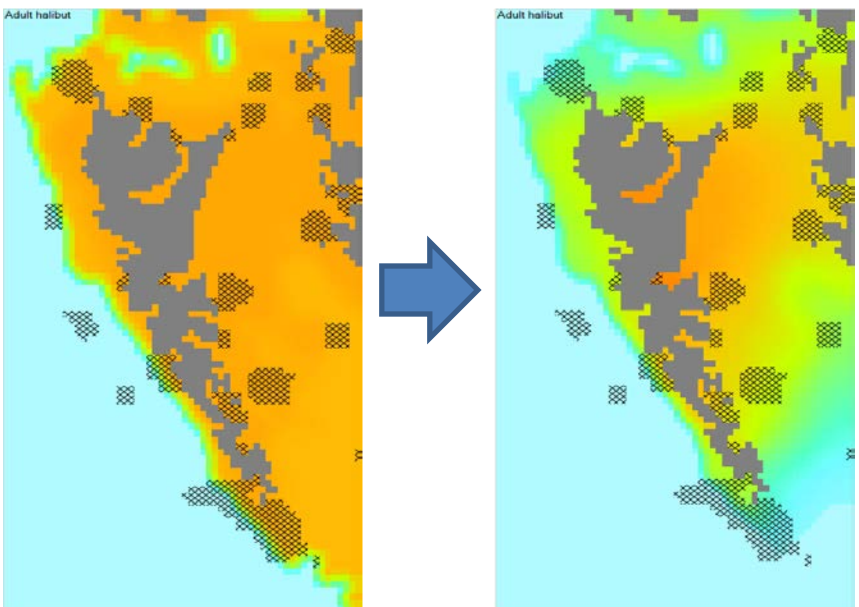
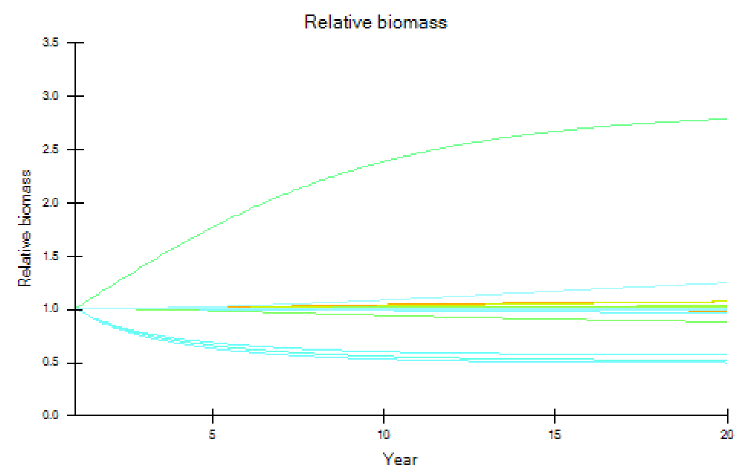
Community modeling: what to expect

What community models can do

- Numerically estimate stable equilibria (spatial or temporal) for models too complex for analytical solutions
- E.g., Are there enough prey to support your predators?
- Let’s you know *why* species distribute the way they do





What community models can do

- Project trends under forcing functions acting on state variables
  - (e.g., numbers trend under environmental forcing on recruitment)
  - (e.g., catch trend under fishing forcing acting on mortality)
  - **Mississippi R. diversions: salinity, turbidity effects on benthos**
- Provide descriptive statistics
  - Target species
  - Ecosystem metrics (structure, function)
- *Anticipate unintuitive interactions
  - Synergies
  - Antagonisms
  - E.g., do single species management plans work together?

What community models can do

- Provide bioeconomic data
- EwE and other models have an economic component
- Gross fisheries indicators: value, cost, profit
- Relevant biological data (body size, CPUE)
- Socially important indicators (some models)
  - E.g., days away from port with effort prediction model (Atlantis)
  - Catch constancy (e.g., important for food/employment security)
  - Extinction risk

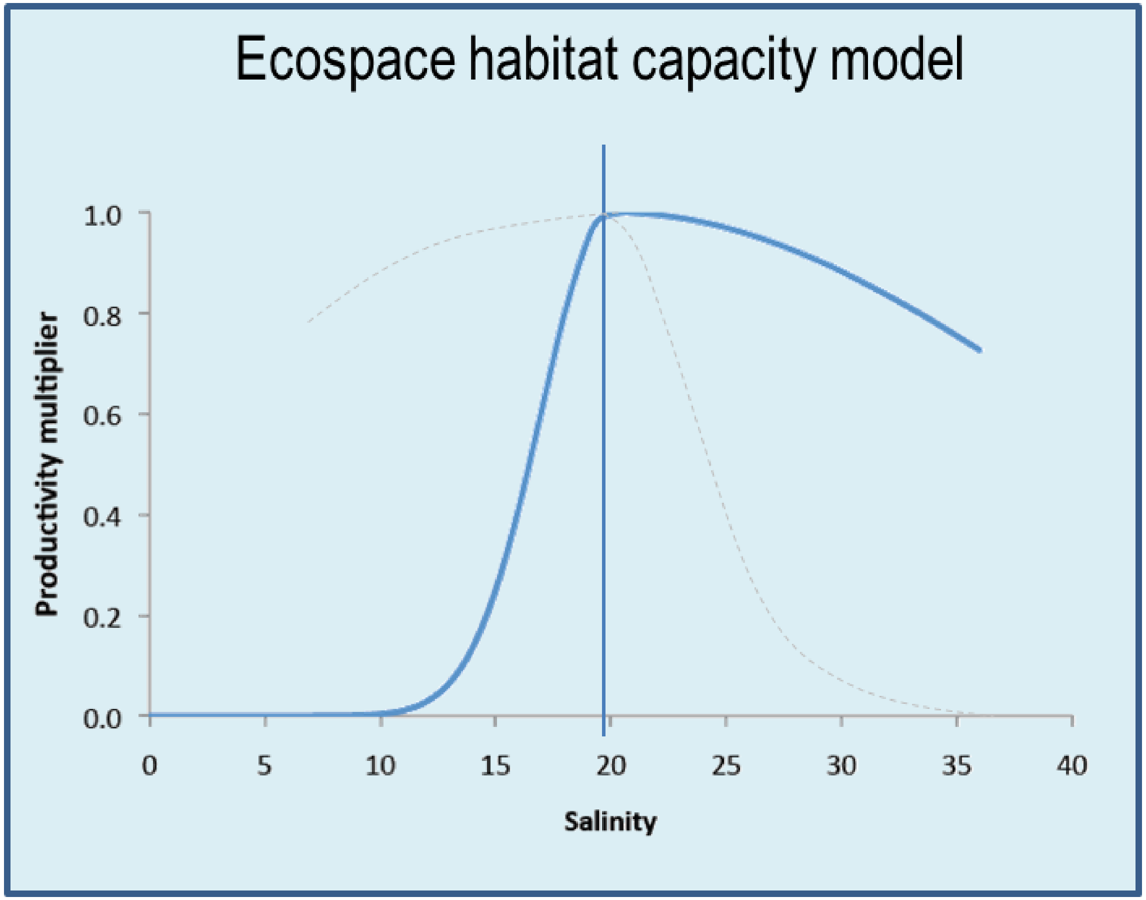
What community models can’t do

Represent unknown processes

- E.g., EwE does not have organism physiology…
  - Q. So how do we represent salinity, temperature, O2, pH effects?
- EwE does not have explicit recruitment…
  - Q. So how do we represent fecundity, toxicology, larval impacts?
- Ecospace does not have vertical structure…
  - Q. So how do we represent light attenuation? Vertical segregation of predator/prey?
- Represents these dynamic processes implicitly through “black-box” production modifiers

The real magic is done outside of EwE with the functional response

What community models can't do



The real magic is done outside of EwE with the functional response

What community models can't do

See outside the model domain

- Typically assume similar influences outside of modeling domain
  - Sometimes inappropriate
  - Often unacknowledged
- E.g., Busch et al. 2013 modeled blade strike mortality on salmonids from Washington State hydrokinetic farms
- All organisms interact with migrators to some extent; particularly affects smaller spatial domains

Busch, S., Green, C., Good, T., 2013. Estimating impacts of tidal power projects and climate change on threatened and endangered marine species and their food web. Conservation Biology DOI: 10.1111/cobi.12164

What community models can't do

Make decisions on data quality

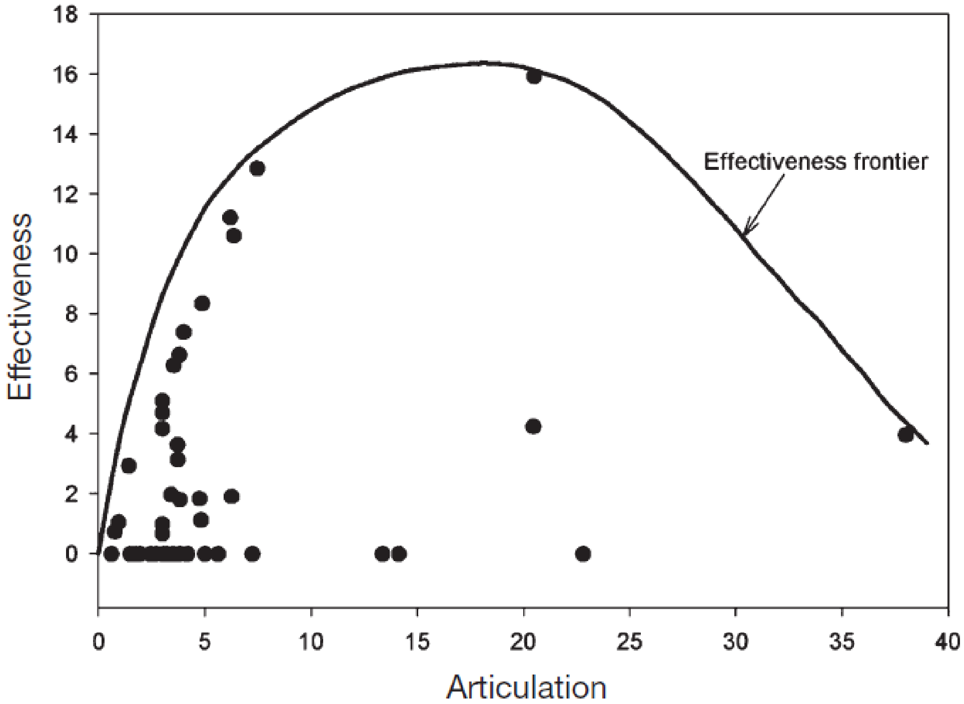
- Mass-balance models (like EwE) are great at finding thermodynamic inconsistencies
- But can't tell you which data are right or wrong
- Automated balancing in EwE (e.g., Kavanagh) never really took off because of that
- Monte Carlo is troubled by same problem

Kavanagh, P., Newlands, N., Christensen, V., and Pauly, D., 2004. Automated parameter optimization of Ecopath ecosystem models. Ecological Modelling, 172, 141-149

Model complexity

More detail can be prescriptive not predictive

- info-content of data low, so large models with lots of noisy data vs. slim-line model with few precise data
- trade-off detail vs. ease of parameterization

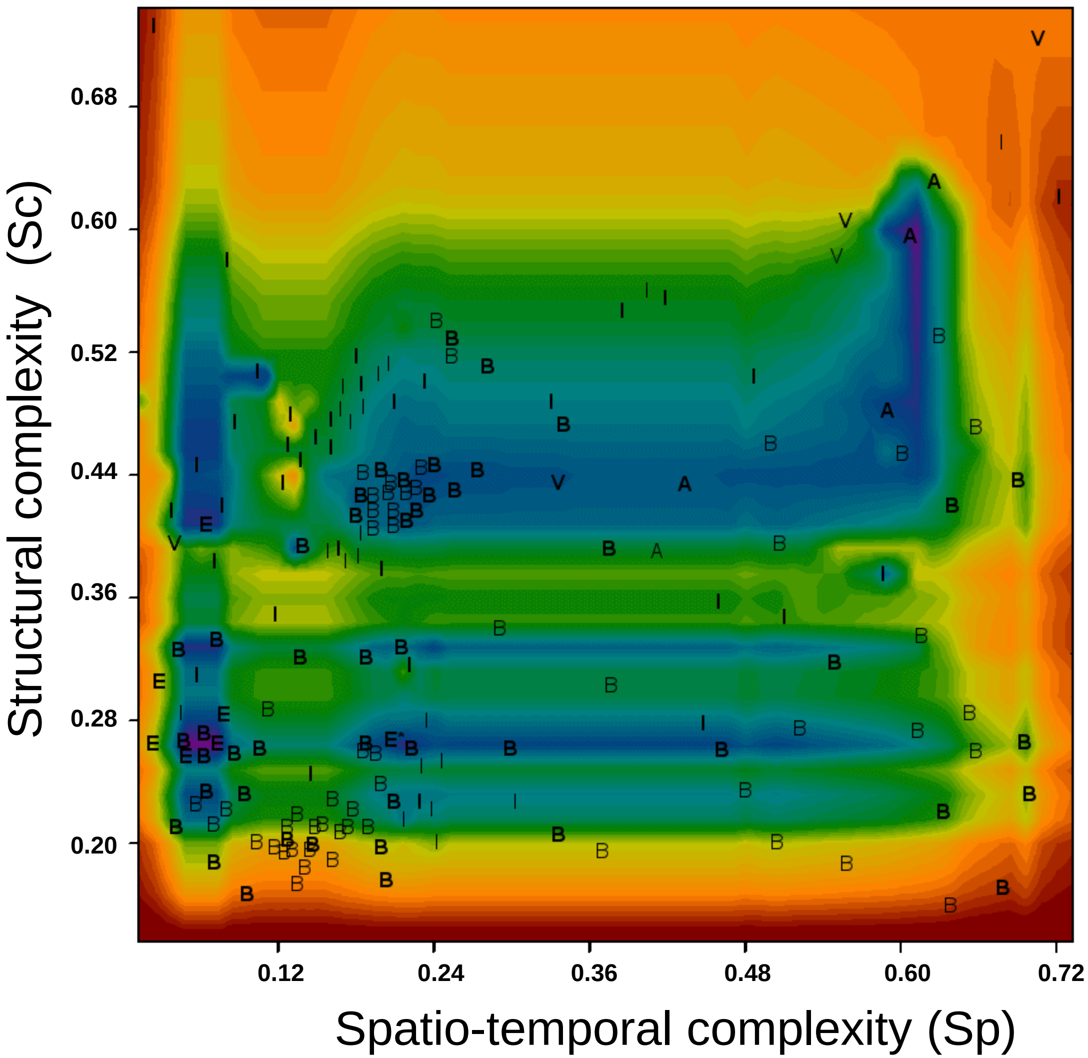


critical scales and processes lost

Interpretation difficult, noisy data, overfitting

Fulton, E., Smith, A., Johnson, C. Effect of complexity on marine ecosystem models. Marine Ecology Progress Series, 253: 1-16

Performance Spectra



Simple models have the potential to perform just as well as complex models

Performance Key

0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

Model Key

A – ATLANTIS
B – BM2
E – ECOPATH / ECOSIM
E* – ECOSPACE
I – IGBEM
V – INVITRO

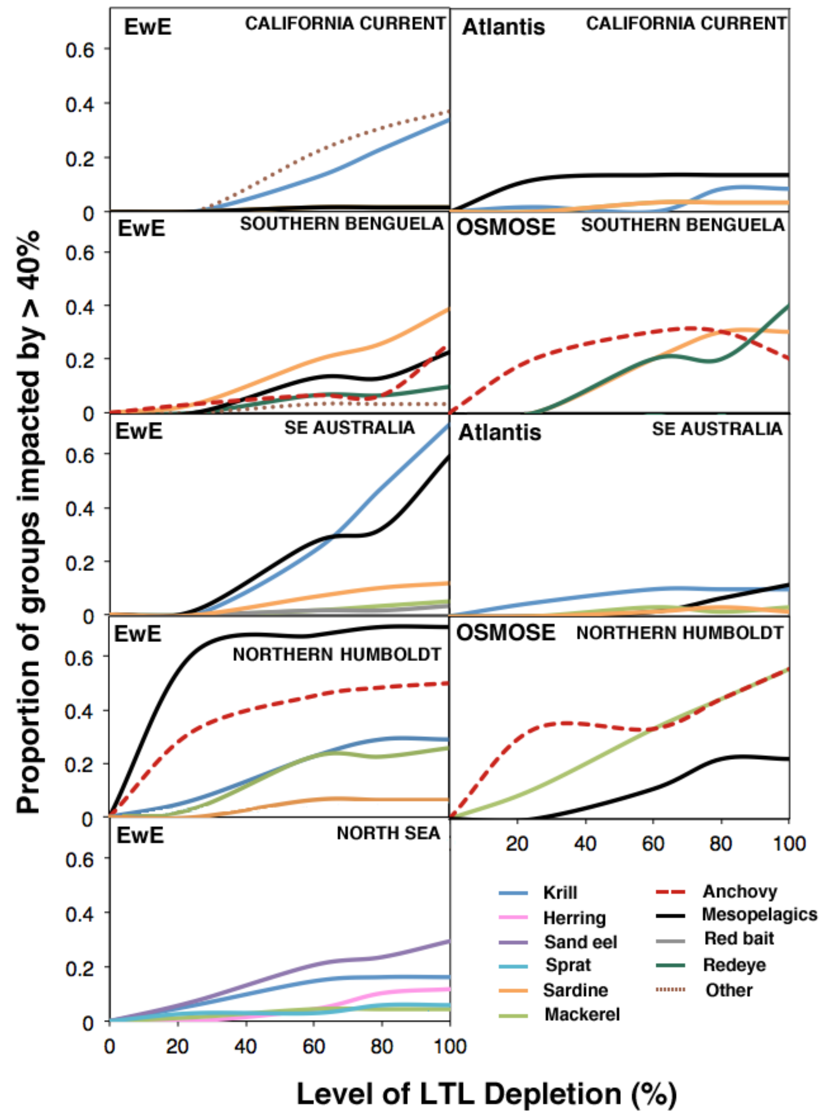
Fulton EA (2001) The effects of model structure and complexity on the behaviour and performance of marine ecosystem models. PhD thesis, School of Zoology, University of Tasmania, Hobart, Australia

Ensemble approach

Models are not like religion,
you can have more than one

Villy Christensen

- Recommended practice
- Challenge structural & process assumptions
- Alternative: coupling takes advantage of different strengths

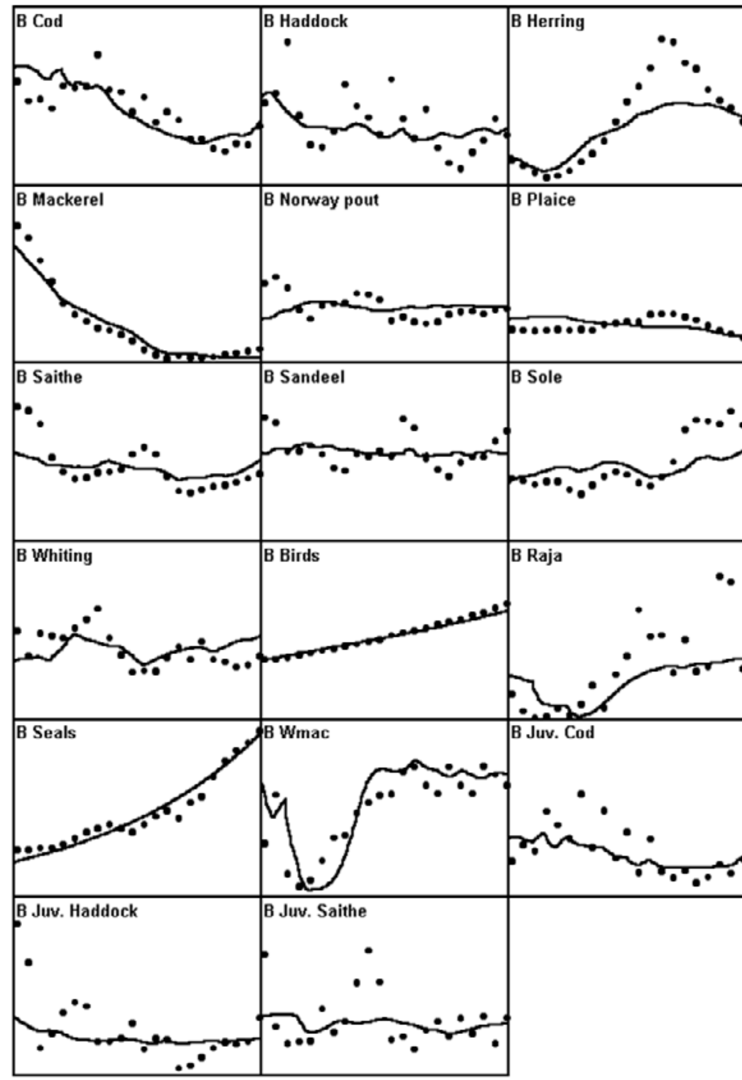


Assessing model performance

- Most common approach is to compare aggregate biomass or numbers against observations
- Best to start with a historical model
- Although even forward projections can be constrained based on stock history
- Depending on model, other data may be tracked
  - (may or may not be easily accessible)

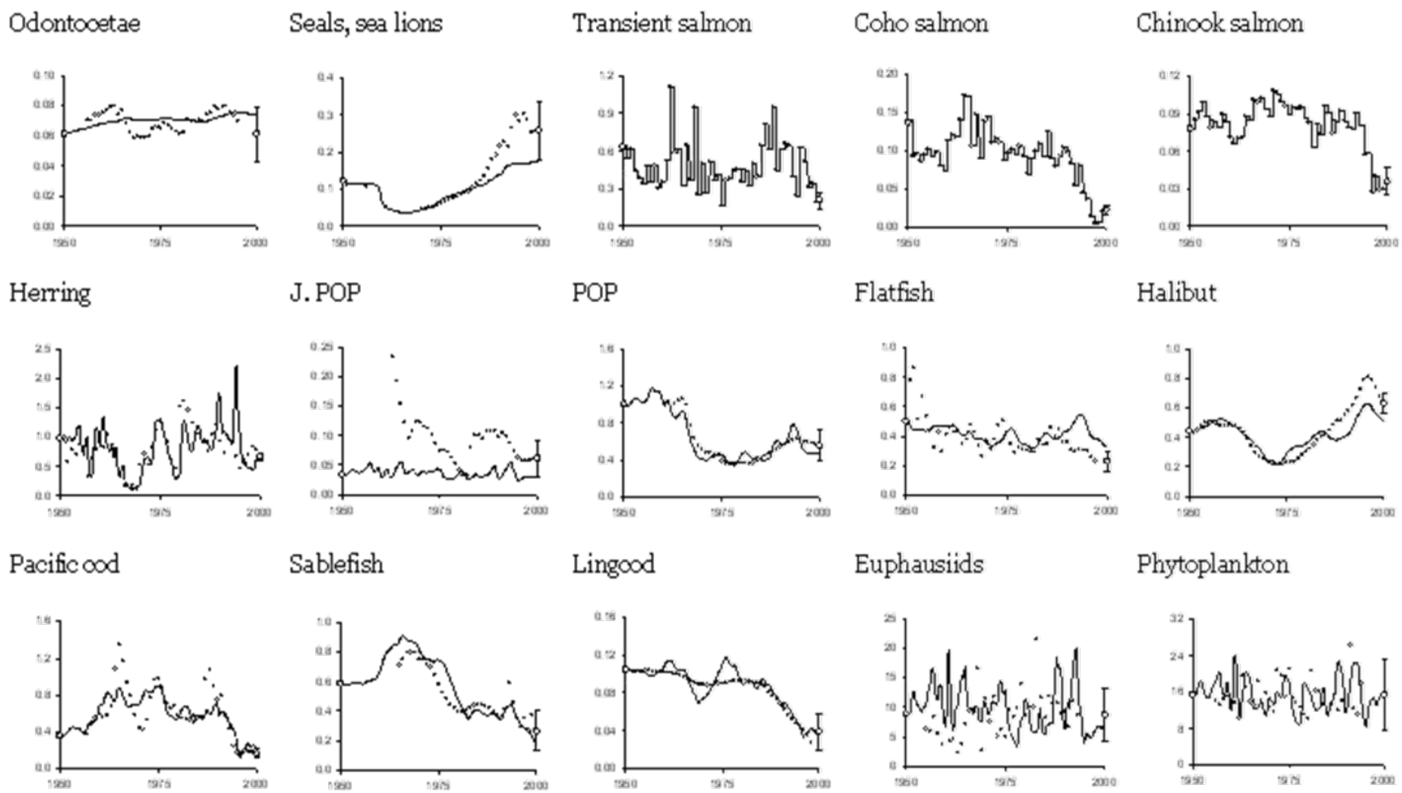
Evaluating model skill

- Several thousand EwE models developed
- At least 400 have been fitted to data
- Model skill sometimes evaluated by fitting to data outside of the training set
- Expect a loss of performance in extreme conditions



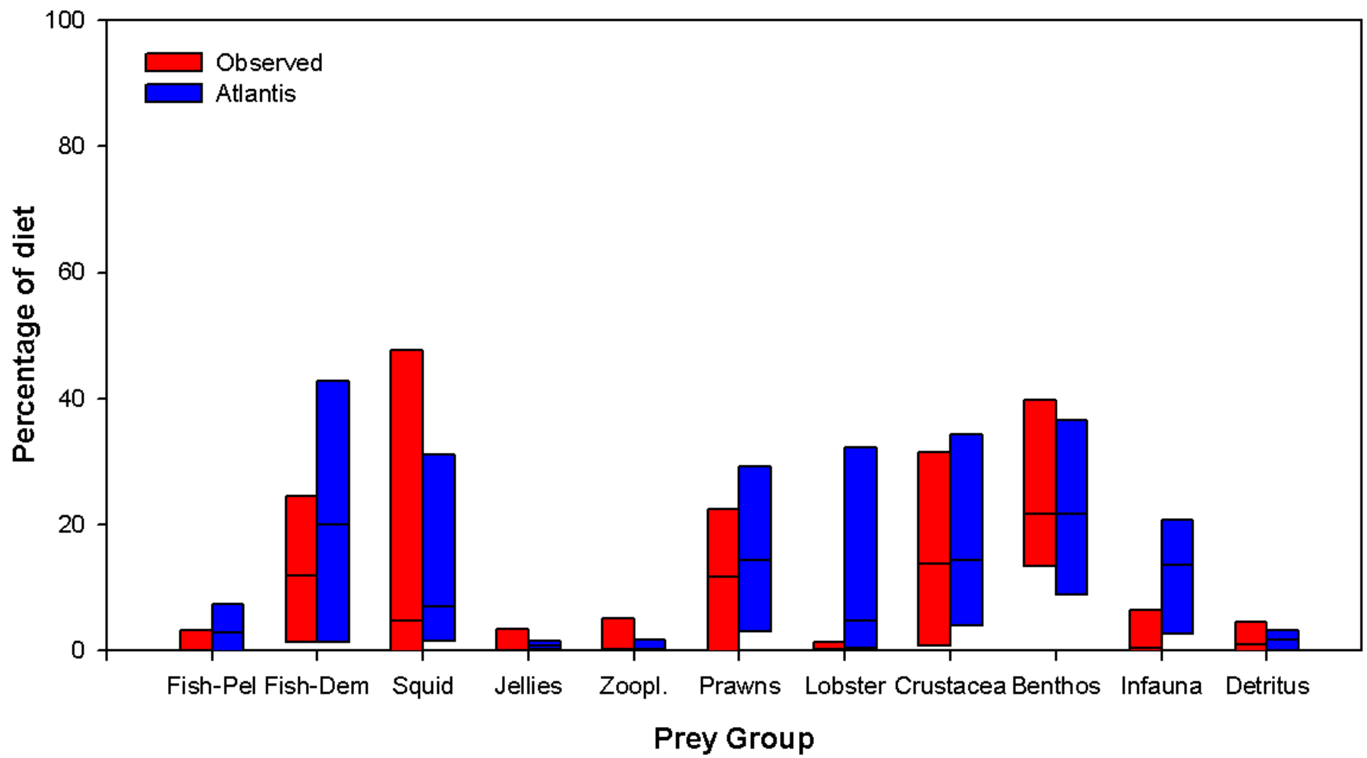
Biomass or numbers

- Compared to relative abundance (CPUE) from fisheries, FIM, or single species model estimates

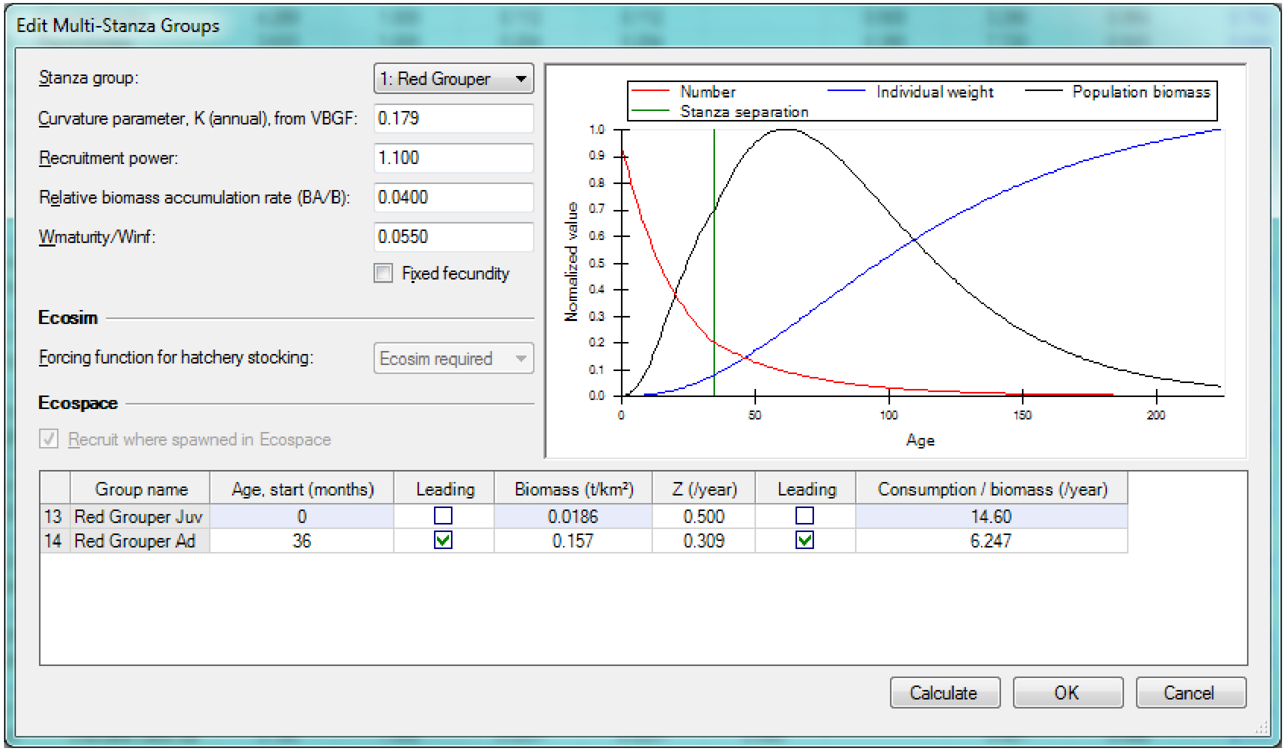


Diet outputs over time

- Observed/predicted diets
- Relevant to any dynamic model: responding to spatio-temporal co-occurrence of predator and prey, spp concentrations
- Some models predict diet based on size structure (e.g., OSMOSE) or gape limitation (Atlantis)



Age structure

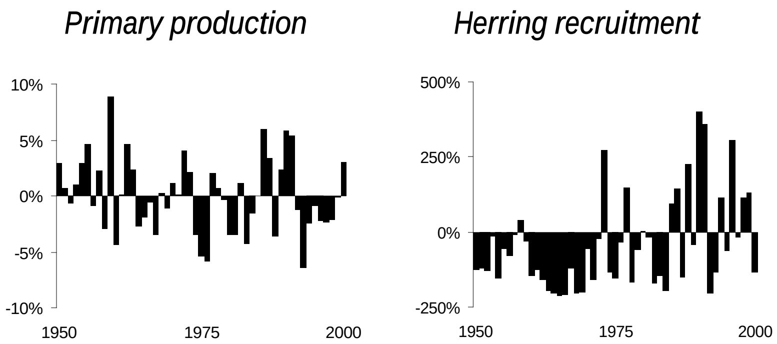


- Numbers/biomass/catch at age data are often available
- Cohort strength can indicate lagged recruitment responses (e.g., to environment, pollutants), fisheries value

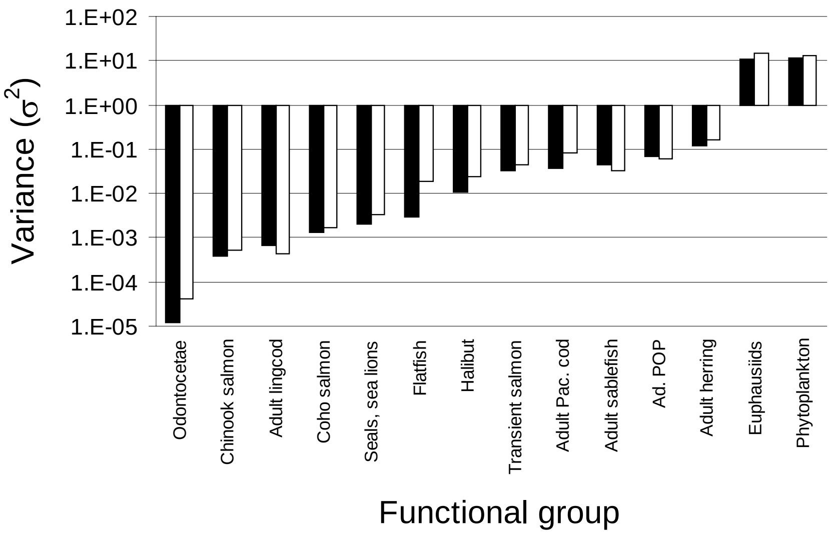
Variability

- Simple models like EwE can be run stochastically
- Extinction risk, variance in catch are useful outputs
- May be compared against data

Predicted climate anomalies (1950-2000)



Predicted vs. observed variance



For MC depletion risk forecasting

Ainsworth, C., Pitcher, T., Heymans, J.J., Vasconcellos, M. 2008. Reconstructing historical marine ecosystems using food web models: Nothern British Columbia from Pre-European contact to present. Ecological Modelling, 216: 354-368.

Univariate metrics of model fit

- Average error
  - Measures model bias (direction of discrepancy)
- Average absolute error
  - Difference between predicted and observed values
- Root mean square error
  - Same, penalizes outliers
- General standard deviation
  - Same, native units
- Reliability index
  - Describes how accurate your model is on average
- Modeling efficiency
  - Does model predict better than simply averaging the data?
  - Values < 0 means averaging the data is a better prediction
- Coefficient of determination
  - Tendency of predicted & observed values to vary together
  - May still be offset, influenced by outliers
- Spearman's rank correlation
  - Non-parametric, does not require normalcy

Stow, C.A.,Jolliff,J.,McGillicuddyJr.,D.J.,Doney,S.C.,Allen,J.I.,Friedrichs,M.A.M., Rose, K.A.,Wallhead,P., 2009. Skill assessment for coupled biological/physical models of marine systems. Journal of Marine Systems, 76:4–15.
Biber, P.D.,Harwell,M.A.,CropperJr.,W.P.,2004.Modeling the dynamics of three functional groups of macroalgae in tropical seagrass habitats. Ecological Modelling, 175: 25–54

Options for univariate metrics

- Log-transform data to emphasize residuals on small values (e.g., low-biomass species)
- PCA or MDS to look for systematic errors between groups
- Cost functions that consider observational error
- Tests for phase errors using lagged values
- Use of empirical orthogonal functions for multidimensional phase errors

Stow, C.A.,Jolliff,J.,McGillicuddyJr.,D.J.,Doney,S.C.,Allen,J.I.,Friedrichs,M.A.M., Rose, K.A.,Wallhead,P., 2009. Skill assessment for coupled biological/physical models of marine systems. Journal of Marine Systems, 76:4–15.
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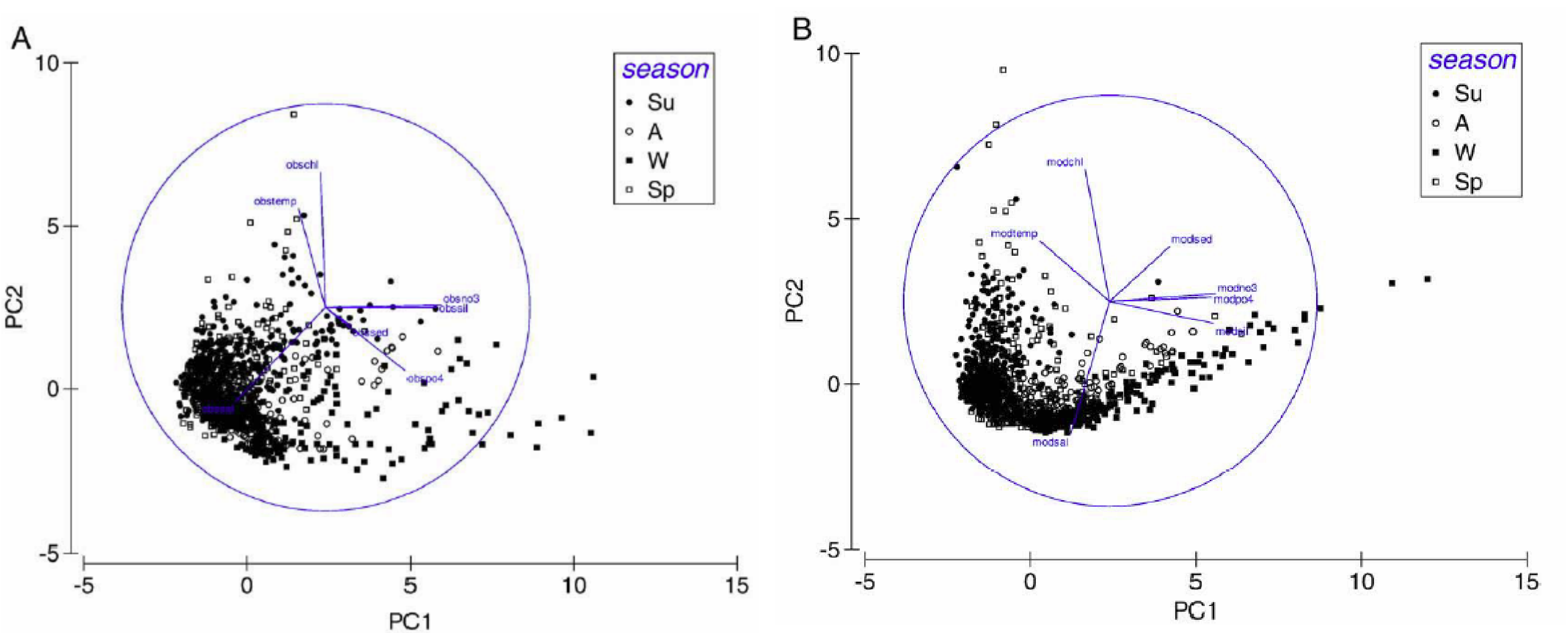
Multivariate skill assessment

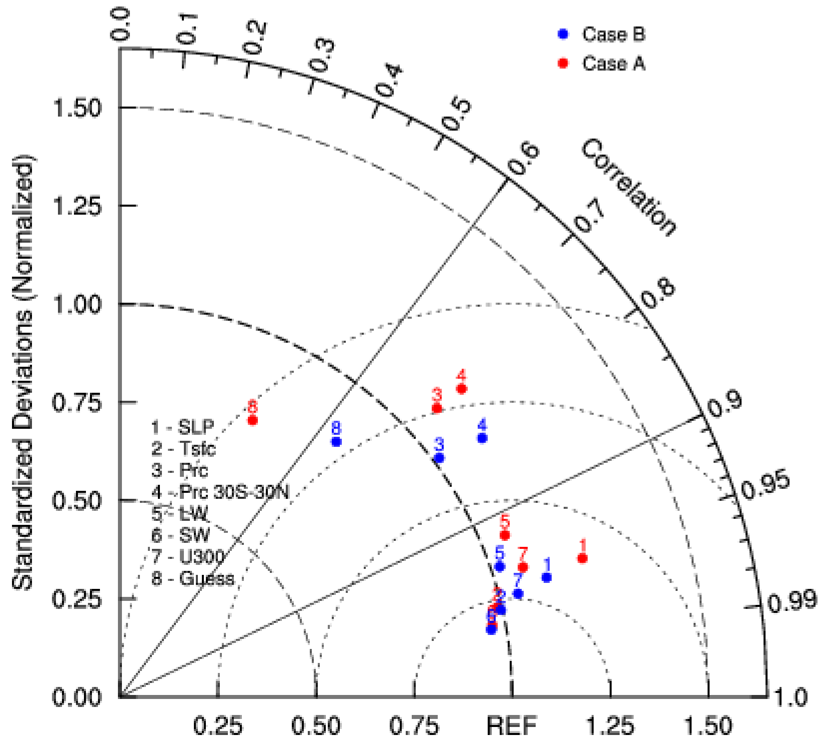
- POLCOMS-ERSEM model
- Predicting patterns



Allen, J., Somerfield, P. 2009. A multivariate approach to model skill assessment. Journal of Marine Systems, 76(2009): 83-94.

Multivariate skill assessment

- Taylor diagrams:
  - statistical summary of how well patterns match each other in terms of their correlation, their root-mean-square difference and the ratio of their variances



Taylor diagram

Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. Journal of Geophysical Research, 106(D7): 7183-7192.