| Zone 3 | $m_{3 \rightarrow 1}$ | $m_{3 \rightarrow 2}$ | $R_{3 \rightarrow 3}$ | $\ldots$ | $m_{3 \rightarrow 7}$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| Zone 7 | $m_{7 \rightarrow 1}$ | $m_{7 \rightarrow 2}$ | $m_{7 \rightarrow 3}$ | $\ldots$ | $R_{7 \rightarrow 7}$ |

## Gravity Method

Direct estimation of residency

|  | Zone 1 | Zone 2 | Zone 3 | $\ldots$ | Zone 7 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Zone 1 | $R_{1 \rightarrow 1}$ | $m_{1 \rightarrow 2}$ | $m_{1 \rightarrow 3}$ | $\ldots$ | $m_{1 \rightarrow 7}$ |
| Zone 2 | $m_{2 \rightarrow 1}$ | $R_{2 \rightarrow 2}$ | $m_{2 \rightarrow 3}$ | $\ldots$ | $m_{2 \rightarrow 7}$ |
| Zone 3 | $m_{3 \rightarrow 1}$ | $m_{3 \rightarrow 2}$ | $R_{3 \rightarrow 3}$ | $\ldots$ | $m_{3 \rightarrow 7}$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| Zone 7 | $m_{7 \rightarrow 1}$ | $m_{7 \rightarrow 2}$ | $m_{7 \rightarrow 3}$ | $\ldots$ | $R_{7 \rightarrow 7}$ |

## Long-term Spawning Stock Biomass



## Spawning Stock Biomass

Bulk Transfer Method


## Spawning Stock Biomass

Gravity Method


# Yield Composition <br> Bulk Transfer Method 



## Yield Composition

Gravity Method


## Conclusions

- Assuming no connectivity may give a false impression of productivity and sustainable yield for western stock.
- Different movement estimates produce substantially different expectations of SSB and yield.
- Interaction between maturity, movement, and fishing mortality drives results.


## Model Sensitivities

- New model....same old problems
- Are life history parameters representative of stock?
- Recruitment, maturity, growth, natural mortality
- Consistency in estimation of parameters
- Use of parameter estimates from stock assessments that assume no movement may be unrealistic
- Interaction between maturity, movement and fishing mortality
- Evaluate alternative maturity assumptions and new approaches to estimating movement rates


## Approaches to Assessment \& Management

- Current approach: VPA
- Ignores mixing
- Confounds management
- Spatially explicit assessment
- Estimates movement
- Over-parameterized or overly simplified
- Intermediate Approach
- Build stock composition data into existing assessment
- Spatially-explicit two stock projections



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Funding:


## Spawning Stock Biomass





## Simulation Scenarios

 Research Institute|  | Scenarios |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | $\mathbf{1}$ | $\mathbf{2}$ | $\mathbf{3}$ | $\mathbf{4}$ |
| Recruitment <br> Western Stock | Low | Low | High | High |
| Movement <br> Rates | Gravity | Bulk <br> transfer | Gravity | Bulk |
| Managemer |  |  |  |  |



## Bulk Transfer Method

Direct estimation of movement ( $\mathrm{R}=1-\sum \mathrm{m}$ )

|  | Zone 1 | Zone 2 | Zone 3 | $\ldots$ | Zone 7 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Zone 1 | $m_{1 \rightarrow 1}$ | $m_{1 \rightarrow 2}$ | $m_{1 \rightarrow 3}$ | $\ldots$ | $m_{1 \rightarrow 7}$ |
| Zone 2 | $m_{2 \rightarrow 1}$ | $m_{2 \rightarrow 2}$ | $m_{2 \rightarrow 3}$ | $\ldots$ | $m_{2 \rightarrow 7}$ |
| Zone 3 | $m_{3 \rightarrow 1}$ | $m_{3 \rightarrow 2}$ | $m_{3 \rightarrow 3}$ | $\ldots$ | $m_{3 \rightarrow 7}$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| Zone 7 | $m_{7 \rightarrow 1}$ | $m_{7 \rightarrow 2}$ | $m_{7 \rightarrow 3}$ | $\ldots$ | $m_{7 \rightarrow 7}$ |

Gravity Method
Direct estimation of residency ( $m=1-R / z-1$ )

|  | Zone 1 | Zone 2 | Zone 3 | $\ldots$ | Zone 7 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Zone 1 | $\mathrm{m}_{1 \rightarrow 1}$ | $\mathrm{~m}_{1 \rightarrow 2}$ | $\mathrm{~m}_{1 \rightarrow 3}$ | $\ldots$ | $\mathrm{~m}_{1 \rightarrow 7}$ |
| Zone 2 | $\mathrm{m}_{2 \rightarrow 1}$ | $\mathrm{~m}_{2 \rightarrow 2}$ | $\mathrm{~m}_{2 \rightarrow 3}$ | $\ldots$ | $\mathrm{~m}_{2 \rightarrow 7}$ |
| Zone 3 | $\mathrm{m}_{3 \rightarrow 1}$ | $\mathrm{~m}_{3 \rightarrow 2}$ | $\mathrm{~m}_{3 \rightarrow 3}$ | $\ldots$ | $\mathrm{~m}_{3 \rightarrow 7}$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| Zone 7 | $\mathrm{m}_{7 \rightarrow 1}$ | $\mathrm{~m}_{7 \rightarrow 2}$ | $\mathrm{~m}_{7 \rightarrow 3}$ | $\ldots$ | $\mathrm{~m}_{7 \rightarrow 7}$ |



# An integrated modeling framework for assessing Antarctic krill (Euphausia superba) 

Doug Kinzey, George Watters<br>Antarctic Ecosystem Research Division<br>NOAA/NMFS/SWFSC<br>La Jolla, CA 92037 USA



## Krill length-compositions 1992-2011

Combined areas and legs


Year

## Length-compositions 1992-2011 separated by area and month



## Model framework

- Age-structured
- Modified from Amak v.0.1
- Movement, mortality-emigration, steepness, etc. can be estimated or pre-specified
- Uses data from
- 1) length-compositions from the trawls
- 2) biomass densities from trawls, and
- 3) biomass densities from acoustics


## Model configurations

- Logistic or double logistic selectivities
- Single source (nets or acoustics) of biomass data, or combined biomass data sources
- Areas can be modeled as
- combined
- separately without movement
- with movement among areas


## Movement

- Movement is estimated as an emigration rate from each of the four areas to the other three (12 rates estimated)


## Results from example model configurations

- Fits to data and MCMC results
- 1-area combined models
- 4-area separated models


## 1-area models with single data source for biomass fit with CVs of 0.01

Acoustic biomass only





## Simulated data (self-check)

- Use the parameter estimates from a "generating model" based on the original field data to assemble a simulated data set
- Supply the simulated data to an estimating model, check fits of estimated to "observed" values
- Purpose is to check internal consistency of the model structure and equations


## 4-area, both biomasses, logistic, movement among areas: biomass fits to simulated data

Model vs. Biomass Data


## 4-area, both biomasses, logistic, movement: composition fits to simulated data, E. I.



1993 E.I. (Jan)
( $\mathrm{N}=10000$ )


1998 E.I. (Jan)
( $\mathrm{N}=10000$ )


2003 E.I. (Jan)









## 4-area, both biomasses, logistic selectivity, movement: biomass fits to original data










Year

## 4-area, both biomass sources, logistic selectivity, movement: composition fits to original data





















## MCMC results (models based on original data vs. simulated data)

- Spawning biomass
- Recruitment abundance
- Mortality (and emigration outside sampled areas)


## 1-area model MCMCs, logistic selectivity

Spawning biomass $(\log t)$



Recruitment Abund. (log N)



Mortality-emigration



## 1-area model MCMCs, double logistic

Spawning biomass $(\log t)$



Recruitment Abund. (log N)
Mortality-emigration





## 1-area model selectivities

Logistic selectivities

Double logistic selectivities


## 4-area model MCMCs: Elephant Island

Spawning biomass $(\log t)$




Recruitment Abund. ( $\log \mathrm{N}$ )




Mortality-emigration




## Summary

- Fits using simulated data verified that the modeling framework could reproduce "perfect" data.
- The MCMC patterns using the original and simulated data of estimated spawning biomass, recruitment, and M-emigration were similar but in some cases scaled differently between models.
- Models with logistic selectivity tended to estimate much lower spawning biomass, higher recruitment, and higher mortality-emigration than double logistic models.
- Double-logisitic models sometimes failed to converge (i.e. when movement was estimated), and when they did converge needed longer MCMC run times (at least) than applied in this study.


## Future work

- Pre-specify high rates of movement instead of estimating movement.
- Apply longer MCMC sampling runs.
- Calibrate acoustic densities using krill lengths from the model instead of lengths observed in the trawls.
- Supply simulated data sets representing a system with movement to estimating models without movement to assess the effect of ignoring movement when it occurs.


# Modeling intermixing lake whitefish populations: a simulation study to evaluate alternative stock assessment methods 



Quantitative Fisheries Center at Michigan State University

## Comparing fishery management and assessment methods in context of movement among areas

- Separate population assessment
- Pooled assessment with two TAC allocation rules
- Catch Per Effort (average of last 3 year)
- Equilibrium Yield
- Meta-population assessment


## Basic simulation approach

Repeat the simulation loop 1000 times


## Spawning season



## Spawning

 site of MLP populationSpawning site of MHP population

Spawning site of HP population
Spawning site of LP population

## 4 hypothetical populations

- LP~HP: low to high productivity populations

Without intermixing

| LP area | MLP area |
| :---: | :---: |
| Spawning site of LP population | $\leftarrow\left[\begin{array}{l}\text { Spawning } \\ \text { site of MLP } \\ \text { population }\end{array}\right.$ |
| - Spawning site of HP population | $\leftarrow \begin{aligned} & \text { S-2wning } \\ & \text { Spawe of MHP } \\ & \text { ispulation } \\ & \text { popur } \end{aligned}$ |
| HP area | MHP area |


|  |  |
| :--- | :--- |
| Spawning <br> site of LP <br> population | Spawning <br> site of MLP <br> population |
|  |  |
| Spawning <br> site of HP <br> population | Spawning <br> site of MHP <br> population |

Fishing season

## Quantitative Fisheries Center at Michigan State University

## Population model details

- Age structured with stochastic Ricker StockRecruitment
- Harvest Control Rule is $65 \%$ total annual mortality on maximally selected age
- Model includes process error (recruitment), observation error (assessment), and implementation error


## Experimental Design

- 4 levels of stay rate (SR)
- High: 0.9; Mid-high: 0.75; Mid-low:0.5; Low: 0.25
- 7 mixing scenarios
- 4 stay rates given above (same for each population)
- 3 Scenarios with stay rates varying among pops


## Performance statistics

Based on the result of last 25 years

- Proportion of years SSB < 20\% unfished by population
- The average total yield achieved across all areas
- Inter-annual variation in total yield
- Median relative error of estimating SSB


## Proportion of years SSB $<20 \%$ of unfished



LP, MLP, MHP, HP :

Low, mid-low, mid-high, and high productivity populations

## Results for other performance statistics

Pool(CPE) assessment method provided slightly higher total
yield than separate assessment method.

Pooled assessments have lower annual variation of yield.

Pooling stocks provided a nearly unbiased estimator of SSB.
Separate method had negative bias.

## Results for two other assessment methods

- Meta-population assessment did not work with high mixing rate. Population-specific data needed.
- Pooled assessment with constant allocation did poorly with very low and very high intermixing.


## Management Implications

- Current 65\% total mortality control rule: not conservative enough for low productivity population?
- Without knowing the productivity level and mixing rates, pooled(CPE) method could outperform separate assessment method
- Stable performance and good across the performance statistics


## Acknowledgements



## Thank you! Questions?



Quantitative Fisheries Center at Michigan State University

## The average total yield achieved across all areas




## Inter-annual variation in total yield



## Median relative error (MRE) of estimating SSB




## A spatio-temporal simulation model to evaluate assessment methods and management strategies

Dr Coby L. Needle

Marine Laboratory, Aberdeen

## marinescotland science

## Introduction: Problems with MSEs

Fish stocks
Fishery


Assessment and advice
Regulations


## Introduction: Problems with MSEs

## marinescotland <br> science



WCSAM
Boston, 17-19 July 2013

## Introduction: Spatial data (VMS)

## Whiting Aggregated landings

(VMS linked with daily landings declaration)


## Introduction: Spatial data (REM)



WCSAM

## Spatial model: area definition

- Hexagonal structure
- Layers built up by random walks:
- Deep
- Medium
- Shallow
- Land
- Coast
- Home port chosen at random


## Spatial model: fish stock dynamics

## marinescotland

## science



- Based on North Sea cod:
- Growth
- Natural mortality
- Maturity
- Recruitment
- Selectivity
- Plus hypotheses on:
- Carrying capacity
- Diffusion
- Price

Spatial model: skipper decision-making

Week 229


Distance $=12$ hexes; Yield $=10.5$; Profit $=£ 5111$

- One hex fished per week
- Decision based on harvest rule
- e.g. Maximise profit
- Stays in port if profit likely to be negative
- Assume perfect knowledge
- A* path-finding


## Case study: real-time closures

- 4 runs:
- With and without RTCs
- Two simulated maps
- 100 iterations for each:
- Only differing in recruitment time-series
- 30 years in each:
- Years 1-10: no fishing
- Years 11-20: unregulated fishing
- Years 21-30: either unregulated fishing, or
- If SSB < "B(lim)"
- Then close 2 hexes with highest abundance

Case study: real-time closures
total numbers $=390$


Scaled age dist for cod

total SSB $=41026 \mathrm{~kg}$



## Case study: real-time closures

Fishing location summary (year 21)

- Inland Coast - Shallow - Medium • Deep

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## Case study: real-time closures

Fishing location summary (total)

- Inland - Coast - Shallow - Medium • Deep

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## Case study: real-time closures






## Case study: real-time closures






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## Case study: real-time closures

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On average: ~50\% of weeks spent in port

## Case study: real-time closures

Fishing location summary (total)

- Inland - Coast - Shallow - Medium • Deep

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Case study: real-time closures



On average: ~5\% of weeks spent in port

## Case study: real-time closures

- Effectiveness of closures depends on spatial orientation of vessels and fish
- Closures increase catch only if home port close to fishing grounds
- Closures increase SSB in both cases
- Would not have been apparent without explicit modelling of space
- For next time: application to real world examples


## Conclusions

- If the stock and/or fishery is not evenly distributed
- Then consideration should be given to spatial evaluation of assessment and management
- Spatial management measures should always be evaluated spatially
- The simulation should be parsimonious:
"The danger in creating fully detailed models of complex systems is ending up with two things you don't understand - the system you started with, and your model of it." (Paola 2011)


## Thanks...


marinescotland science

University of Strathclyde Glasgow

## Dealing with Temporal Structure with Bayesian Surplus Production Models:

 Georges Bank Yellowtail Flounder

## Joseph O'Malley ${ }^{1}$, Jon Brodziak ${ }^{1}$, Yi-Jay Chang ${ }^{\mathbf{2}}$

${ }^{1}$ National Marine Fisheries Service, Pacific Islands Fisheries Science Center ${ }^{2}$ Joint Institute for Marine and Atmospheric Research, University of Hawai'i


## Overview

Bayesian Surplus Production Model

- hierarchical framework for time-varying productivity - hypotheses
- scaling via prior

Strategic Initiative on Stock Assessment Methods (SISAM) Exercise

- GB yellowtail flounder issues
- potential changes in productivity
- retrospective patterning

Results

- best fit model
- model averaging
- temporal variability?
- retrospective pattern?

Final Statements


## Bayesian Surplus Production Model

$$
B_{t}=B_{T-1}+r * B_{T-1}\left\{1-\left(\frac{B_{T-1}}{K}\right)^{M}\right\}-C_{T-1}
$$

## Process error

- population biomass dynamics

Observation error

- heterogeneous
- observed data from multiple surveys

3 parameters

- $r$ = intrinsic growth rate
- $K=$ carrying capacity
- $M$ = production shape parameter

Key estimates

- biomass
- harvest rate
- biological reference points
- BMSY = biomass that maximizes surplus production
- Bratio = B/BMSY
- HMSY = harvest rate that maximizes surplus production
- Hratio = H/HMSY


## Strategic Initiative on Stock Assessment Methods (SISAM) Exercise

## Yellowtail Flounder Retrospective Patterning



Why retrospective pattern?
1- large amounts of unreported catch
2- an increase in natural mortality
3- changes in survey catchability since 1995
"Residual patterns are indicative of a discontinuity starting in 1995"
Solution - split time series into pre- and post-1995

- retrospective adjustment to terminal year

Different approach
Time-varying hierarchical Bayesian surplus production model

## Data available

Catch (landings and discards) $=$ 1958-2012 Catch-at-age = 1973-2011

Surveys:

- DFO spring survey index 1987-2011
- NMFS fall survey index 1973-2011
- NMFS spring survey index 1973-2011
- split in 1981


Last assessment - 2011

- VPA calibrated using the adaptive framework ADAPT


## Hypotheses: Time-Varying Population Dynamics

## Data and Model Parameters

1) Abundance Indices (surveys)

- single series (4 surveys) vs. split-series (7 surveys)

2) Intrinsic Growth Rate (r)

- $r$ (one $r$ for all years)
- $2 r$ (one $r$ for 1973-1994, one $r$ for 1995-2011)
- ${ }^{*} r$ (every year gets an $r$ )
- "multiple $r$ "

3) Carrying Capacity ( $K$ )

- $K$ (one $K$ for all years)
- 2K (one K for 1973-1994, one K for 1995-2011)

4) Production Shape and Scale ( $M$ )

- $M$ (one $M$ for all years)
- 2M (one $M$ for 1973-1994, one $M$ for 1995-2011)


## Hypotheses testing

| Model | surveys split at <br> $1994 / 1995 ?$ | $\# r$ | $\# K$ | $\# M$ | \# MSY |
| :--- | :---: | :---: | :---: | :---: | :---: |
| gbyt_single | no (4) | $\mathbf{1}$ | $\mathbf{1}$ | $\mathbf{1}$ | 1 |

## Model Selection Criteria

## Deviance Information Criteria = DIC

$$
D I C=2 \cdot \bar{D}-D(\theta)=\bar{D}+p_{D}
$$

$\bar{D}=$ the posterior mean of the model deviance,
$D(\theta)=$ the value of deviance evaluated at the posterior mean of the stochastic variables in the model,
$p_{D}=$ the effective degrees of freedom in the model.

## Model Selection

| model | surveys <br> split at <br> 1994/1995? | $\# r$ | $\# K$ | $\# M$ | $\#$ MSY | DIC | Delta DIC | B2011/ <br> BMSY |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| gbyt_ns_*r | no (4) | 39 | 1 | 1 | 1 | 408.03 | 0 | 1.25 |
| gbyt_ns | no (4) | $\mathbf{1}$ | 1 | 1 | 1 | 408.09 | 0.07 | 1.19 |
| gbyt_*r | yes (7) | 39 | 1 | 1 | 1 | 455.72 | 47.69 | 1.03 |
| gbyt | yes (7) | 1 | 1 | 1 | 1 | 455.92 | 47.90 | 0.98 |
| gbyt_2r | yes (7) | 2 | 1 | 1 | 2 | 457.16 | 49.13 | 1.26 |
| gbyt_2rKM | yes (7) | 2 | 2 | 2 | 2 | 457.72 | 49.69 | 1.37 |
| gbyt_2rK | yes (7) | 2 | 2 | 1 | 2 | 460.34 | 52.31 | 1.83 |

## Scaling

## Yankee 36 trawl <br> - NMFS spring survey - 1982-2011 <br> - NMFS fall survey - 1973-2011

## Survey catchability coefficents $=0.39$ (precision $=105.2$ ) <br> - (Edwards, 1968)



Setting the Yankee 36 net in the snow, Albatross IV, circa 1966.
(Credit: Robert Brigham/NOAA)

| model | surveys split at 1994/1995? | \# | $\begin{aligned} & \# \\ & K \end{aligned}$ | $\begin{gathered} \# \\ M \end{gathered}$ | $\begin{gathered} \text { \# } \\ \text { MSY } \end{gathered}$ | DIC | Delta DIC | $\begin{aligned} & \text { B2011// } \\ & \text { BMSY } \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| gbyt_ns_*r | no (4) | all | 1 | 1 | 1 | 408.03 | 0 | 1.25 |
| gbyt_ns | no (4) | 1 | 1 | 1 | 1 | 408.09 | 0.07 | 1.19 |
| gbyt_*r | yes (7) | all | 1 | 1 | 1 | 455.72 | 47.69 | 1.03 |
| gbyt | yes (7) | 1 | 1 | 1 | 1 | 455.92 | 47.90 | 0.98 |
| gbyt_2r | yes (7) | 2 | 1 | 1 | 2 | 457.16 | 49.13 | 1.26 |
| gbyt_2rKM | yes (7) | 2 | 2 | 2 | 2 | 457.72 | 49.69 | 1.37 |
| gbyt_2rk | yes (7) | 2 | 2 | 1 | 2 | 460.34 | 52.31 | 1.83 |
| gbyt_ns_*r_Q | yes (7) | all | 1 | 1 | 1 | 391.14 | 0 | 1.16 |
| gbyt_ns_Q | no (4) | 1 | 1 | 1 | 1 | 391.90 | 0.76 | 1.07 |

Model averaging is appropriate

## Best Fit Model Survey Residuals



NMFS fall STD_LOG_RESID


All chains converged to posterior distributions.

## Biomass Comparisons



## Retrospective Analysis




VPA Mohn's rho SSB = 1.62

## Time-Varying $r$



## Georges Bank Yellowtail Flounder

- Results indicate time variation is important
- as evident by annual $r$ estimates plot
- no need to split the data in 1995
- best fit models were both "non-split"
- Survey catchability estimates helped with scaling issue
- Reduced retrospective patterns



## Hierarchical Bayesian Surplus Production Model

- Relative abundance indices are suitable for biomass dynamic models
- Time varying processes affect biomass production
- Explore alternative hypotheses:
- constant or time-varying productivity
- Model selection/averaging to assess credibility of alternative hypotheses
- Parsimony
- easy to run


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## Parameter Estimates

| Model | BMSY1 | BMSY2 | HMSY1 | HMSY2 | K | K2 | MSY1 | MSY2 | r1 | r2 | B2011 | B2011_status1 | B2011_status2 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| gbyt | 65.40 |  | 0.16 |  | 139.20 |  | 8.94 |  | 0.45 |  | 55.49 | 0.9854 |  |
| gbyt ns | 63.63 |  | 0.19 |  | 134.50 |  | 10.08 |  | 0.48 |  | 99.32 | 1.192 |  |
| gbyt_ns_Q | 27.38 |  | 0.42 |  | 57.32 |  | 10.28 |  | 1.03 |  | 27.89 | 1.066 |  |
| gbyt_2r | 67.52 | 67.52 | 0.13 | 0.31 | 144.10 |  | 7.44 | 19.27 | 0.38 | 0.95 | 77.97 | 1.264 | 1.15 |
| gbyt_2rK | 61.39 | 71.83 | 0.18 | 0.39 | 138.80 | 163.30 | 8.79 | 24.47 | 0.59 | 1.19 | 100.20 | 1.834 | 1.39 |
| gbyt_2rKM | 69.77 | 79.47 | 0.15 | 0.41 | 167.10 | 177.10 | 7.99 | 28.30 | 0.74 | 1.16 | 112.00 | 1.367 | 1.41 |
| gbyt_mr | 66.66 |  | 0.16 |  | 143.00 |  | 9.29 |  | 0.49 |  | 59.14 | 1.03 |  |
| gbyt_ns_mr | 67.61 |  | 0.19 |  | 143.60 |  | 10.71 |  | 0.54 |  | 76.50 | 1.251 |  |
| gbytns_mr_Q | 33.50 |  | 0.36 |  | 71.28 |  | 10.40 |  | 1.11 |  | 35.76 | 1.158 |  |
| VPA assessment | 43.20 |  |  |  |  |  | - |  |  |  | 46.00 | 0.11 |  |
| gbyt model avg | 31.01 |  | 0.38 |  | 65.60 |  | 10.35 |  | 1.02 |  | 32.56 | 1.1205 |  |


| Model | split models |  |  |  |  |  |  | non-split models |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | DFO spring 1 | DFO spring 2 | NMFS Spring 1 | NMFS <br> Spring 2 | NMFS Spring 3 | NMFS <br> Fall 1 | NMFS Fall 2 | $\begin{gathered} \text { DFO } \\ \text { spring } \end{gathered}$ | NMFS Spring 1 | NMFS <br> Spring 2 | NMFS <br> Fall |
| gbyt | 0.13 | 0.20 | 0.03 | 0.05 | 0.08 | 0.05 | 0.09 |  |  |  |  |
| gbyt_ns |  |  |  |  |  |  |  | 0.14 | 0.04 | 0.05 | 0.05 |
| gbyt_ns_Q |  |  |  |  |  |  |  | 0.34 | 0.08 | 0.13 | 0.13 |
| gbyt_2r | 0.13 | 0.15 | 0.03 | 0.05 | 0.06 | 0.04 | 0.07 |  |  |  |  |
| gbyt_2r_K | 0.15 | 0.18 | 0.04 | 0.06 | 0.07 | 0.05 | 0.08 |  |  |  |  |
| gbyt_2r_KM | 0.14 | 0.17 | 0.03 | 0.05 | 0.06 | 0.05 | 0.07 |  |  |  |  |
| gbyt_mr | 0.18 | 0.19 | 0.03 | 0.05 | 0.07 | 0.04 | 0.08 |  |  |  |  |
| gbyt_ns_mr |  |  |  |  |  |  |  | 0.13 | 0.03 | 0.05 | 0.05 |
| gbyt_ns_mr_Q |  |  |  |  |  |  |  | 0.27 | 0.06 | 0.10 | 0.10 |



## SISAM - The Proble 1) Catch vs. Survey trends



## Relative F

## Survey Z



Figure 20. Trends in total mortality $(Z)$ for ages 2, 3, and 4-6 from the four surveys.

## Leads to...

## Retrospective pattierni



Figure 26b. Relative retrospective plots for Georges Bank yellowtail flounder from Split Series VPA with Mohn's rho calculated from seven year peel for age 4+ fishing mortality (top panel), spawning stock biomass (middle panel), and age 1 recruitment (lower panel)

## Hypotheses $\left(\right.$ con $\left.^{\prime} \%\right)$ :

| Model Name | Two Time Periods? | Intrinsic Growth Rate (r) Prior | Carrying Capacity (K) Prior | Production Shape (M) Prior |
| :---: | :---: | :---: | :---: | :---: |
| gbyt | Yes | - simple Bayes lognormal | - simple Bayes lognormal | - simple Bayes Gamma |
| gbyt 2 2r | Yes | - hierarchical normal hyperprior <br> - lognormal prior | - simple Bayes lognormal | - simple Bayes Giamma |
| gbyt_2rK | Yes | - hierarchical normal hyperprior <br> - lognormal prior | - hierarchical normal hyperprior <br> - lognormal prior | - simple Bayes Gamma |
| gbyt_2rKM | Yes | - hierarchical normal hyperprior <br> - lognormal prior | - hierarchical normal hyperprior <br> - lognormal prior | - hierarchical normal hyperprior Gamma Prior |
| gbyt_*r | Yes | - hierarchical normal hyperprior for all years - lognormal prior | - simple Bayes lognormal | - simple Bayes Gamma |
| gbyt_ns | No | - simple Bayes Lognormal | - simple Bayes lognormal | - simple Bayes Gamma |
| gbyt_ns_*r | No | - hierarchical normal hyperprior for all years <br> - lognormal prior | - simple Bayes lognormal | - simple Bayes Gamma |

## Prior values

Target_K_Prior_Avg=150,
CV_K=1.0,
CV_Hyper_K=1.0,
Target_r_Prior_Avg=0.5,
CV_r=1.0,
CV_Hyper_r=1.0,
M_shape_Hyper_Avg=2.0,
M_shape_Hyper_Precision=1.0,
M_scale_Hyper_Avg=2.0,
M_scale_Hyper_Precision=1.0,
Target_P1_Prior_Avg=0.50, CV_P1=1.0,
q_shape_S1=0.01,
q_scale_S1=0.01,
q_shape_S2=0.01,
q_scale_S2=0.01,
q_shape_S2a=0.01,
q_scale_S2a=0.01,
q_shape_S3=0.01,
q_scale_S3=0.01,

## Model Run Specifics

- Markov Chain Monte Carlo Simulation (WinBUGS software)
- 3 chains
- 310,000 Iterations
- 25 Thinning rate
- 10,000 Initial burn-in


## Best Fit Model Survey Residuals




## Yellowtail Flounder Limanda ferruginea

## Range:

- Southern Labrador to Chesapeake Bay


## 3 Stocks:

- S. New England/Mid-Atlantic Bight
- Georges Bank
- Cape Cod/Gulf of Maine



