Evaluation of three standardization methods to estimate CPUE from observer data

John Walter\textsuperscript{1}, Arnaud Gruss\textsuperscript{2}, Elizabeth Babcock\textsuperscript{2}, Matt Lauretta\textsuperscript{1}, Francesca Forrestal\textsuperscript{2}, Michael Schirripa\textsuperscript{1}, Clay Porch\textsuperscript{1}

\textsuperscript{1}SEFSC, NOAA, Miami
\textsuperscript{2}University of Miami, RSMAS


The problem: observed sets are only a subset of trips, not always random

Logbook data (census)
Observer sets (subset)
How to predict in unfished areas and downweight clusters of high catches

Naïve mean (assume mean of unfished=mean of fished)

Imputation
- use last value (Walters Folly and Fantasy 2006)
- use mean of adjacent cells (Carruthers et al 2011)
- use model to input Campbell (2015)

Geostatistics (statistical interpolation)
- Thorson et al 2015,
- Walter et al 2014a, 2014b


Walter, Christman & Hoenig. 2014. a Reducing Bias and Filling in Spatial Gaps in Fishery-Dependent catch-per-Unit-Effort Data by Geostatistical Prediction, I. Methodology and Simulation; 2014b. II. Application to a Scallop Fishery. NAJFM. 34(6)
Experimental design and methods

LLsim (Goodyear 2013)
3 populations
3 subsets of each population
   Full data
   10% random sample of trips
   10% biased sample
Apply standardization approaches
Blind study design, analyst did not know true population trend
Dataset creation - mimics US longline fleet

Probability of trip being sampled under observer bias
3 methods (no model selection applied)

\[ g(\eta) = year + season + area + hook + bait + light + hbf + year * area \]

1. Status quo delta GLM in R  
   - with/wo year*area interactions as random or fixed effects

2. Campbell spatial weight and gap filling  
   - with/without interactions (fixed)  
   - with/without weighting obs in fitting

3. Thorson VAST, delta model

\[ \text{weight}_{y,a} = \frac{\text{Nobs}}{\text{Nstrata}} \cdot \frac{1}{n_{y,a}} \]

\[ \text{CPUE}_{y,s} = \sum_{a=1}^{Na} \text{SA}_a \text{prob}_{y,s,a} \text{u}_{y,s,a} \]

\( \text{SA}_a \) is the surface area (in km²) of area \( a \)

Uses reduced model to fill in missing year*area cells
Key distinction is how random effects are treated in predictions

1. Status quo delta GLM
   predict on grid of only fixed effects (e.g. SAS LSmeans),
   average over spatial areas
   Random year*area interactions drop out

2. Campbell
   predict on grid of fixed effects, sum spatial areas

3. Thorson VAST
   Predict over spatial area, sum predictions
Results

Caveat, results based on 5 iterations
Metrics for evaluation

$R^2$ between predicted and true

Mean absolute error (both normalized to a mean of one)
Results on full dataset

Population 4

- DLN
- Cambell
- VAST

Population 1

- DLN
- Cambell
- VAST

R2, MAE, and CV values for each population and dataset.
QQ Diagnostics on full dataset

- **DLN**
- **DLN year*area RE**
- **Campbell wtd**
- **Campbell wtd, fixed year*area**

Sample quantiles vs. Theoretical quantiles for each dataset and model configuration.
Results ($R^2$ mean, min and max)

Slight decline with 10% random

Greater decline, higher variability with 10% bias

Negligible difference between methods, except Campbell weighting
Results, Mean absolute error

Fixed interactions performed poorly

Campbell weighted with fitting also performed poorly
Some really bad fits - why?
Why: dodgy estimates of year*area interactions (not explicitly put in Llsim)

often models select year*area interactions, fixed interactions do not converge or lead to very poor estimates

<table>
<thead>
<tr>
<th></th>
<th>sig year*area</th>
<th>Not sig year*area</th>
<th>year*area not converged</th>
</tr>
</thead>
<tbody>
<tr>
<td>binomial</td>
<td>27%</td>
<td>18%</td>
<td>55%</td>
</tr>
<tr>
<td>lognormal</td>
<td>64%</td>
<td>36%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Plot interaction term, evaluate trend vs randomness
- If random, model as RE
- If poorly estimated, model as RE to harness N(0,sigma) shrinkage
- If there is a trend, need good spatial weights
BEST: Avoid them in the first place
Why: Low sample coverage of spatial areas

Disparate sizes of areas
Figure 1. from Link et al 2011. Guidelines for incorporating fish distribution shifts into a fisheries management context. Fish and Fisheries

Teaser: interpreting with spatial trends

Range shift
Population is same

contraction
Population declines

expansion
Population increases
Pop 1, range shift

Effective area occupied

\[ \text{Effective area occupied} \]

Year

\[ \ln(\text{km}^2) \]

Year

\[ \text{Location} \]

Year

\[ \text{Eastings} \]
Pop 4 contraction

Effective area occupied

Year

Location

Year

Eastings
Conclusions

• Take simulation results with grain of salt
• All 3 methods generally work well on reduced and biased datasets, appear robust to weak range shifts - further testing needed
• Real loss in performance was with spatial weights
  • (Not methodological *per se* but due to nature of spatial areas)
• And with fixed interactions - again due to areas and poor estimation
• Beware of Year*area interactions!
  • plot year*area coefficients, if random, model as RE
  • If not random….may want to model as RE to harness N(0,sigma) shrinkage
• Create ‘good’ spatial areas or...
• Avoid “tyranny of the grid” entirely - use VAST and similar approaches
Acknowledgements

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Augmenting fishery data: adding additional samples

Random spatial field, maps kriging variance, points are fishing locations

add 20 samples to minimize the kriging variance

Results in substantial reduction in kriging variance and bias

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