

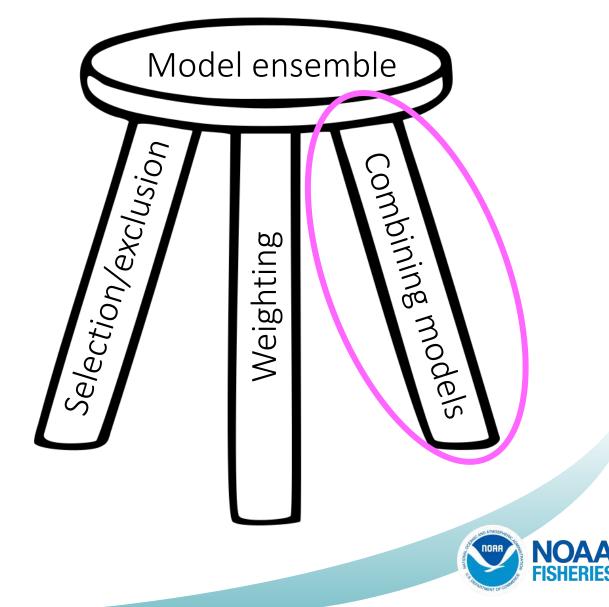
Key decisions: How should ensembles be constructed and combined?

Nicholas Ducharme-Barth (NOAA PIFSC)

Matthew Vincent (NOAA SEFSC)

December 01, 2022 CAPAM/IATTC Model Weighting Workshop

- How are model ensembles constructed?
- 2. How are models in the ensemble combined to present the central tendency in stock status?
- 3. How was uncertainty in stock status from the ensemble presented?



- How are model ensembles constructed?
- 2. How are models in the ensemble combined to present the central tendency in stock status?
- How was uncertainty in stock status from the ensemble presented?



Focusing on the front end: A framework for incorporating uncertainty in biological parameters in model ensembles of integrated stock assessments

Nicholas D. Ducharme-Barth ^{a, b} റ്റ¹ 🖾, Matthew T. Vincent ^{c, 1}

Show more 🗸

+ Add to Mendeley 🦂 Share 🍠 Cite

https://doi.org/10.1016/j.fishres.2022.106452

Get rights and content

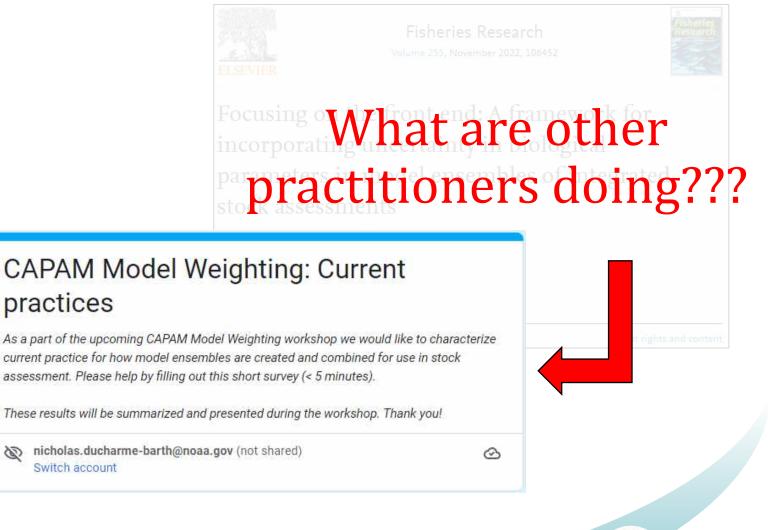


practices

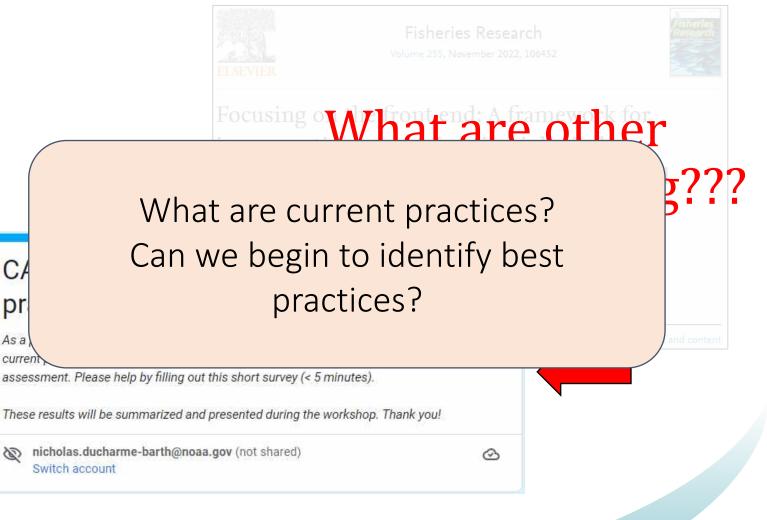
Switch account

60

- How are model ensembles constructed?
- 2. How are models in the ensemble combined to present the central tendency in stock status?
- 3. How was uncertainty in stock status from the ensemble presented?



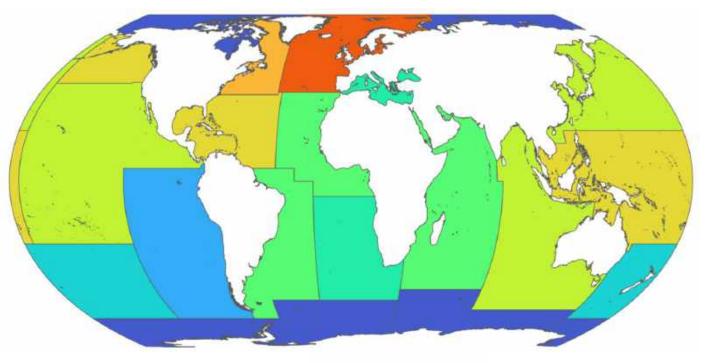
- How are model ensembles constructed?
- 2. How are models in the ensemble combined to present the central tendency in stock status?
- How was uncertainty in stock status from the ensemble presented?





Survey overview

- 42 responses (globally)
- 25 of 42 (~60%)
 participants had used a model ensemble to characterize stock status
- Good response rate across experience level.
- If participants had used an ensemble, all had used one within the last 3 years.



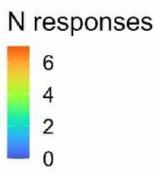
Ν	responses
	10.0
	7.5
	5.0
	2.5
	0.0



Where are ensembles being used?

- RFMOs
 - ICCAT, IOTC, IATTC, WCPFC, IHPC, ICES, ISC, GFCM

- Domestically
 - USA (Southeast/Hawaii)
 - Canada
 - Australia (Queensland)





- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other



- Ad-hoc combination of models
- Hypothesis tree approach (Hierarchical approach)
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other



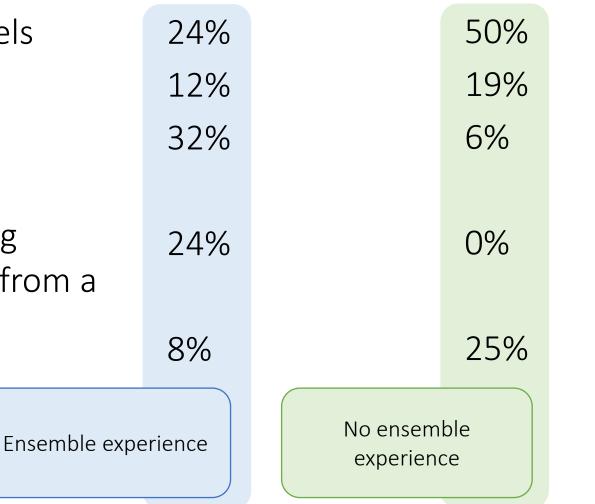
- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other

24% 12% 32% 24% 8%

Ensemble experience

NOAA FISHERIES

- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other





- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution

- Inefficient (model explosion)
- Unrealistic parameter combinations
- *Subjective* choices for parameter levels & model weighting

Natural Mortality (M)		Growth (L2)		Model 1: M=0.2,L2=140	Model 2: M=0.2,L2=160	Model 3: M=0.2,L2=180	
0.2 (low)		140 (low)		Model 4:	Model 5:	Model 6:	
0.3 (medium)		160 (medium)		M=0.3,L2=140	M=0.3,L2=160	M=0.3,L2=180	
0.4 (high)		180 (high)		Model 7:	Model 8:	Model 9:	
				M=0.4,L2=140	M=0.4,L2=160	M=0.4,L2=180	
age Iz							

Can we do better? Monte Carlo Bootstrap (MCB)

- Develop a multivariate distribution for key parameters that would be fixed in an assessment.
- Each model in the ensemble would be parametrized by parameters drawn from distribution.
- Benefits?

A simple simulation approach to risk and cost analysis, with applications to swordfish and cod fisheries

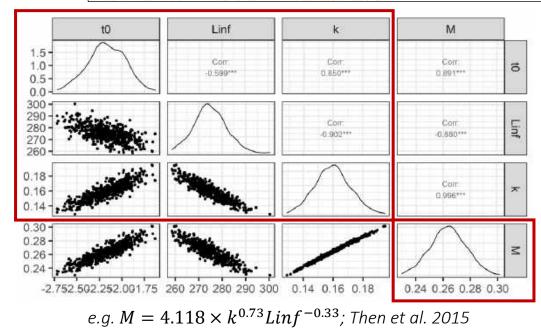
Issue: <u>90(4)</u>

Author(s): Victor R. Restrepo, John M. Hoenig, Joseph E. Powers, James W. Baird, Stephen C. Turner

Cover date: 1992 An Applied Framework for Incorporating Multiple Sources of Uncertainty in Fisheries Stock Assessments

Finlay Scott 🖾, Ernesto Jardim, Colin P. Millar, Santiago Cerviño

Published: May 10, 2016 • https://doi.org/10.1371/journal.pone.0154922





Can we do better? Monte Carlo Bootstrap (MCB)

- Develop a multivariate distribution for key parameters that would be fixed in an assessment.
- Each model in the ensemble would be parametrized by parameters drawn from distribution.

A simple simulation approach to risk and cost analysis, with applications to swordfish and cod fisheries

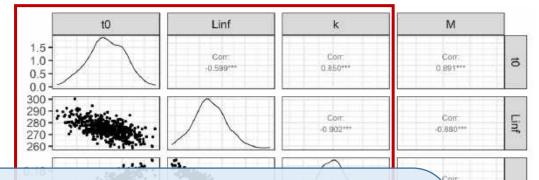
Issue: <u>90(4)</u>

Author(s): Victor R. Restrepo, John M. Hoenig, Joseph E. Powers, James W. Baird, Stephen C. Turner

Cover date: 1992 An Applied Framework for Incorporating Multiple Sources of Uncertainty in Fisheries Stock Assessments

Finlay Scott 🔟, Ernesto Jardim, Colin P. Millar, Santiago Cerviño

Published: May 10, 2016 • https://doi.org/10.1371/journal.pone.0154922



- Benefits?
- Preserves parameter correlation and uncertainty
 - Life history can inform plausible combinations
 - Implicit weighting

e.g. $M = 4.118 \times k^{0.73} Linf^{-0.33}$; Then et al. 2015

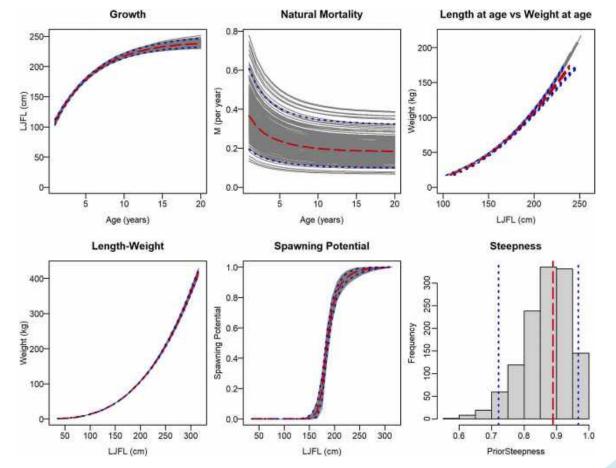


 \leq

0.28 0.30

Case study: 2017 SWPO swordfish

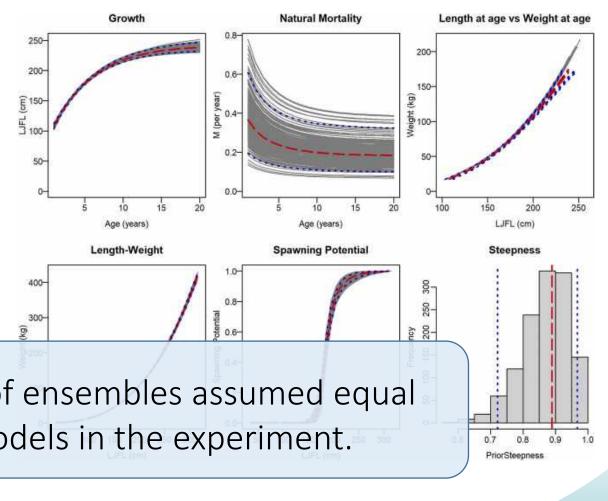
- Develop a multivariate distribution for key biological assumptions (growth, maturity, length-weight, natural mortality & steepness).
- Conduct experiment
 - Develop full-factorial ensemble using 3 levels from 5 biological axes (243 models)
 - Compare to MCB ensembles of varying sizes: 30, 50, 75, 100, 200, 300, 500 models





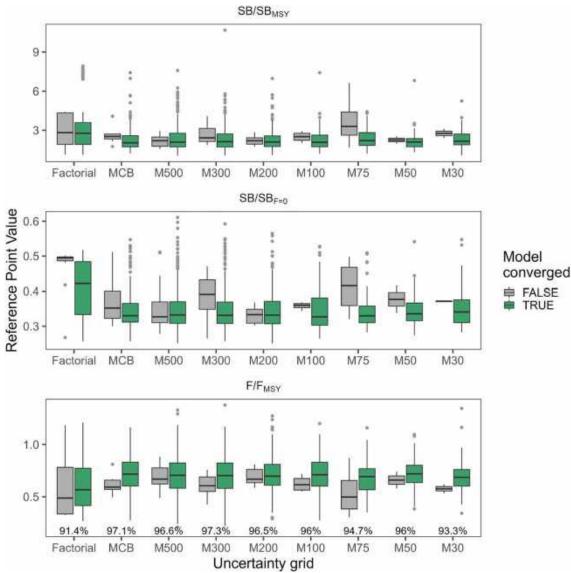
Case study: 2017 SWPO swordfish

- Develop a multivariate distribution for key biological assumptions (growth, maturity, length-weight, natural mortality & steepness).
- Conduct experiment
 - Develop full-factorial ensemble using 3 levels from 5 biological axes (24 Note: Both types of ensembles assumed equal
 - Compar weights for models in the experiment.
 200, 300, 500 models



Case study: 2017 SWPO swordfish

TRUE



- Distributions of the MLEs of management reference points differed in terms of central tendency & uncertainty between the two ensemble types
- MCB ensembles of at least 50 members functionally equivalent in terms of characterizing reference points.



How are model ensembles constructed? Summary

- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other

- Useful for continuous parameters
- Efficient alternative to full-factorial
- Can reduce uncertainty by selfcensoring unlikely combinations
- Shifts scrutiny of weighting decisions from post-hoc discussion to how the multivariate distribution is developed



How are model ensembles constructed? Summary

- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other

- Useful if number of models small or if capturing uncertainty between discrete choices
- Can be combined with MCB ensemble -> this can be a special case of a hypothesis tree.
- Ensemble dispersion (emphasis on tails) dependent of how levels and weighting is selected



How are model ensembles constructed? Summary

- Ad-hoc combination of models
- Hypothesis tree approach
- Full-factorial combination of uncertainties
- Monte-Carlo Bootstrap: fixing parameters to values drawn from a pre-defined distribution
- Other

- Similar pros & cons to the fullfactorial approach
- Can be directly linked to conceptual model
- Hierarchy can be tailored to remove redundant and/or unlikely combinations



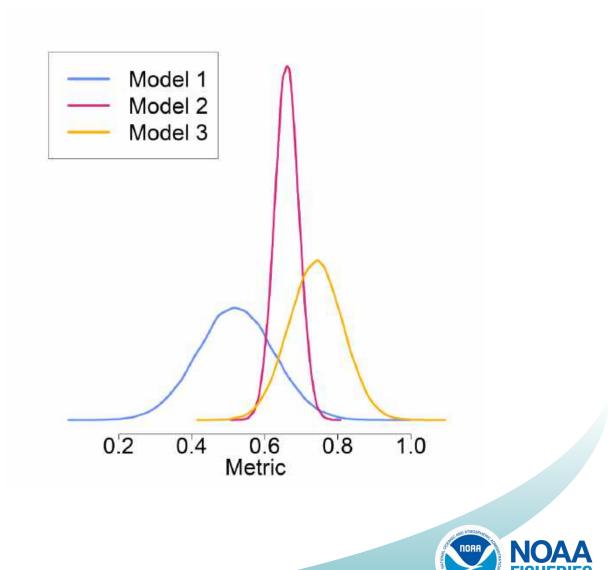
- Models not combined
- Model estimates AVERAGED together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED



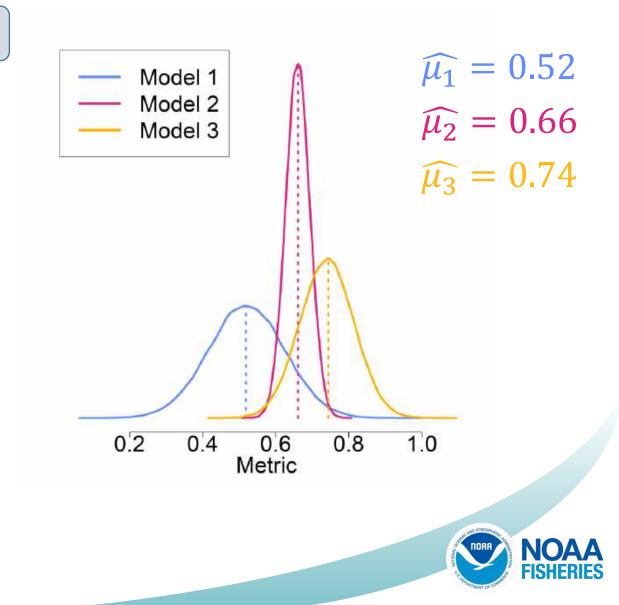
- & How was uncertainty in the ensemble calculated?
- iviouer estimates Averaged together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED



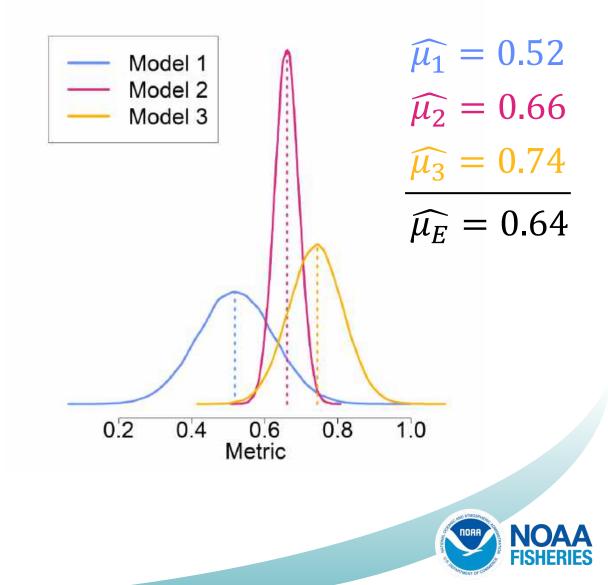
- Models not combined
- Model estimates AVERAGED together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED



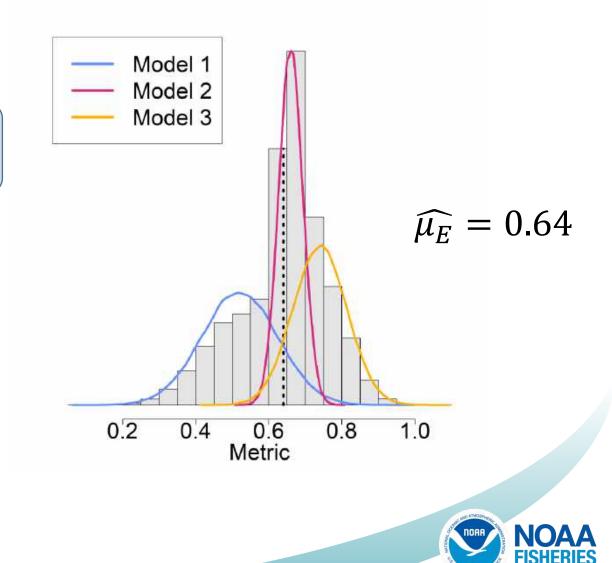
- Models not combined
- Model estimates AVERAGED together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED



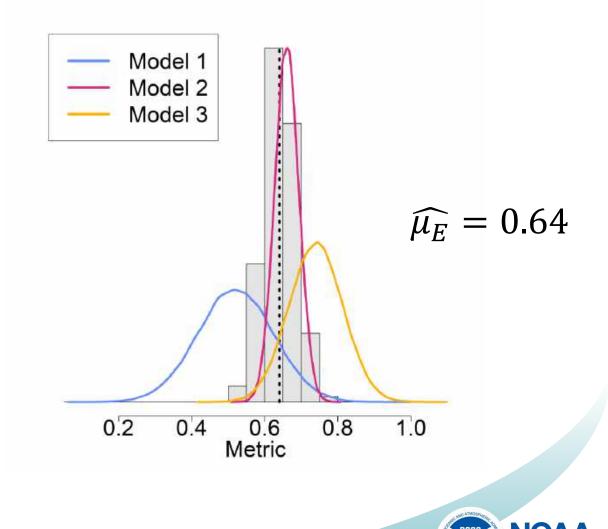
- Models not combined
- Model estimates AVERAGED together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED



- Models not combined
- Model estimates AVERAGED together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED



- Models not combined
- Model estimates AVERAGED together
- Distributions of quantities of interest COMBINED
- Distributions of quantities of interest AVERAGED

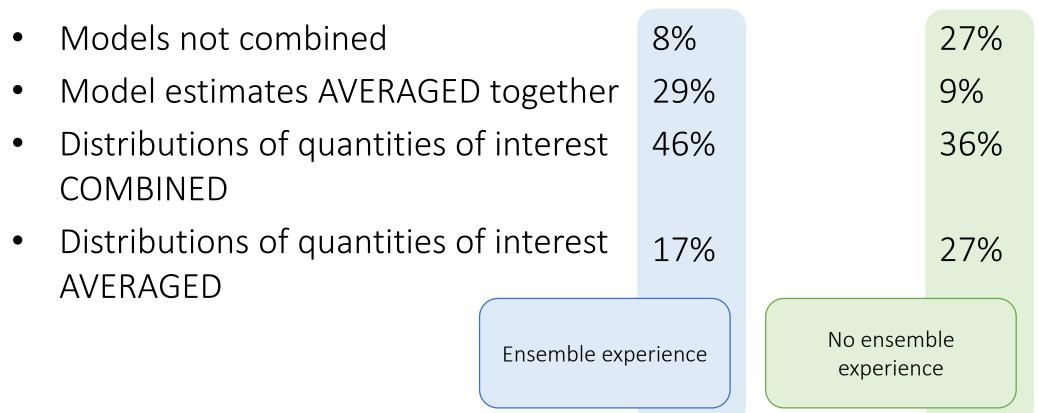


- Models not combined
- Model estimates AVERAGED together 29%
- Distributions of quantities of interest 46%
 COMBINED
- Distributions of quantities of interest 17%
 AVERAGED

Ensemble experience

8%



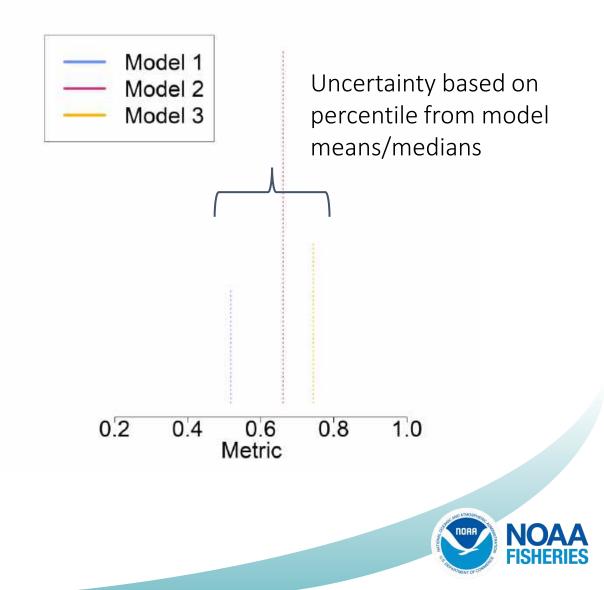




- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution

$$Var\left(\sum_{i=1}^{m} \widetilde{w_{i}}\,\widehat{\mu_{i}}\right) = \sum_{i=1}^{m} \widetilde{w_{i}^{2}}\sigma_{i}^{2}$$



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution

$$Var\left(\sum_{i=1}^{m} \widetilde{w_i} \,\widehat{\mu_i}\right) = \sum_{i=1}^{m} \widetilde{w_i^2} \sigma_i^2$$

Ensemble variance decreases as number of models increases; "losing the tails"



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution

$$Var\left(\sum_{i=1}^{m} \widetilde{w_{i}} \,\widehat{\mu_{i}}\right) = \sum_{i=1}^{m} \widetilde{w_{i}^{2}} \sigma_{i}^{2} + \sum_{i=1}^{m} \sum_{j \neq i} \widetilde{w_{i}} \widetilde{w_{j}} \rho_{ij} \sigma_{i} \sigma_{j}$$



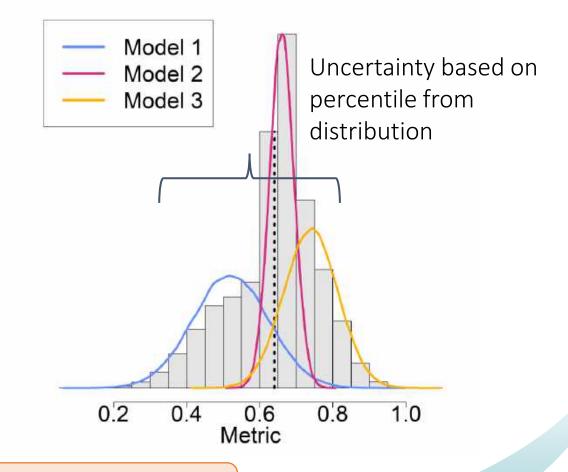
- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution

$$Var\left(\sum_{i=1}^{m} \widetilde{w_{i}} \,\widehat{\mu_{i}}\right) = \sum_{i=1}^{m} \widetilde{w_{i}^{2}} \sigma_{i}^{2} + \sum_{i=1}^{m} \sum_{j \neq i} \widetilde{w_{i}} \widetilde{w_{j}} \rho_{ij} \sigma_{i} \sigma_{j}$$

Conservatively assume ρ_{ij} = 1; still can "lose tails"

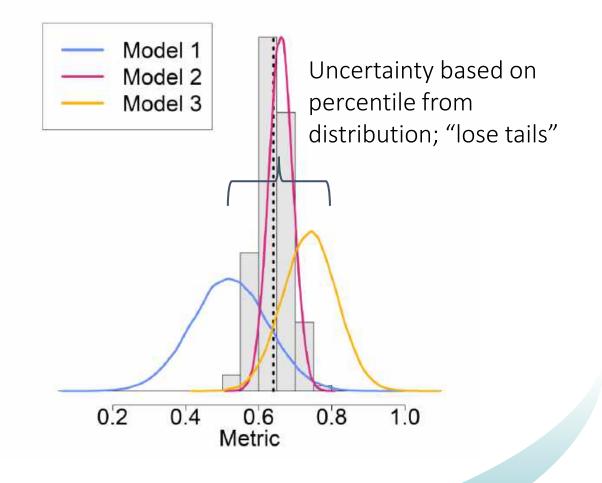


- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution

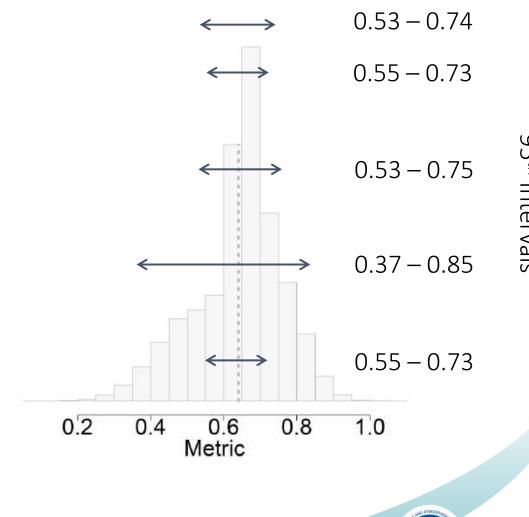


Mixture distribution, super-distribution, 'model stitching'

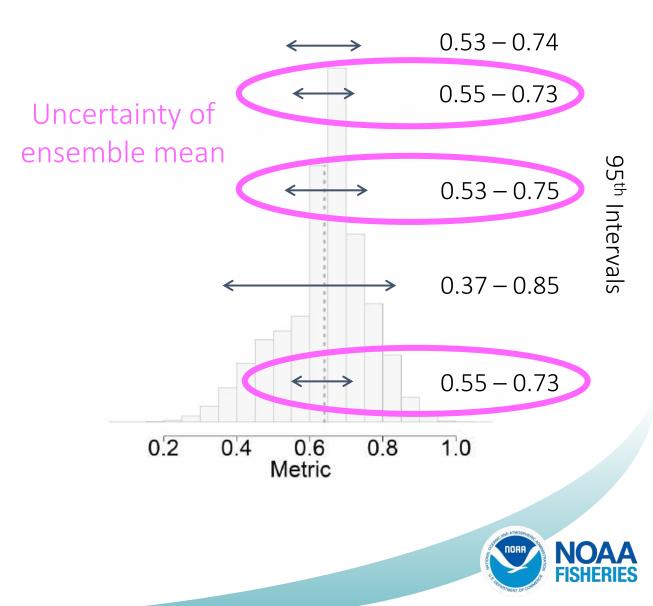
- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution



- Model uncertainty only
- Model + Estimation: Analytical as INDEPENDENT random variables
- Model + Estimation: Analytical as DEPENDENT random variables
- Model + Estimation: Approximated from COMBINED distribution
- Model + Estimation: Approximated from AVERAGE distribution

8%

Ensemble experience

25%

8%

4%

54%



 Model uncertainty only 	25%		9%	
 Model + Estimation: Analytical as INDEPENDENT random variables 	8%		36%	
 Model + Estimation: Analytical as DEPENDENT random variables 	4%		9%	
 Model + Estimation: Approximated from COMBINED distribution 	54%		27%	
 Model + Estimation: Approximated 	8%		18%	
from AVERAGE distribution Ensemble e	Ensemble experience		No ensemble experience	

Case study: 2017 SWPO swordfish

Distribution of metrics Model Model Model SB/SB_{MSY} SB/SBF=0 F/F_{MSY} 1.00 1.00 1.00 0.75 -0.75 0.75 -0.50 -0.50 -0.50 0.25 -0.25 0.25 0.00 0.00 0.00 0.5 1.0 1.5 2.0 0 10 15 0.0 0.5 1.0 0.0 Ensemble Factorial MCB Estimation + Model Estimation + Model Estimation + Model SB/SB_{MSY} SB/SBF=0 F/F_{MSY} 1.00 . 1.00 1.00 0.75 -0.75 -0.75 -0.50 -0.50 -0.50 -0.25 0.25 -0.25 -0.00 0.00 0.5 2.0 1.0 1.5 0 5 10 15 0.0 0.0 0.5 1.0 $SB/SB_{MSY} < 1$ $SB/SB_{F=0} < 0.2$ $F/F_{MSY} > 1$ Error Type Factorial MCB Factorial MCB Factorial MCB Model 0 0 0 10.4 7.2 0 Estimation + Model 2.6 2.3 1.9 2.4 10.79.8

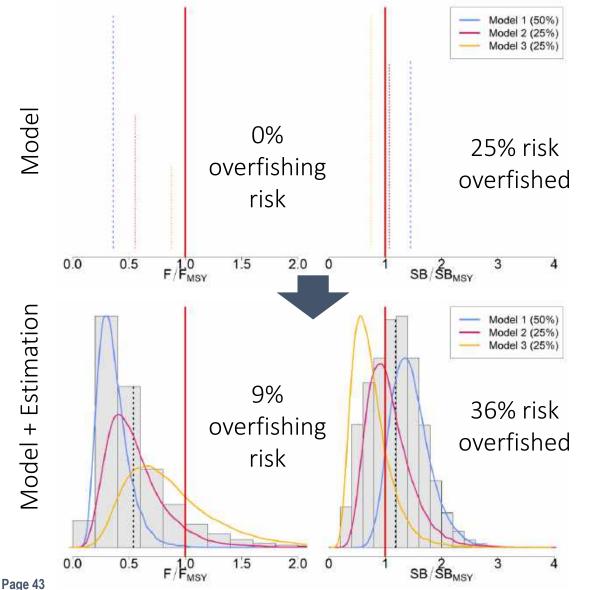
Mixture distribution combining model + estimation uncertainty created using delta-MVLN like approach

۲

- Some increase in uncertainty but did not meaningfully change risk relative to reference points
- Applying sample-importance resampling (likelihood based) weighting did not change distributions

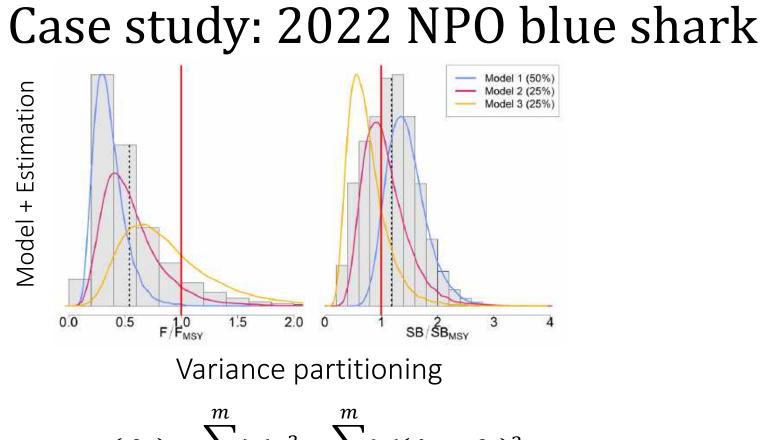


Case study: 2022 NPO blue shark



- 3 model ensemble developed using hypothesis tree approach. Weights assigned *a priori* based on plausibility of each hypothesis. delta-MVLN approach used to create mixture distribution.
- Noticeable increase in risk when estimation uncertainty accounted for.

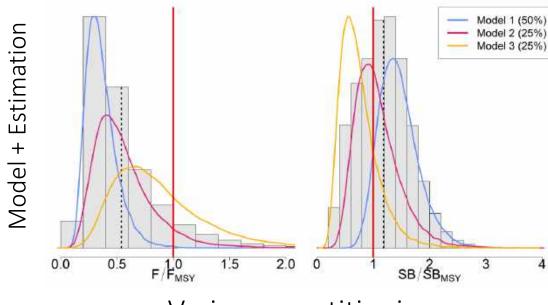




$$Var(\widehat{\mu_E}) = \sum_{i=1}^{m} \widetilde{w_i} \sigma_i^2 + \sum_{i=1}^{m} \widetilde{w_i} (\widehat{\mu_i} - \widehat{\mu_E})^2$$

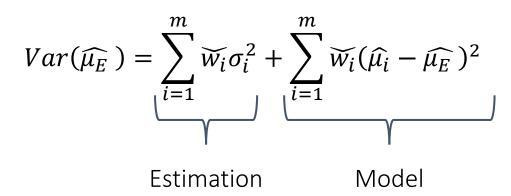
Ducharme-Barth and Vincent (2022), Eq. 4

Case study: 2022 NPO blue shark



	F/F _{MSY}	SB/SB _{MSY}
Model	38%	40%
Estimation	62%	60%

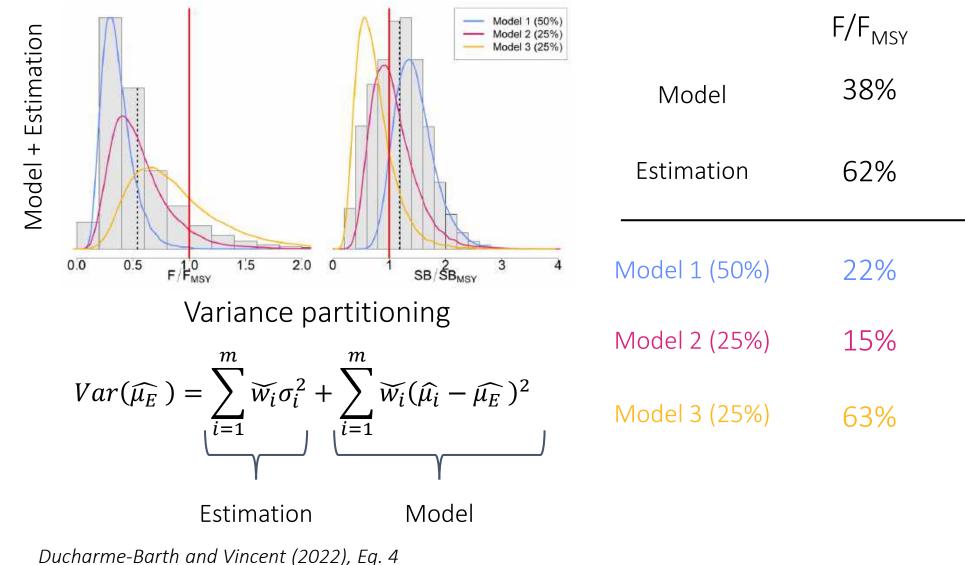
Variance partitioning



Ducharme-Barth and Vincent (2022), Eq. 4



Case study: 2022 NPO blue shark





SB/SB_{MSY}

40%

60%

46%

19%

35%

How are model ensembles combined? Summary & How was uncertainty in the ensemble calculated?

- Most practitioners construct "mixture distributions" which emphasizes "tail retention". This appears different to some other fields where variance reduction is the focus.
- Some ambiguity in terminology? Model averaging implies some level of variance reduction which is not what is usually achieved.
- Accounting for model + estimation uncertainty will always increase uncertainty when creating "mixture distributions". More transparent but can change perceived risk levels.
- Individual model variance (and number of models) related to the importance of including estimation uncertainty.
- Stakeholder education and buy-in are critical as decisions related to ensemble construction & combination change perceptions of risk.



Thank you & Questions?



Nicholas Ducharme-Barth, Ph.D. nicholas.ducharme-barth@noaa.gov



Matthew Vincent, Ph.D. <u>matthew.vincent.@noaa.gov</u>



End slides

