

Center for the Advancement
of Population
Assessment Methodology

Comisión Interamericana del Atún Tropical
Inter-American Tropical Tuna Commission



Model Weighting using cross validation and hindcasting

Virtual meeting, 28 Nov – 2 Dec (8am to 11am - San Diego)

Background papers

- Kell, L. T., Kimoto, A., and Kitakado, T., 2016. Evaluation of the prediction skill of stock assessment using hindcasting. *Fisheries Research*, 183: 119–127.
- Kell, L.T., Sharma, R., Kitakado, T., Winker, H., Mosqueira, I., Cardinale, M., and Fu, F. 2021. Validation of stock assessment methods: is it me or my model talking? *ICES Journal of Marine Science*, 78(6), 2244–2255.

Concept

- Evaluate the model based on how well it can predict out of sample data
- A portion of the data to train the model and a portion of the model to test the model
- Works if data weighting or random effects are not correct
- Can inform whether there is overfitting or bias
- Can't validate situations not observed

Issue 1: Time series

- Stock assessment based on a dynamic model so autocorrelation is inherent
- Simple cross validation does not work for time series models
- Particularly if you are using it for management advice in the following year
- Use one-step-ahead cross validation (hindcasting)

Issue 2: We don't observe the quantities of interest

- Quantities of interest
 - F , B , F/F_{MSY} , B/B_{MSY}
- Observations
 - Catch, Index of abundance (CPUE), age or length compositions, conditional age-at-length, tagging, ...
- Predict the observed data -> good model -> good estimates of management quantities

Example: Predicting catch

- Yellowfin tuna in the EPO
- Change from effort regulation to catch regulation
- Question: What is the appropriate annual catch limit?
- How: Given F_{MSY} what is the next years catch
- One step ahead test: Given the observed effort level, can the model predict the next years catch?
- Result: within 50% to 200% of the actual catch
- Implication: Need an index of recruitment (unless it is catchability)
- Follow-up: Development of a weekly depletion estimator for in-season management (never used)

Decision 1: What data to predict

- Data types
 - Index of relative abundance
 - Age/length composition
 - Mean age/length
 - Conditional age-at-length
 - Tagging
 - Other
- Rationale
 - Closest to management quantity
 - Sensitive to model misspecification
- Recommended
 - Most reliable index of abundance related to spawning biomass
 - Mean age/length of the index
 - Mean age/length of a “recruitment” fishery if recruitment is important to the management quantities

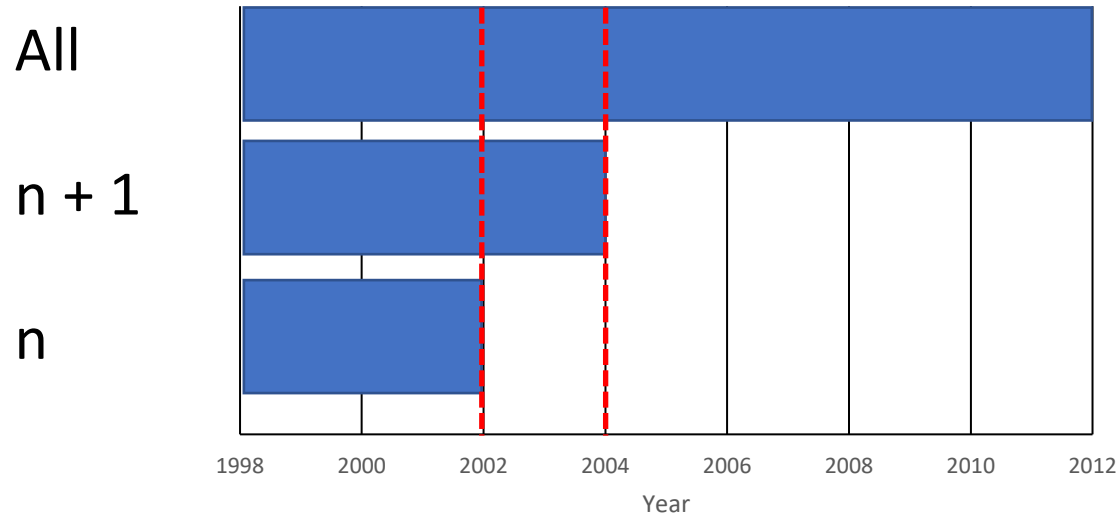
Decision 2: What data to remove

- Series
- Data type
- Fleet
- Time blocks
- Individual points
- Combinations of series or data types
- Allows for data conflicts to be evaluated

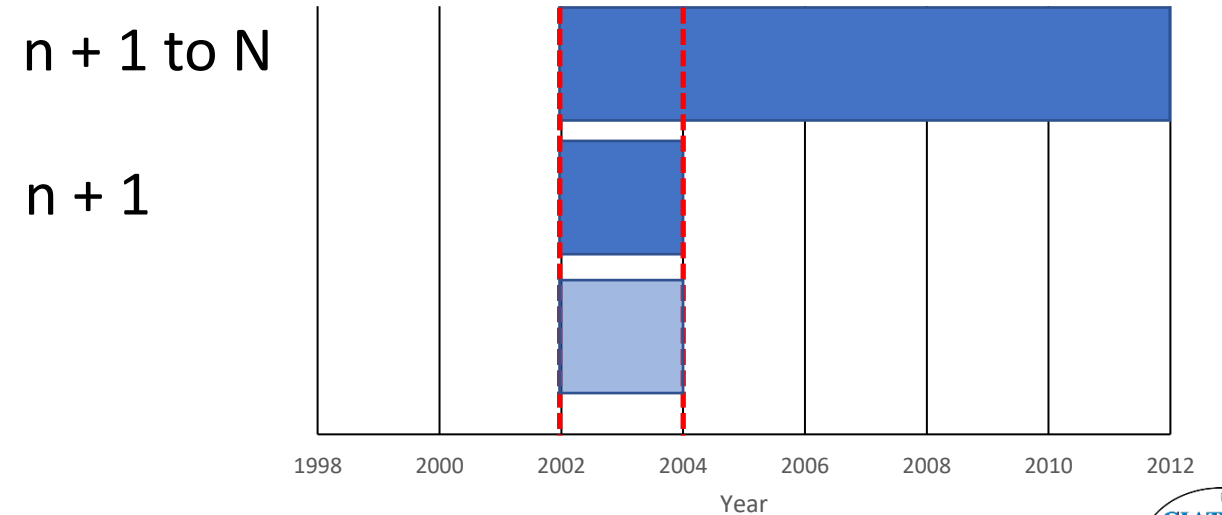
- Recommended
 - One year of data in the previous slide

Decision 3: What data to include and what to predict

Other data to include
(e.g. length comps)



Data to predict



Decision 4: How many years to remove

- Depends on reason for using hindcasting
- 1 year
- Management cycle (e.g. assessment every 3 years)

- Recommended
 - One year

Decision 5: Prediction measures


- Root mean squared error (RMSE)
 - Sensitive to outliers
- Correlation
- Mohn's rho
 - Used for retrospective analysis
- Relative error
- Mean absolute scaled error (MASE)
 - Compared to naive prediction (last years value)
 - Scale invariant, symmetry, interpretability, asymptotic normality
- Likelihood
 - Convert to probabilities?
 - Need good estimate of variance parameter
- Recommended
 - Likelihood

Mean absolute scaled error (MASE)

For a peel of n and a horizon of h years

$$MASE = \frac{\frac{1}{n+1} \sum_{t=T-n}^T |y_t - \hat{y}_{t|t-h}|}{\frac{1}{n+1+h} \sum_{t=T-n-h}^T |y_t - y_{t-h}|} \quad (5)$$

Model prediction:
Based on data from
previous year
lag h



Simple prediction:
Equal to last observed
value (previous year
lag h)

