NOAA FISHERIES
Southeast Fisheries Science Center

Evaluation of three standardization methods to estimate CPUE from observer data

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ROSENSTIEL SCHOOL of MARINE & ATMOSPHERIC SCIENCE

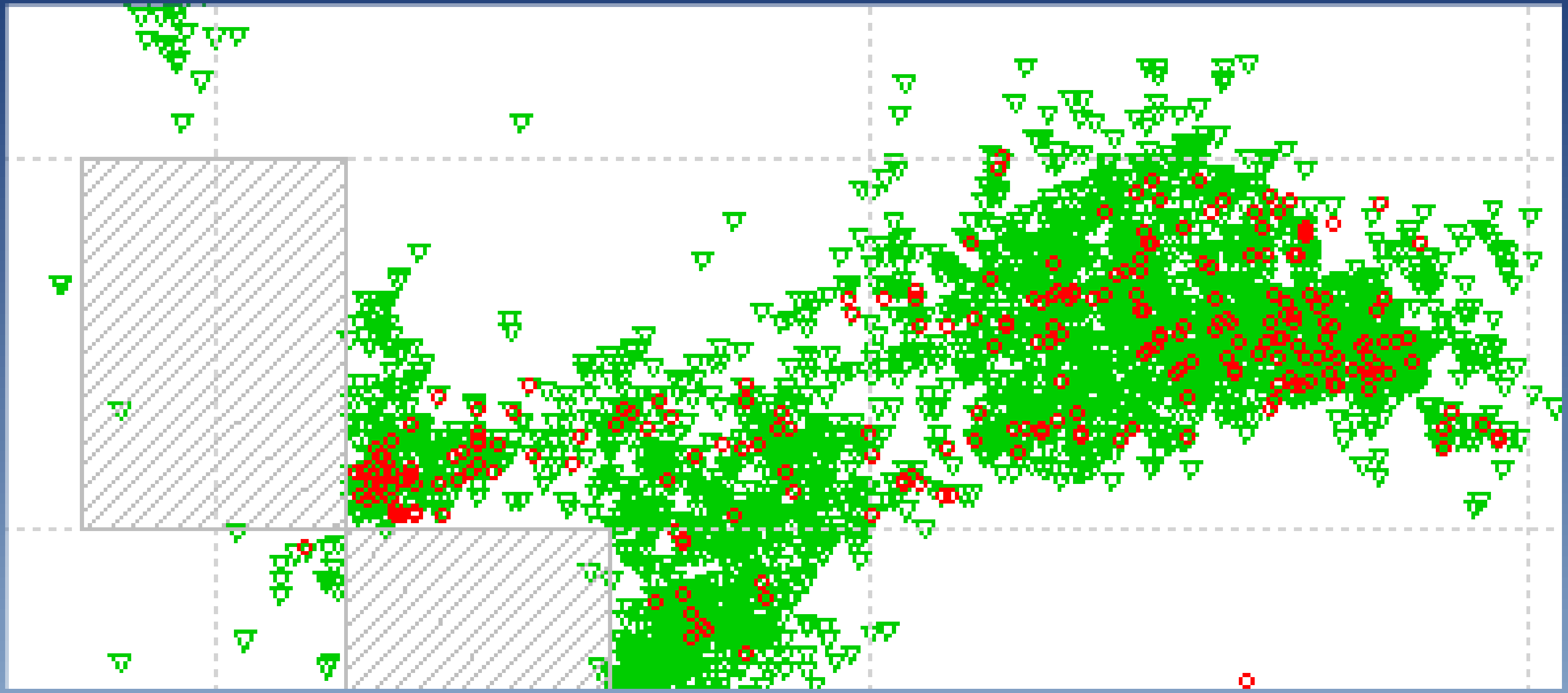

Nancy Lo on the balcony of the original SWFSC building in 2012.

Lo N, Jacobson, L. and Squires, D. 1992. Indices of Relative Abundance from Fish Spotter Data based on Delta-Lognormal Models Delta-lognormal model Can. J. Fish. Aqua. Sci.. Vol. 49, 1992

Campbell, R.A., 2015. Constructing stock abundance indices from catch and effort data: some nuts and bolts. Fisheries Research 161, 109–130.

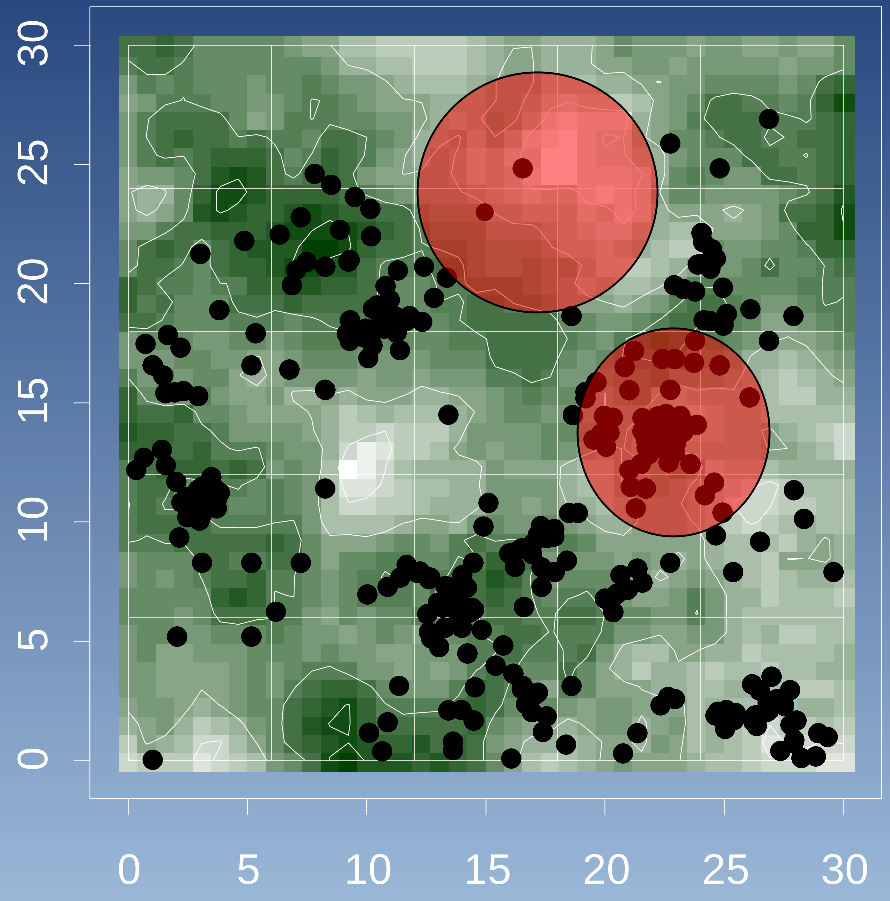
Thorson, J.T., Shelton, A.O., Ward, E.J., Skaug, H.J., 2015. Geostatistical delta-generalized linear mixed models improve precision for estimated abundance indices for West Coast groundfishes. ICES Journal of Marine Science 72, 1297–1310

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)

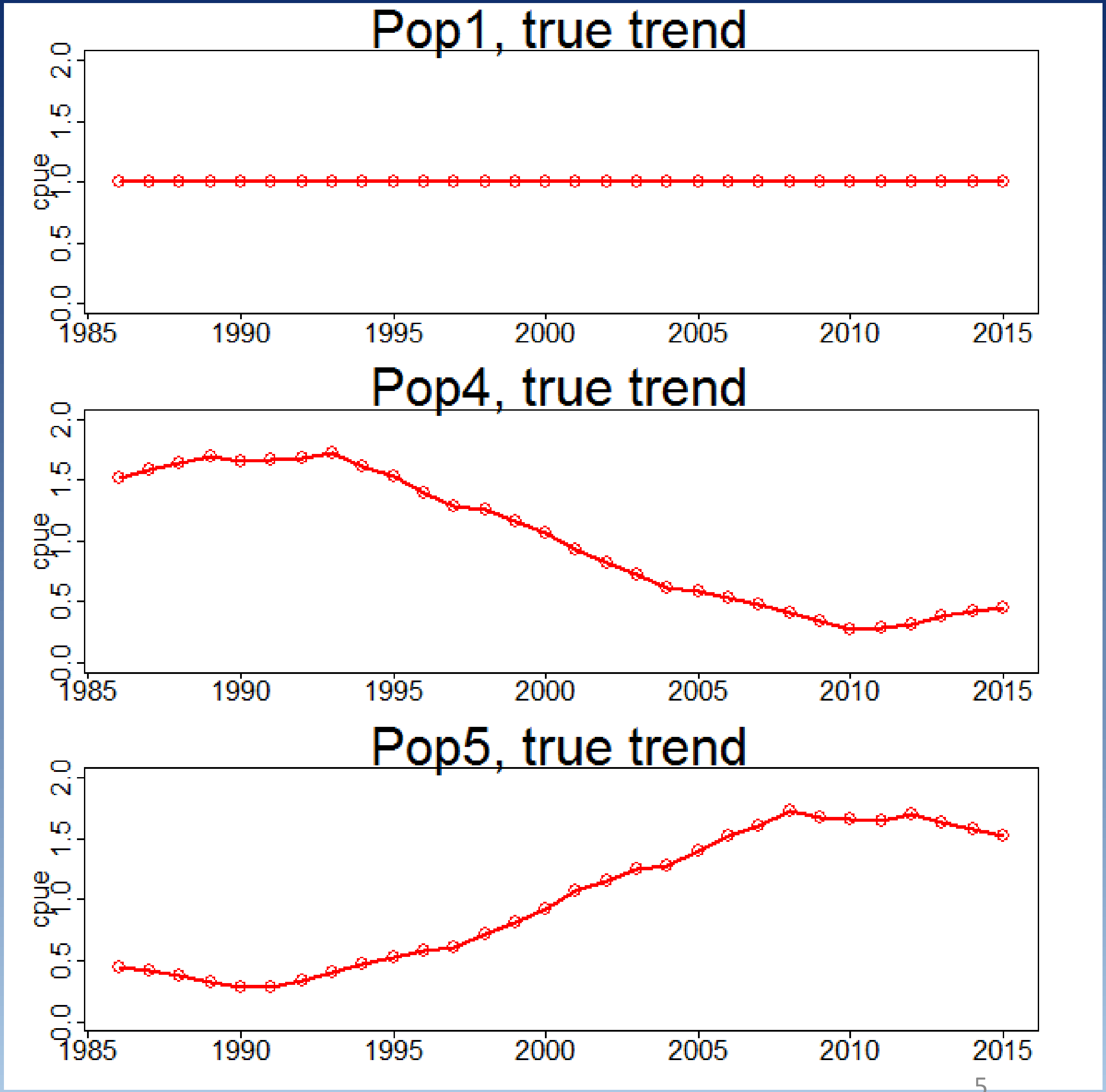
Geostatistics (statistical interpolation)
- Thorson et al 2015,
- Walter et al 2014a, 2014b

Carruthers, et al., 2010. Simulating spatial dynamics to evaluate methods of deriving abundance indices for tropical tunas. CJFAS67, 1409–1427.

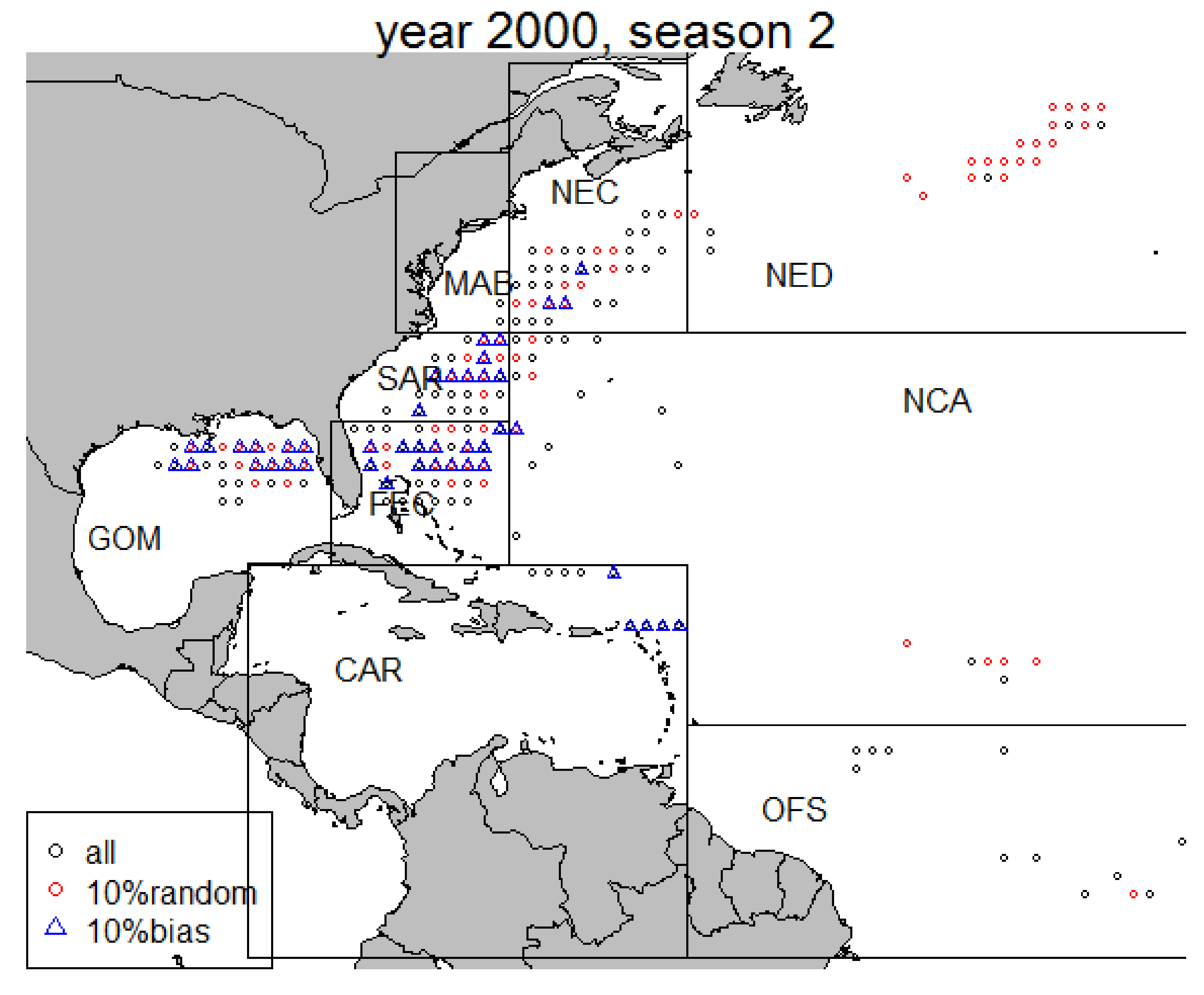
Walter, Christman & Hoenig. 2014. a Reducing Bias and Filling in Spatial Gaps in Fishery-Dependent catch-per-Unit-Effort Data by Geostatistical Prediction, I. Methodology and Simulation; 2014b. II. Application to a Scallop Fishery . NAJFM. 34(6)

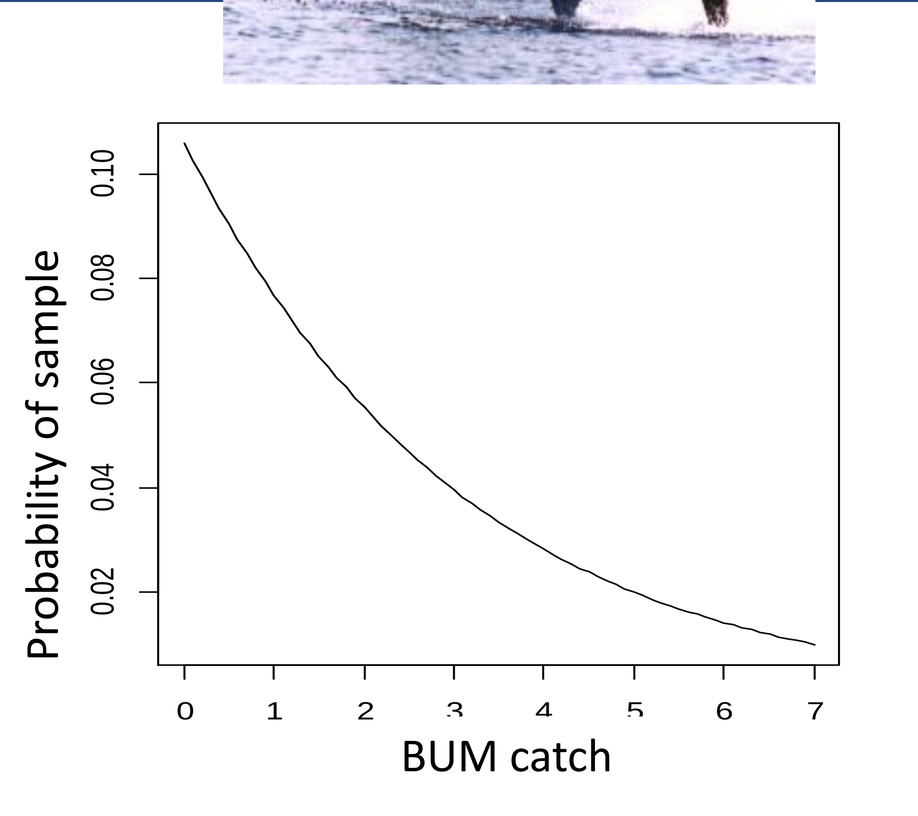
Experimental design and methods

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

1. $weight_{y,a} = \frac{Nobs}{Nstrata} \cdot \frac{1}{n_{y,a}}$

2. $CPUE_{y,s} = \sum_{a=1}^{Na} SA_a \, prob_{y,s,a} u_{y,s,a}$

SA_a is the surface area (in km^2) of area a

3 Uses reduced model to fill in missing year*area cells

3. Thorson VAST, delta model

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

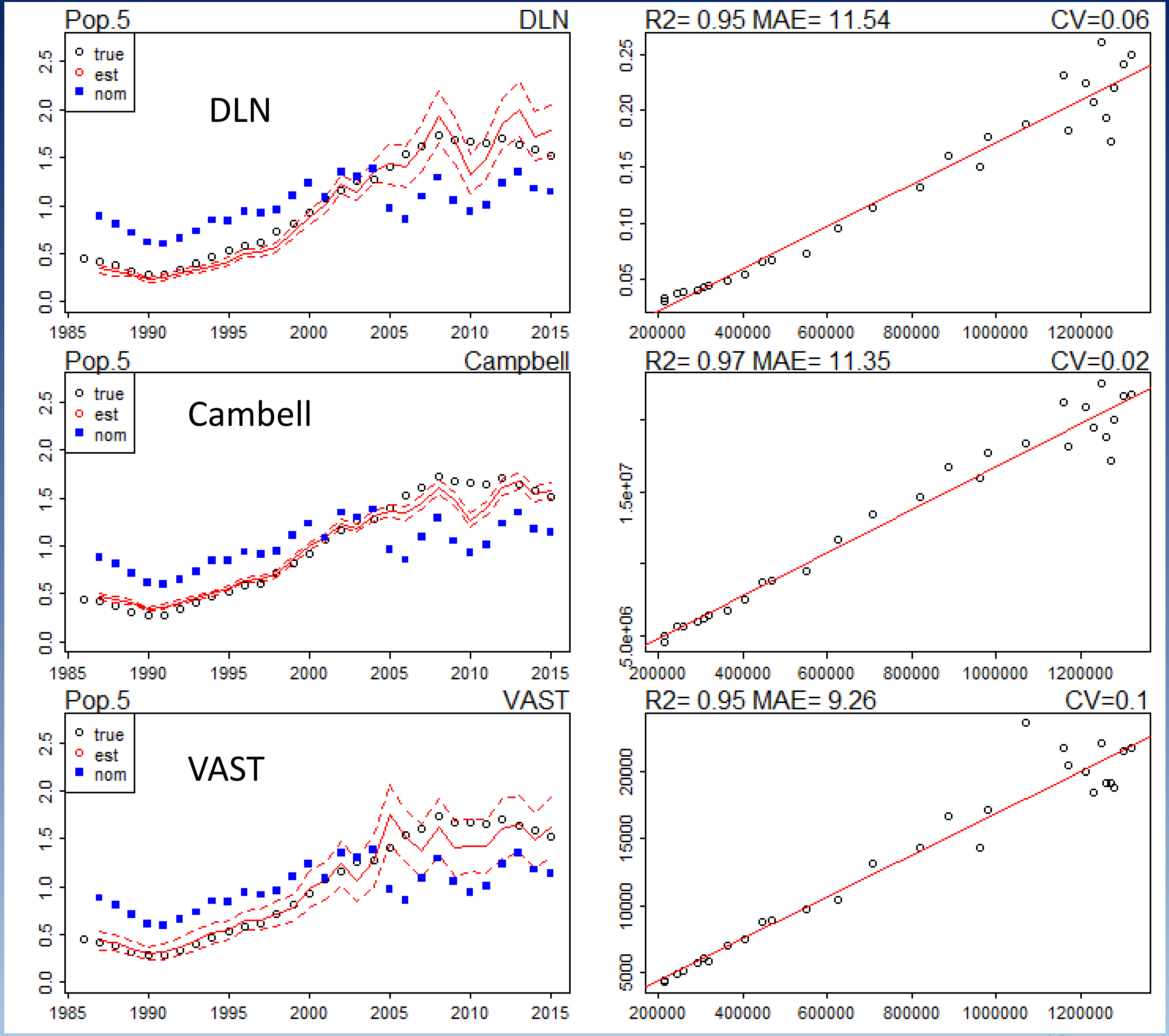
Results

Caveat, results based on 5 iterations

Metrics for evaluation

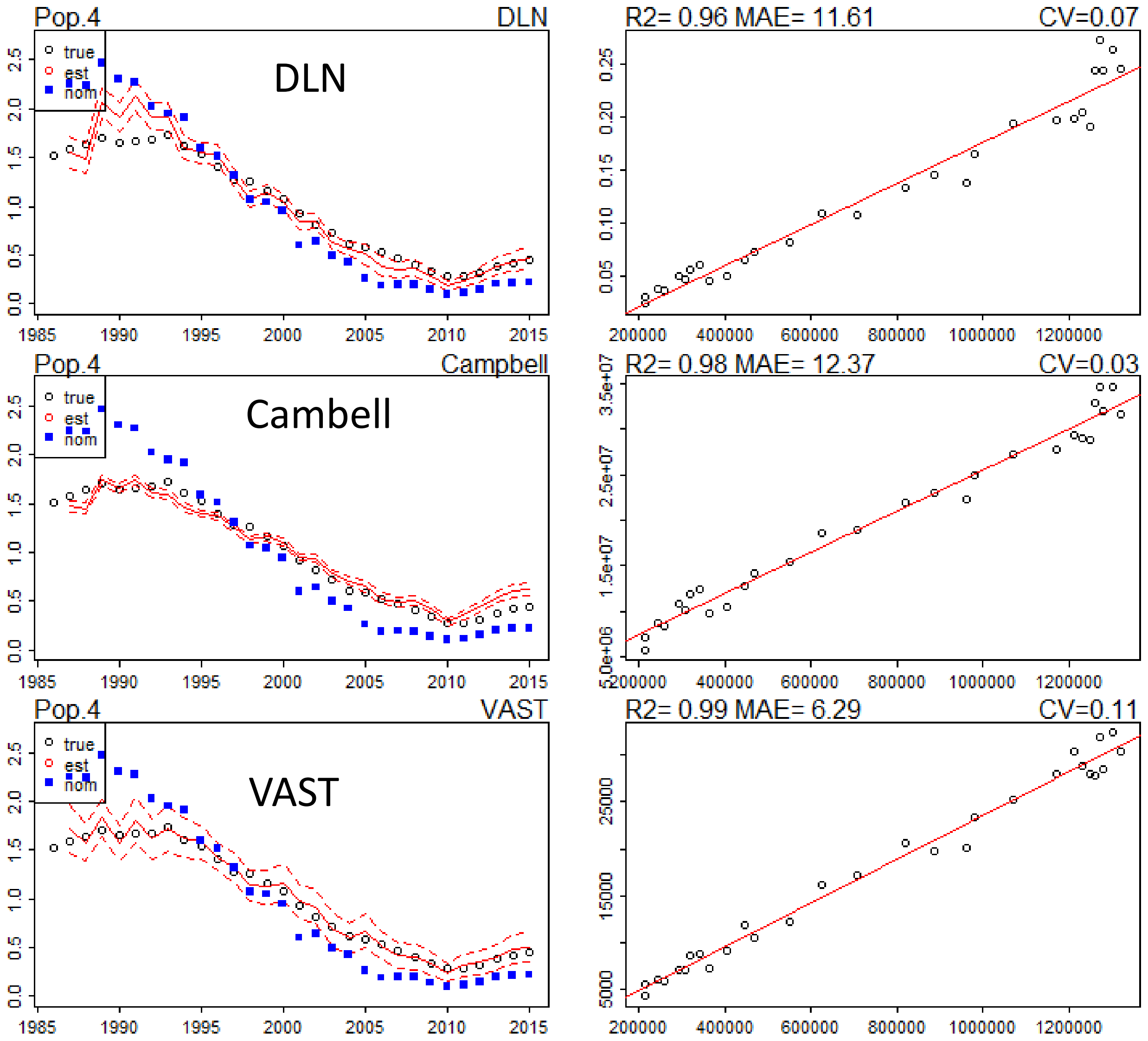
R^2 between predicted and true

Mean absolute error (both normalized to a mean of one)

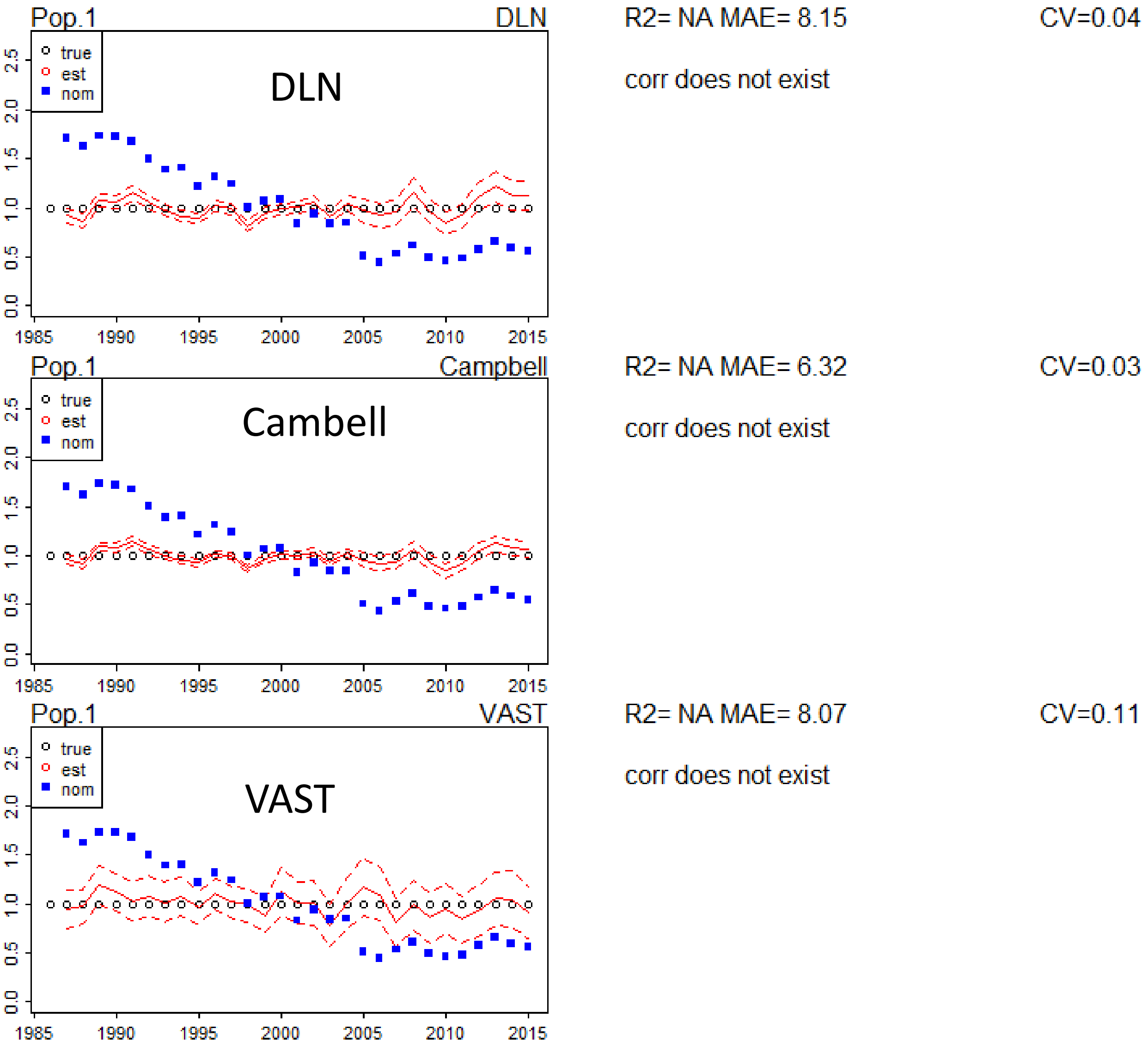


Results on full dataset

Population 4

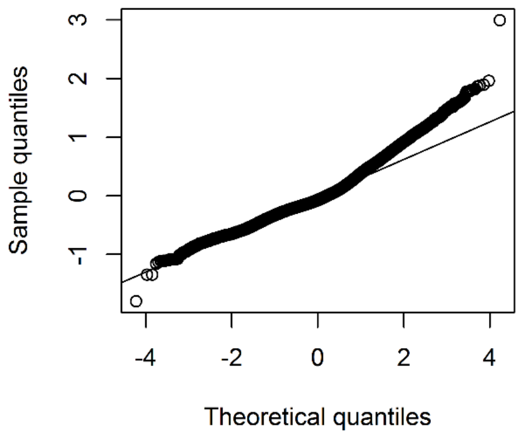


Population 1

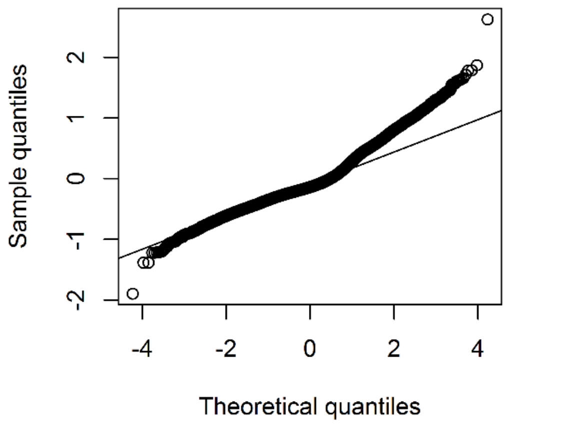


QQ Diagnostics on full dataset

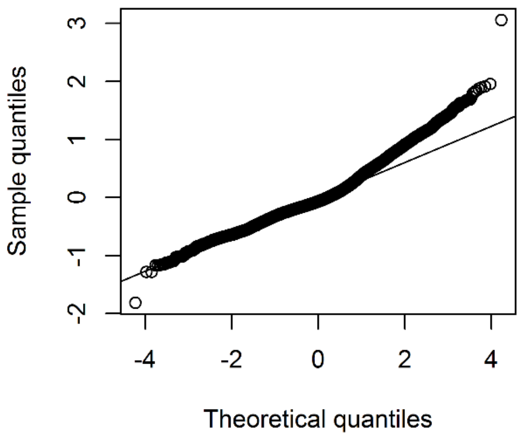
DLN



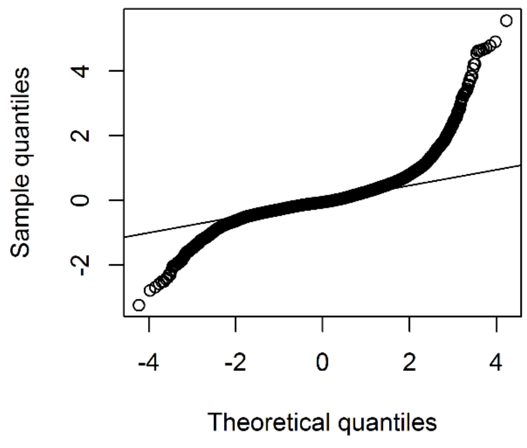
DLN *year*area RE*



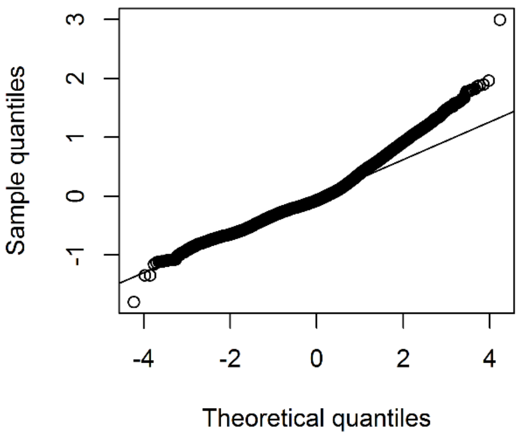
Campbell wtd



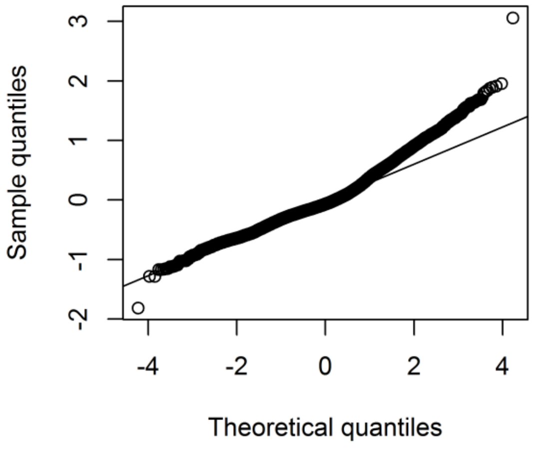
Campbell wtd



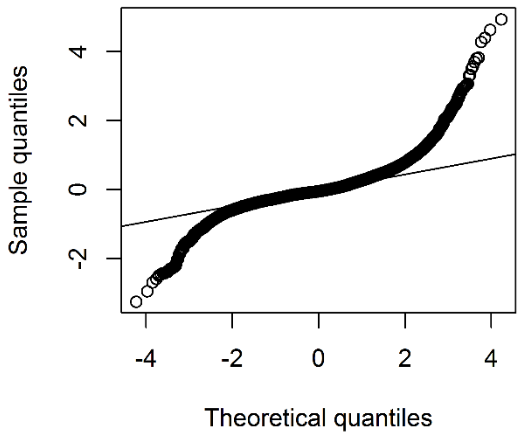
Campbell



VAST



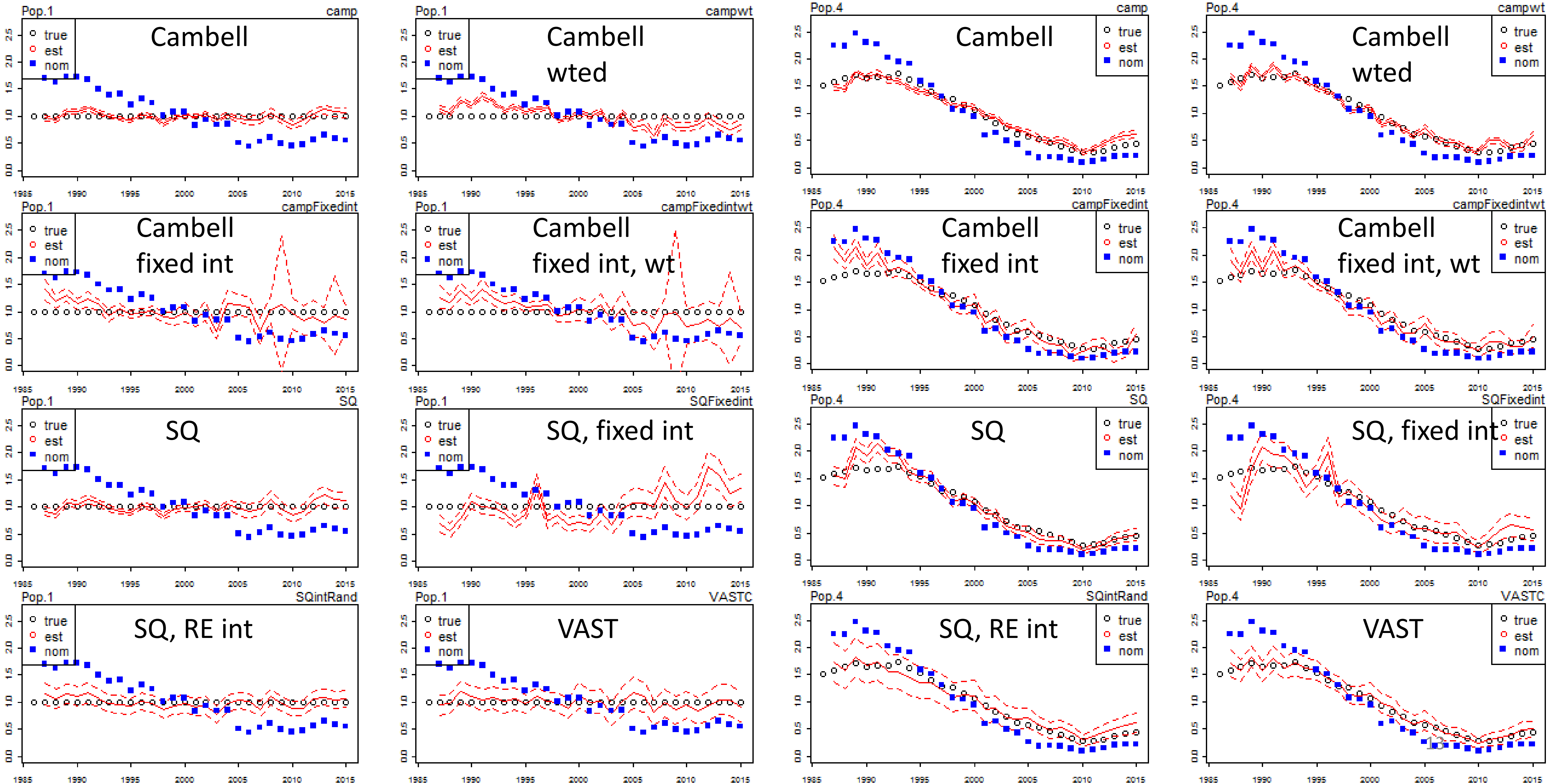
Campbell wtd, fixed year*area



Full dataset, with weighting and interactions

Population 1

Population 4

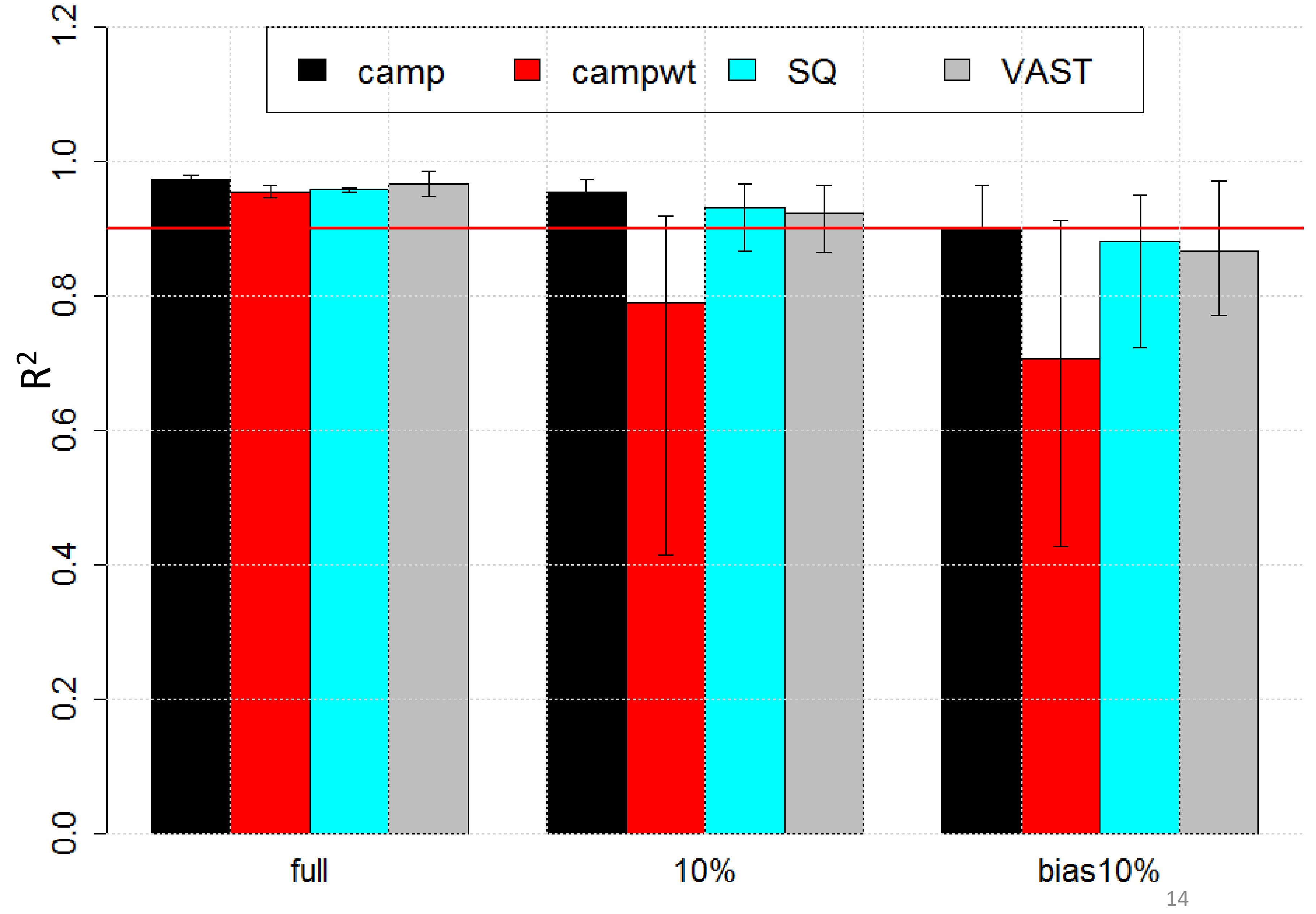


Results (R^2 mean, min and max)

Slight decline with 10% random

Greater decline, higher variability with 10% bias

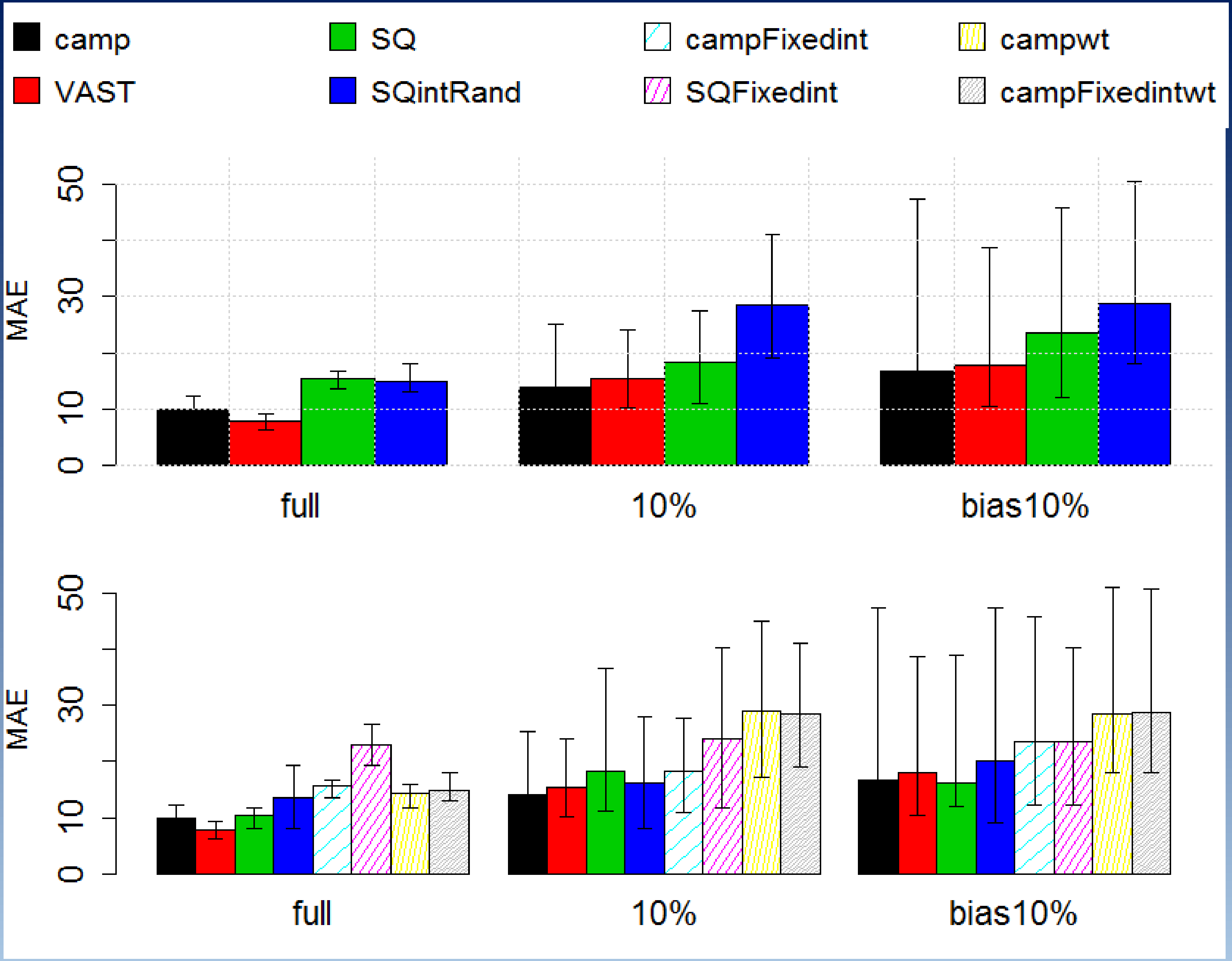
Negligible difference between methods, except Campbell weighting



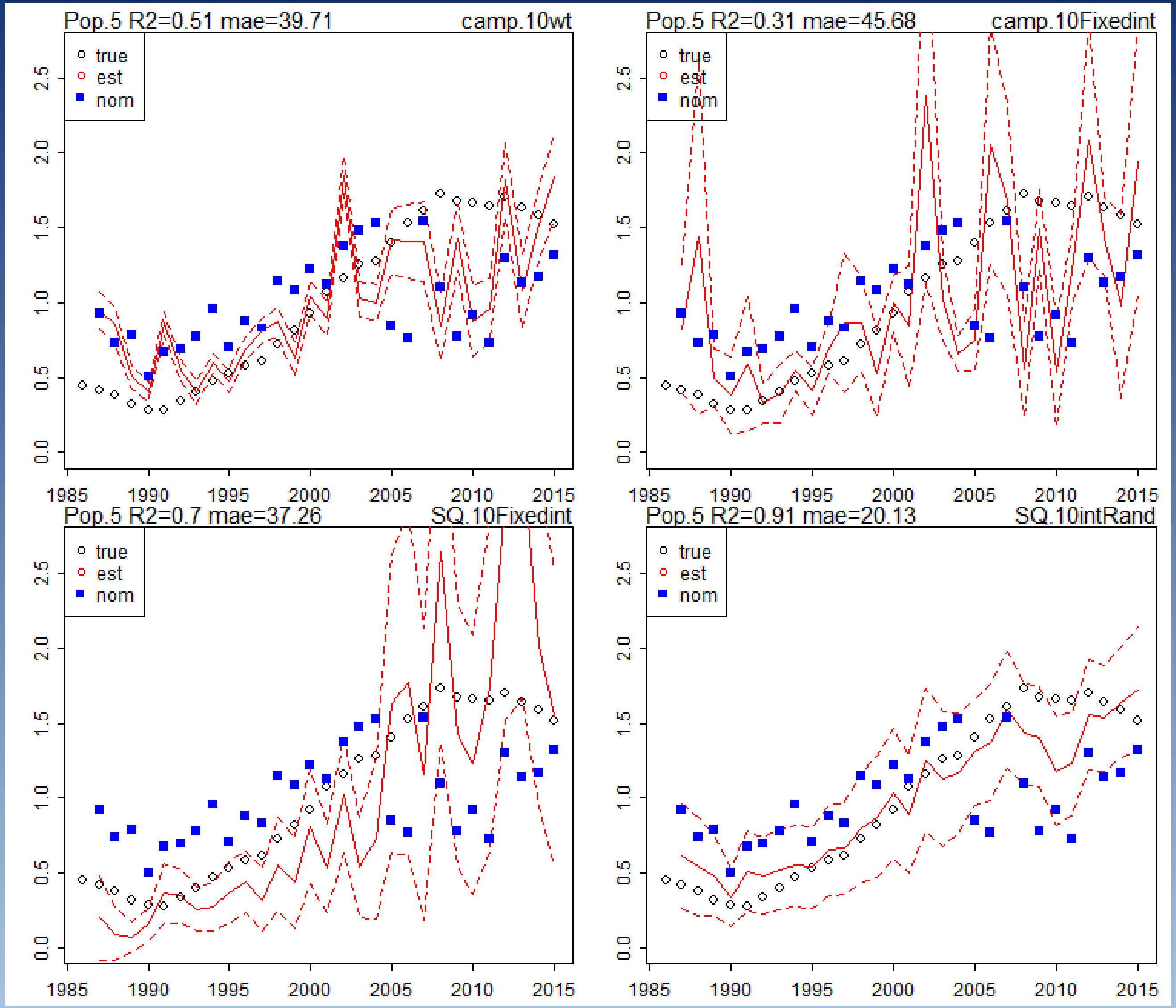
Results, Mean absolute error

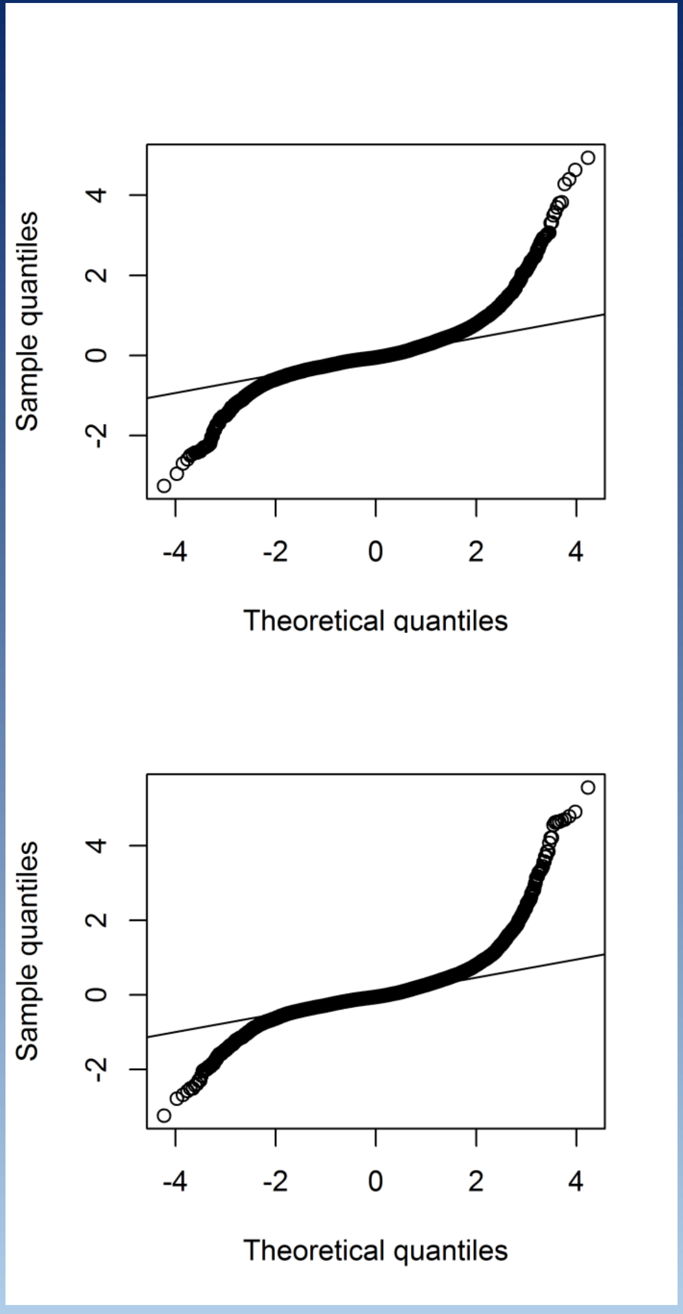
Fixed interactions performed poorly

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

	sig year*area	Not sig year*area	year*area not converged
binomial	27%	18%	55%
lognormal	64%	36%	0%

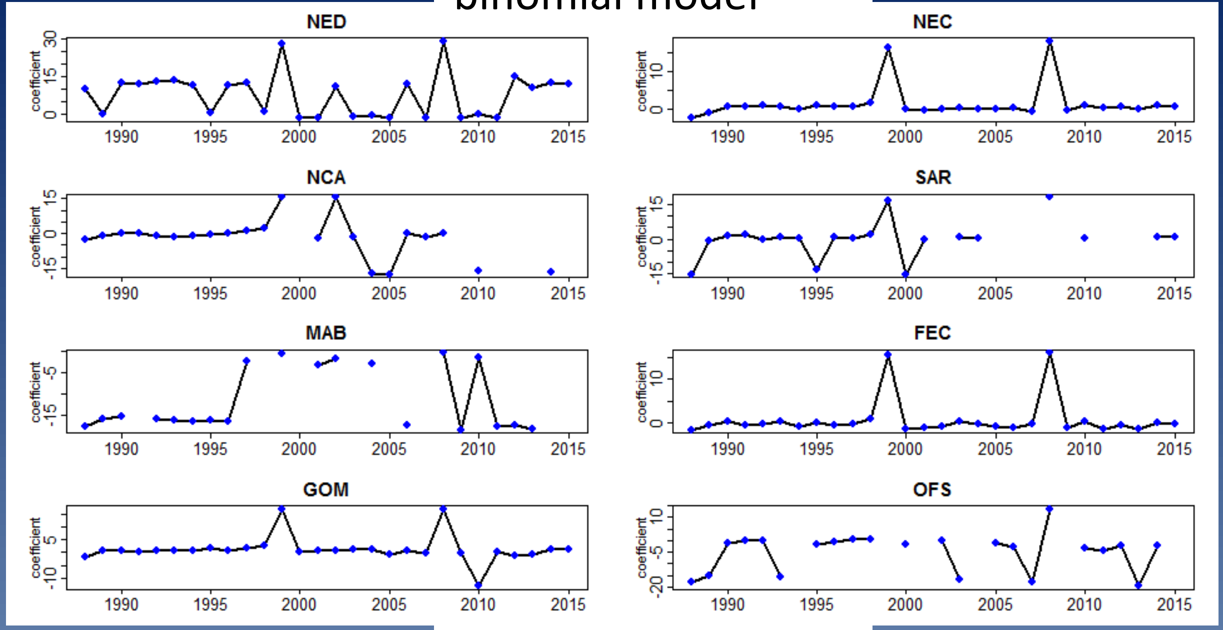
Plot interaction term, evaluate trend vs randomness

- 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

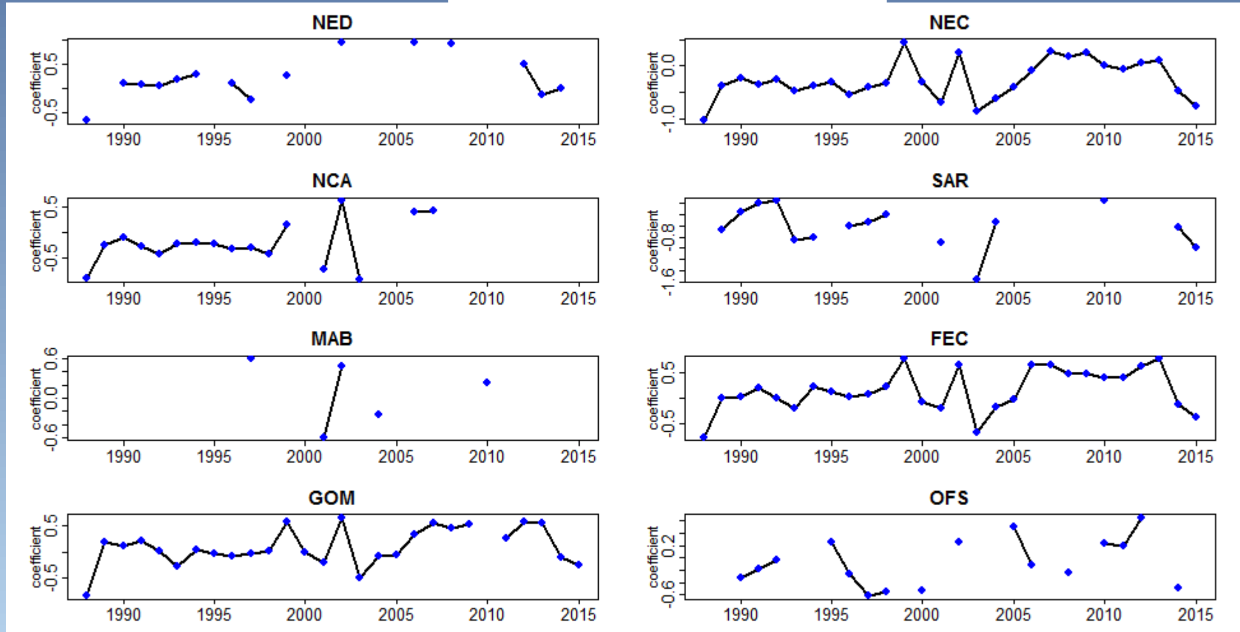
BEST: Avoid them in the first place

Status quo, fixed int., pop 5, 10% bias, rep 1

binomial model

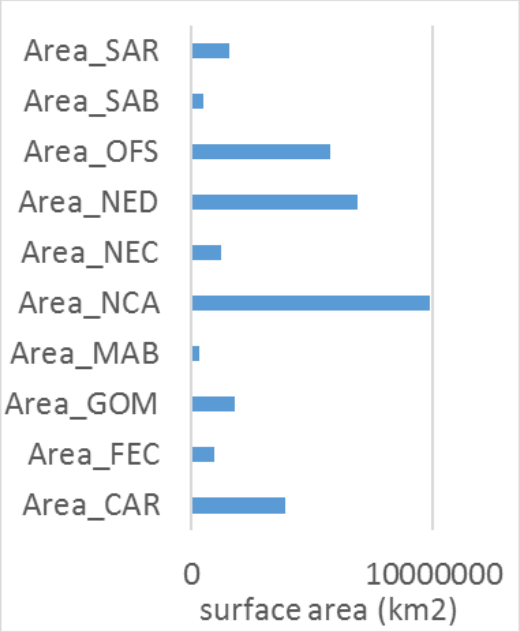


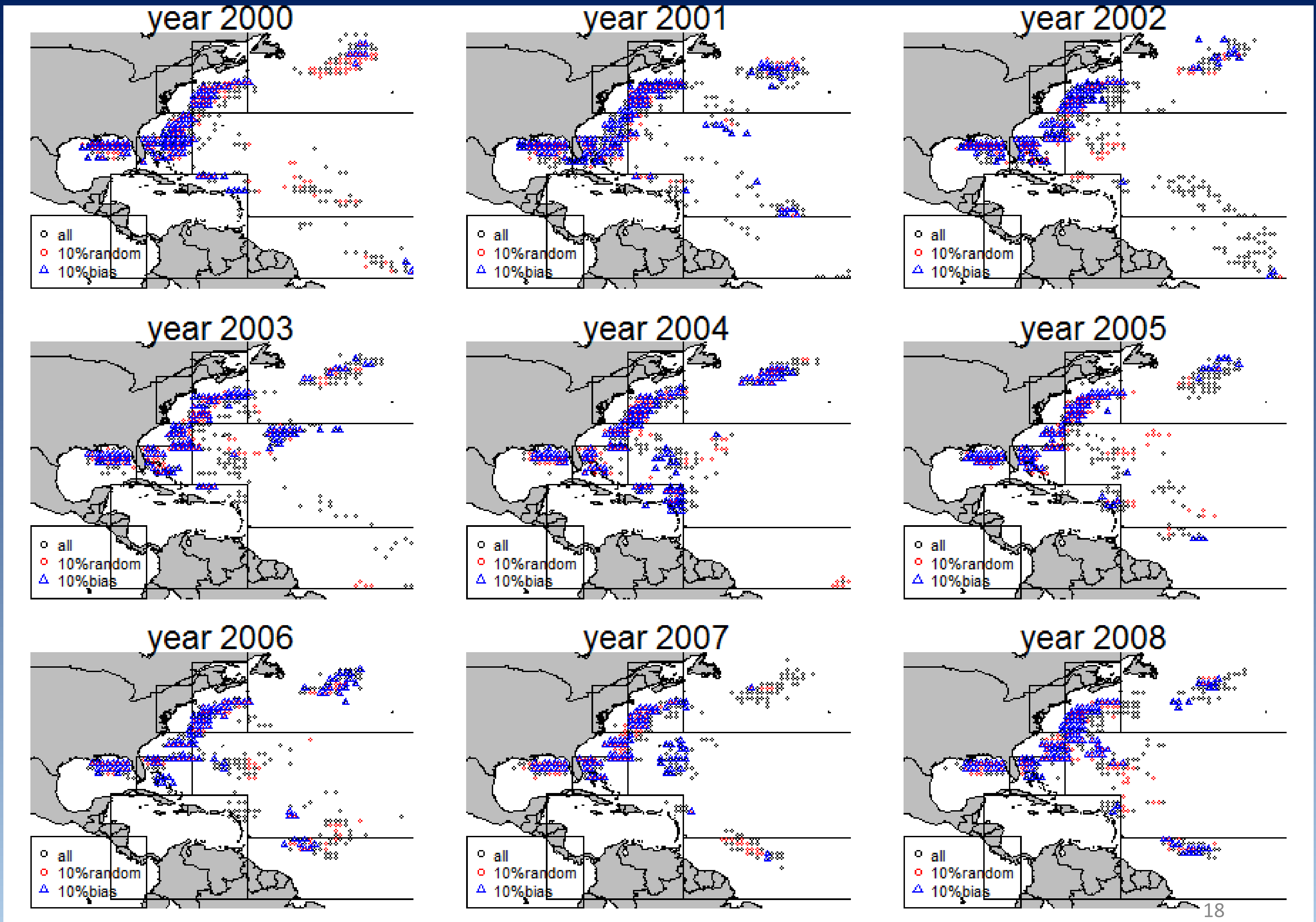
Lognormal model



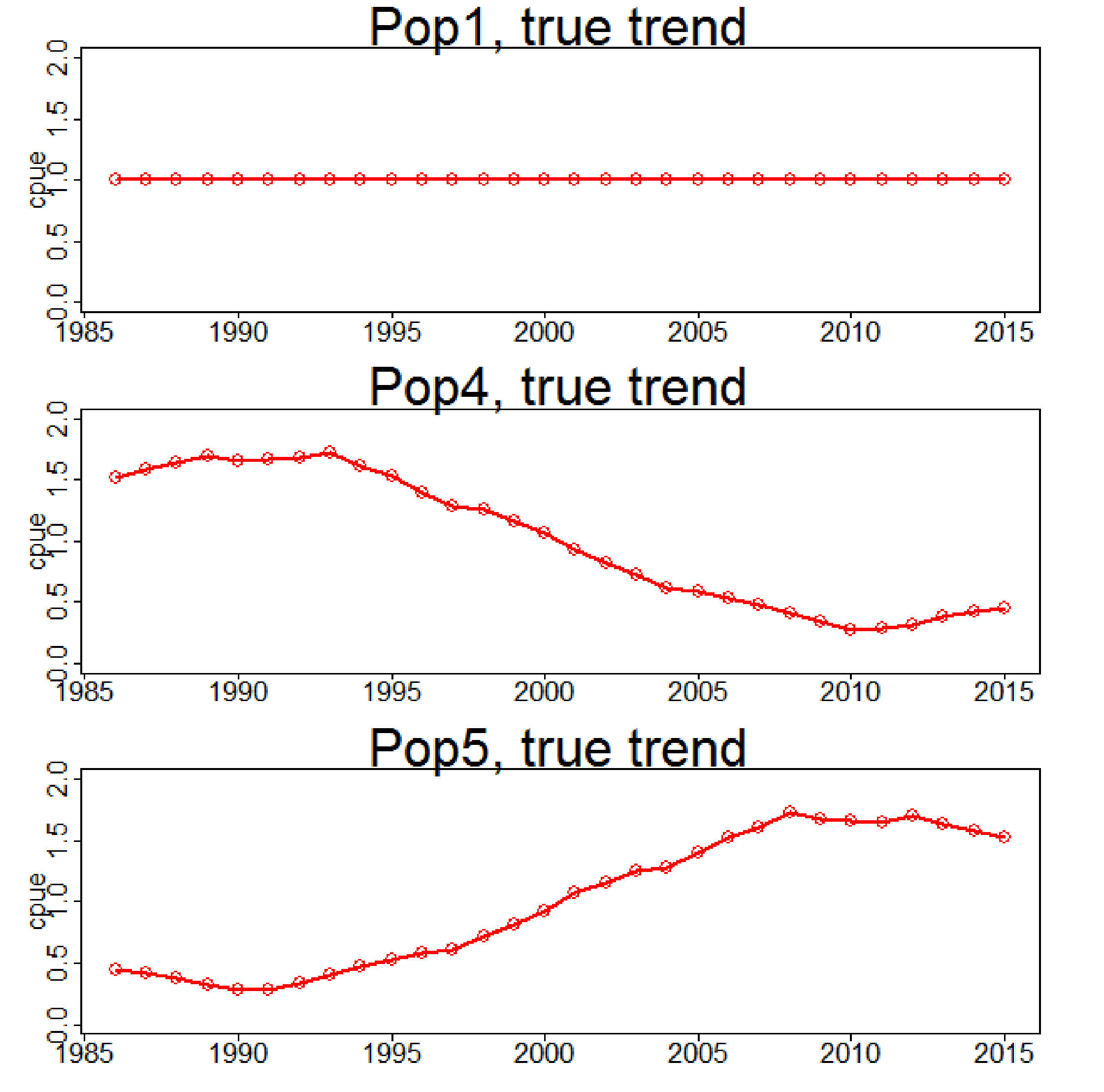
Why: Low sample coverage of spatial areas

Disparate sizes of areas





Teaser: interpreting with spatial trends



Range shift

Population is same

contraction

Population declines

expansion

Population increases

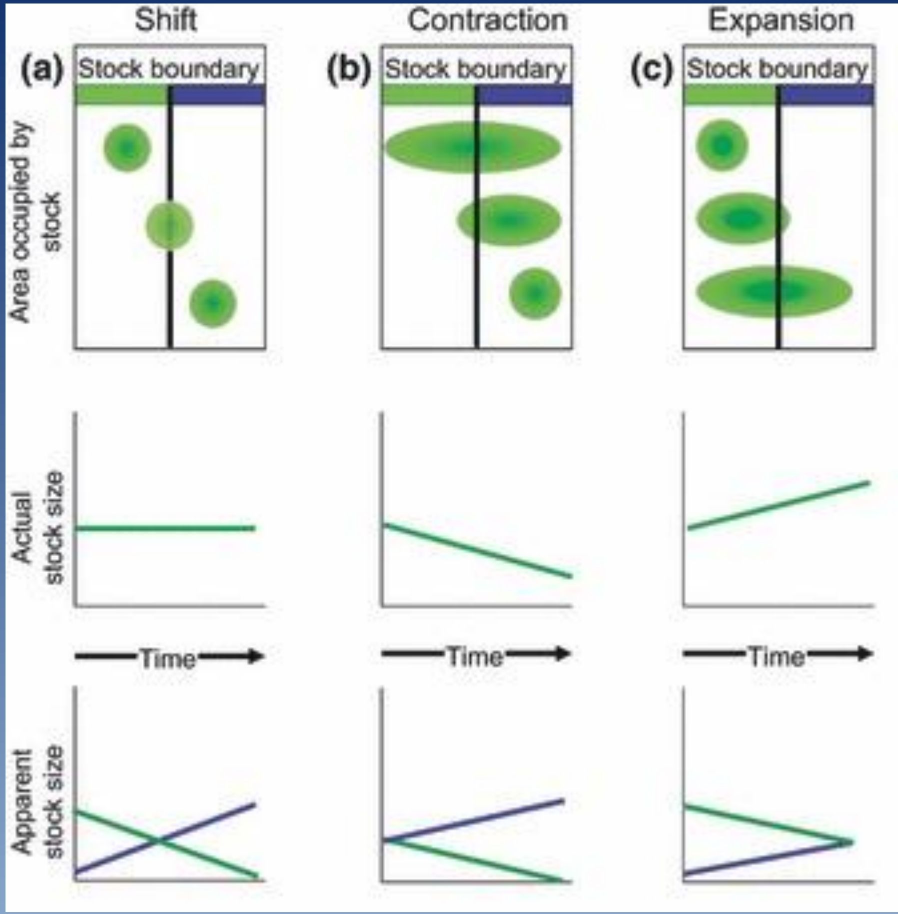
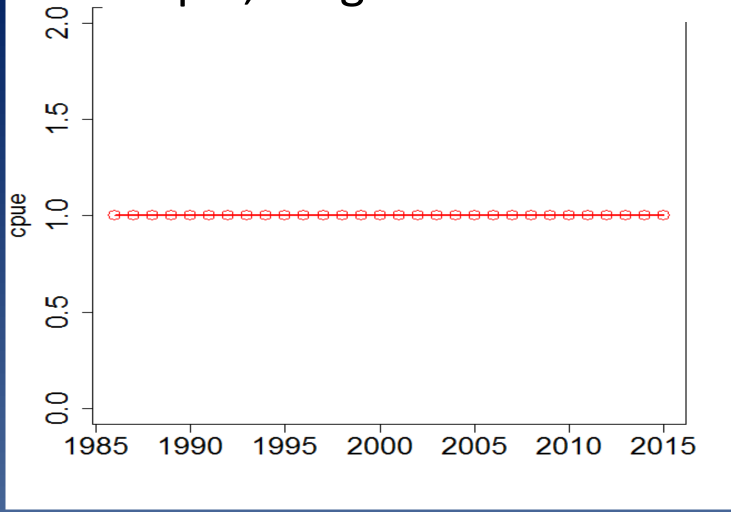
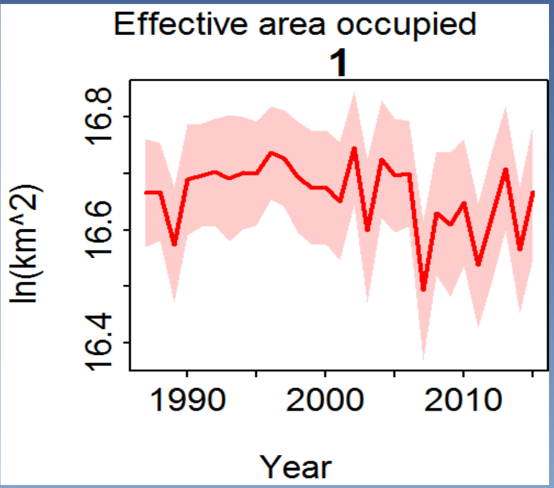
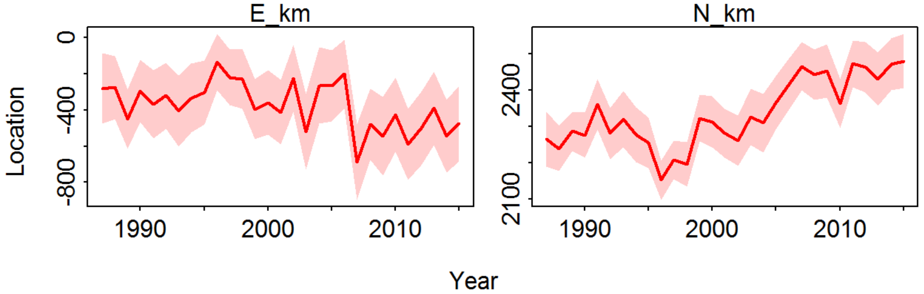


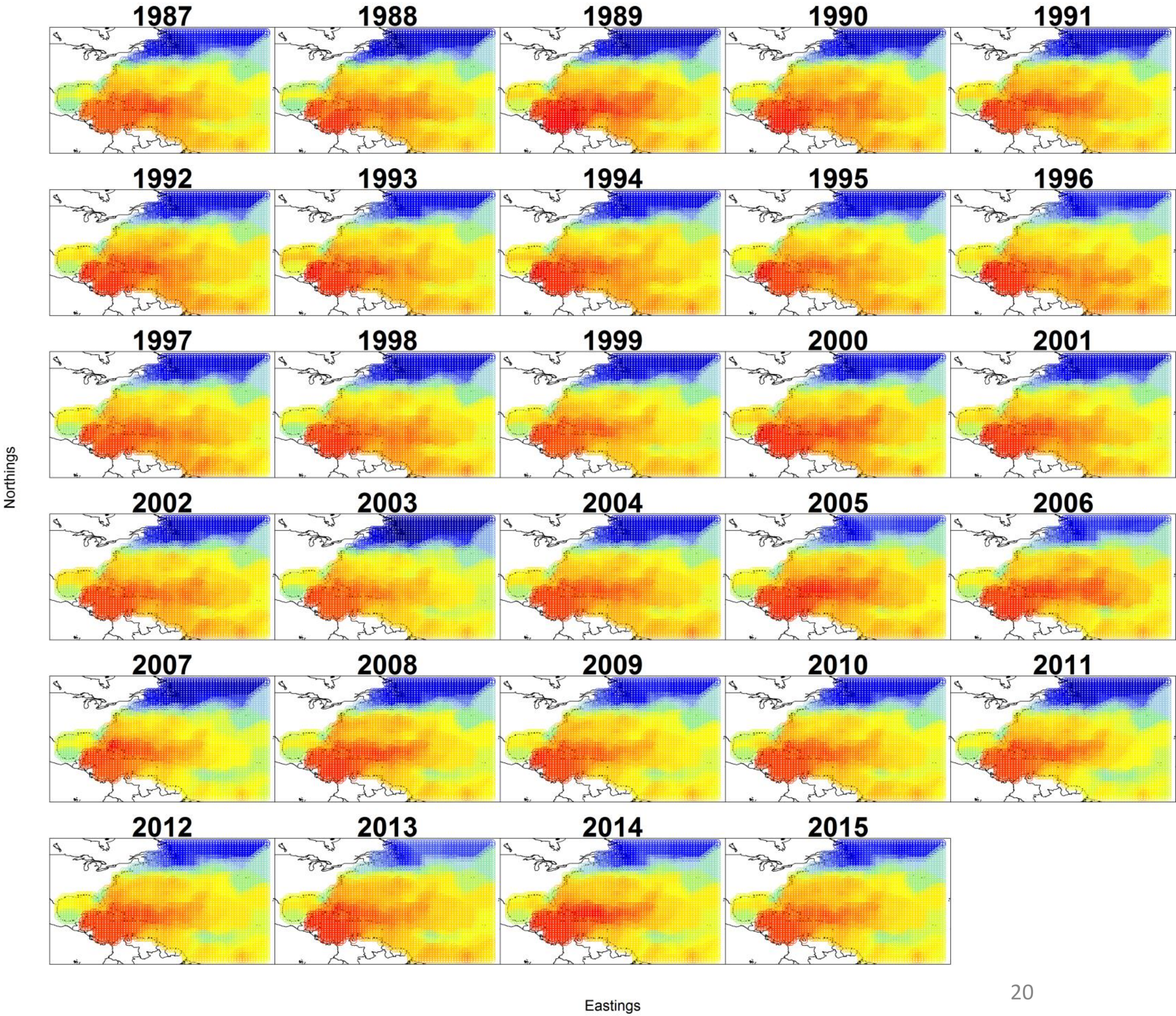
Figure 1. from Link et al 2011. Guidelines for incorporating fish distribution shifts into a fisheries management context. Fish and Fisheries

Pop 1, range shift

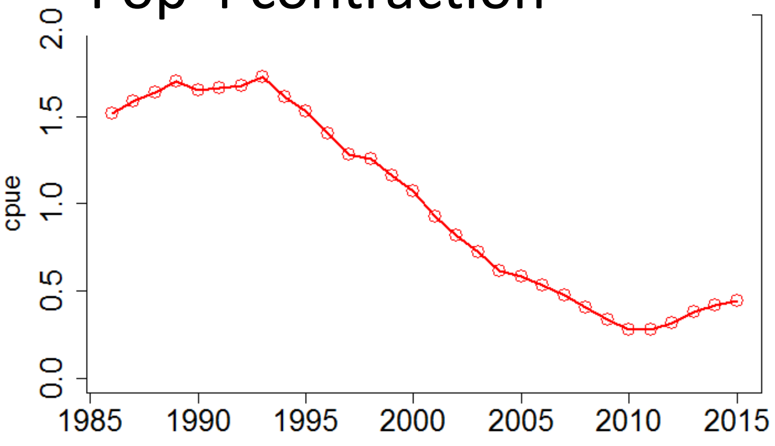


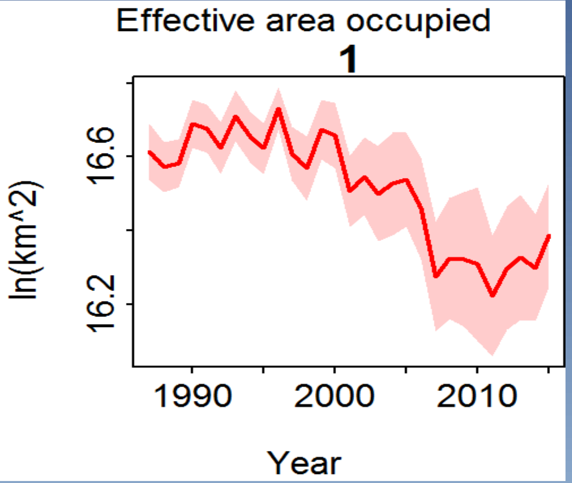


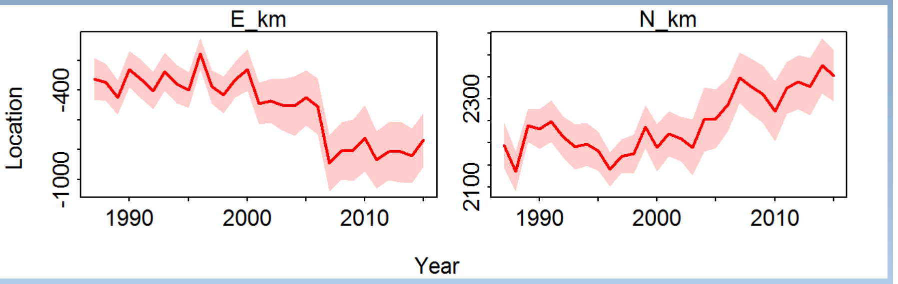


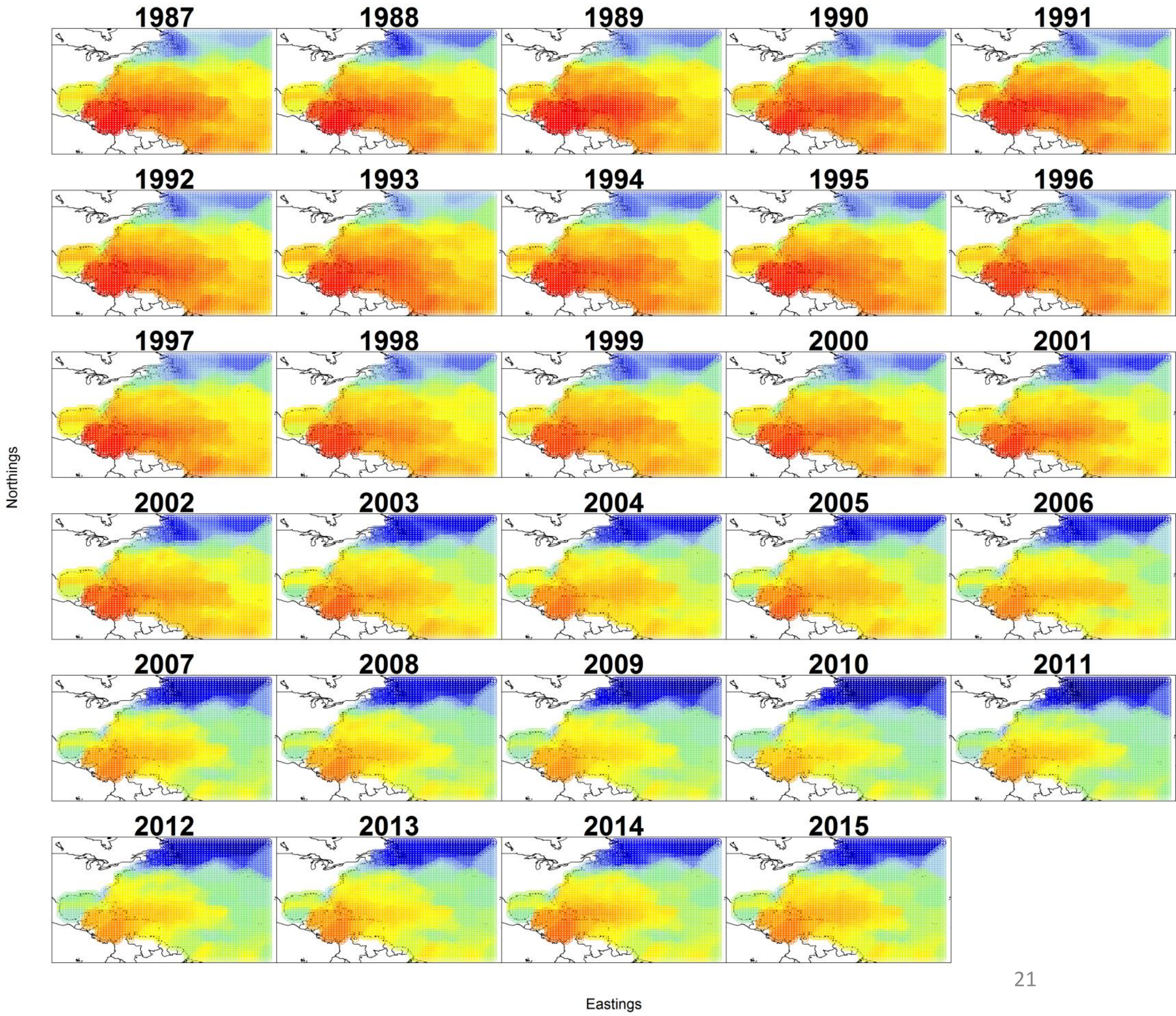


Pop 4 contraction

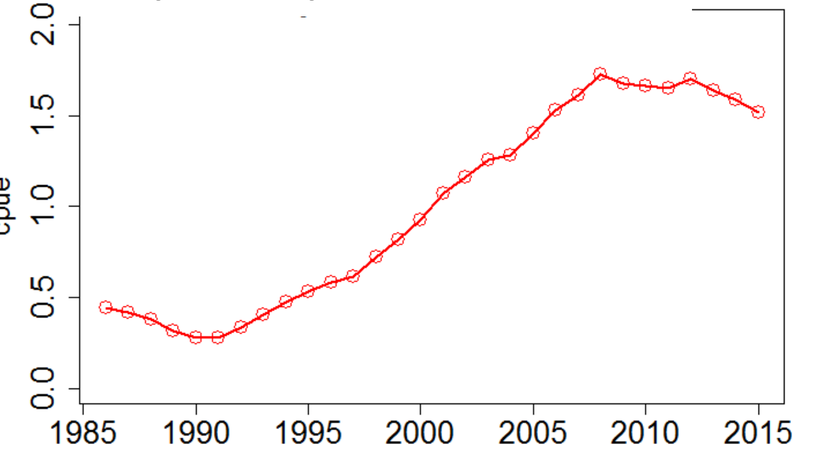


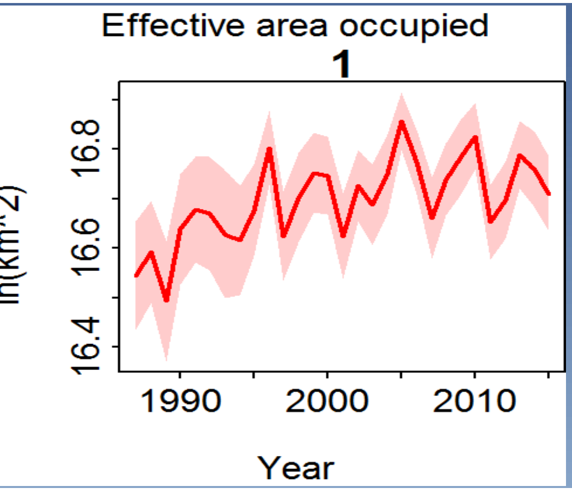


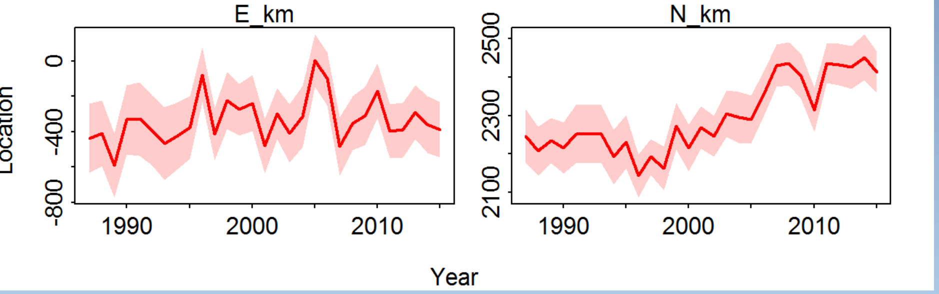


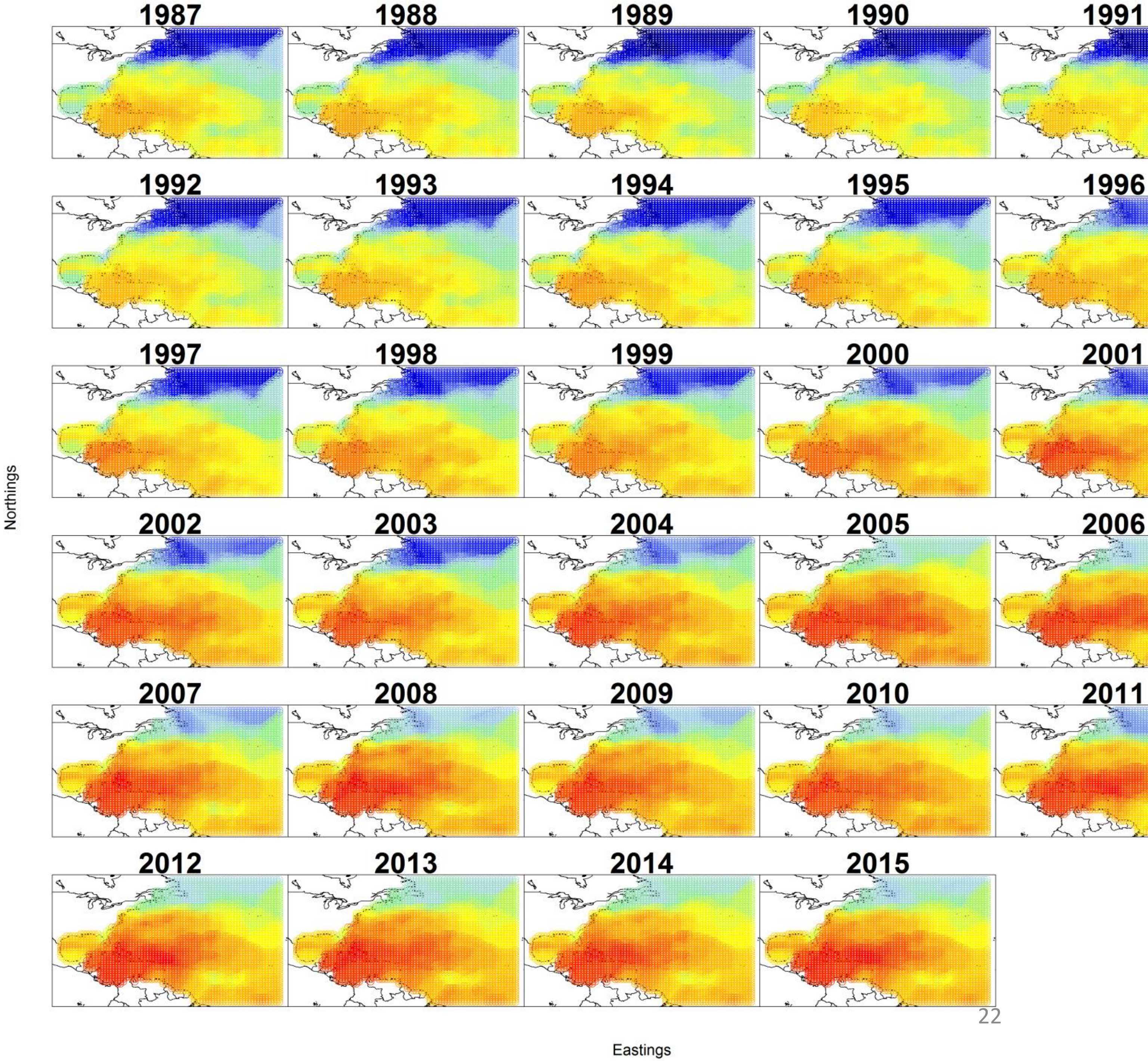


Pop 5 expansion







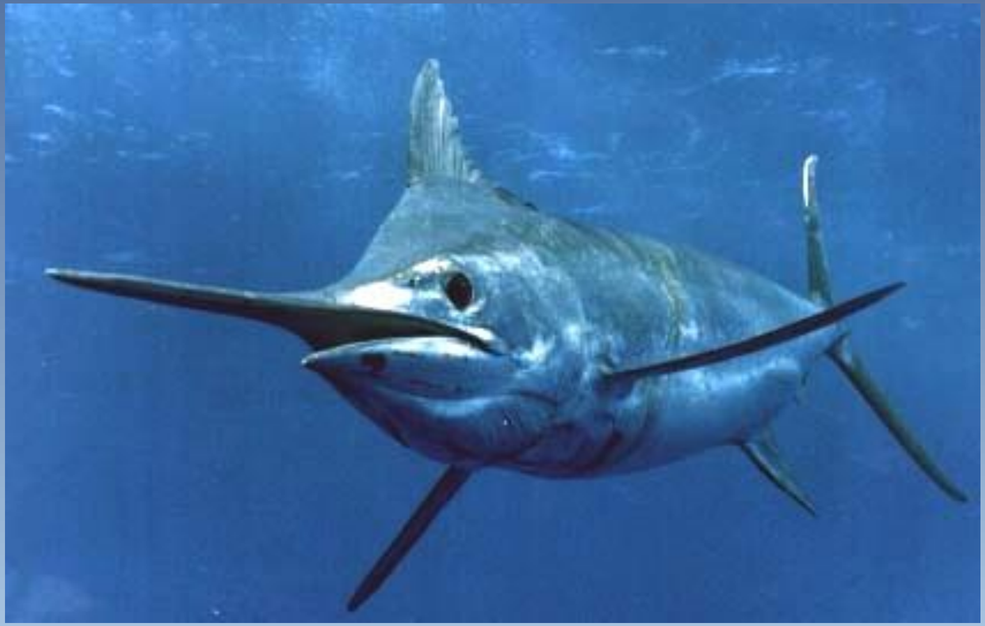


Conclusions

- 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

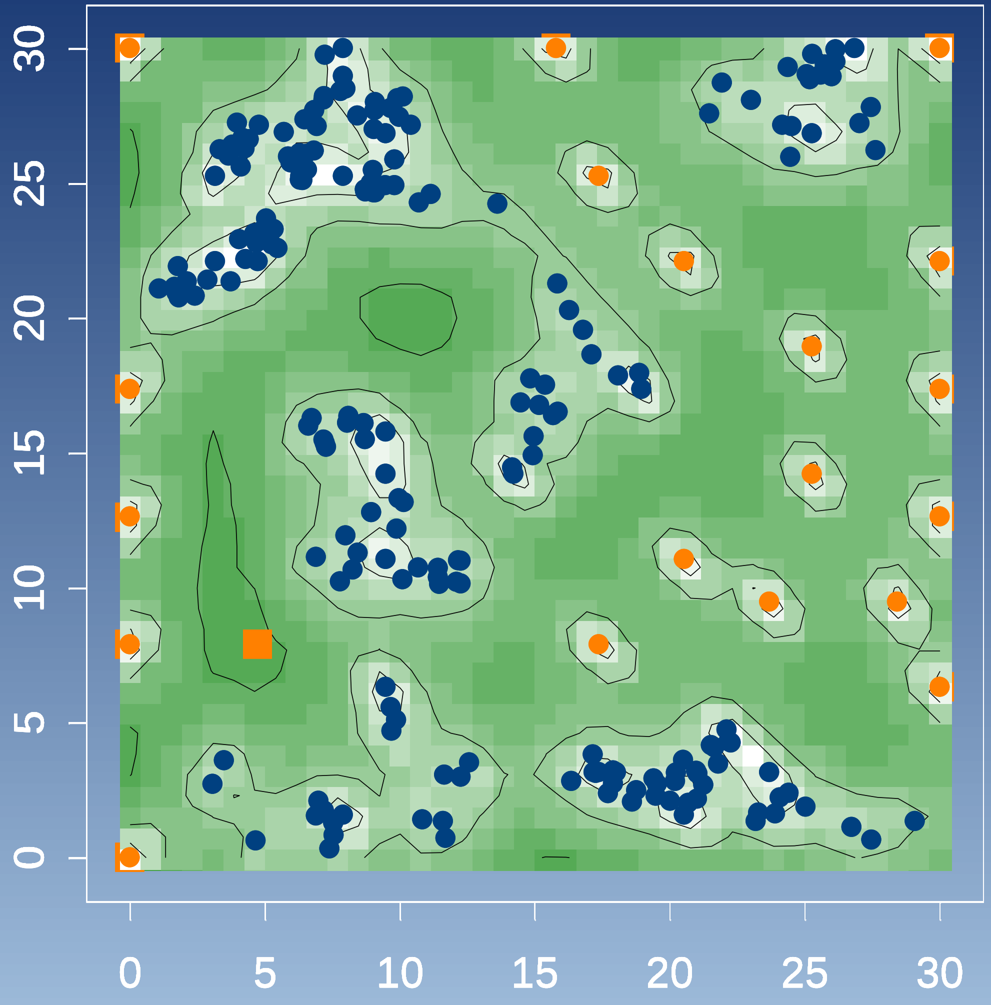
Acknowledgements

Phil Goodyear for LLSIM and many key contributions, Nancy Lo, Robert Campbell and Jim Thorson for advancing methodology. CAPAM organizers and host.



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

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)