MAPPING A FISHERY: A FULLY-SPATIAL STOCK ASSESSMENT FOR SNOW CRAB IN THE BERING SEA

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Crab Plan Team Meeting

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Kodiak

Why a fully-spatial stock assessment model ?

- Need to increase biological realism in population dynamic and stock assessment
 - Spatial homonogeity BUT populations are spatially patchy and locally structured (Boudreau et al 2017, Ehlren & Morris, 2015)
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- Degrading stock assessment performance
- → Leading to overexploitation of weaker populations units
- \rightarrow and to ineffective recovery plans

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- \rightarrow and to ineffective recovery plans
- As a changing climate alters the spatial distribution of stocks and the potential for fisheries interactions increases

Snow crab in the Bering sea

- Spatial considerations are important for snow crab
 - A spatially concentrated fishery

• Migrations (ontogenic)

• The stock's association with the cold pool and the potential for marine heat waves to influence dynamics

OBJECTIVE Implement a spatial stock assessment

• Accepts raw survey data and spatial fishery dependent data as inputs

- Produces maps of
 - exploitable biomass,
 - recruitment,
 - fishing mortality,
 - and other quantities used in management (SSB)

|CHALLENGE| How to implement a spatially-explicit stock assessment model

[CHALLENGE] How to implement a spatially-explicit stock assessment model

POPULATION DYNAMIC MODEL

including fisheries process

SPECIES DISTRIBUTION MODEL

WITHIN A SINGLE STATISTICAL FRAMEWORK

to permit inference for each state variable through space and time

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POPULATION DYNAMIC MODEL

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Simulated fishery catches

SPECIES DISTRIBUTION MODEL

Simulated survey data (biomass)

WITHIN A SINGLE STATISTICAL FRAMEWORK

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ORIGINAL ARTICLE

A novel spatiotemporal stock assessment framework to better address fine-scale species distributions: Development and simulation testing

Jie Cao 🔀, James T. Thorson, André E. Punt, Cody Szuwalski

Model- spatiotemporal size-structured population model of abundance (Cao et al., 2020)

Spatiotemporal population model

- Combines theory and methods from population dynamics and geostatistics
- Assumes population density varies continuously across space
- Joint distribution for density at all locations
- Expanded to account for size-structured population dynamics

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• Size structure model

- Requires no ability to age animals (invertebrate-crabs)
- Uses the data actually available
- Vulnerability / maturity are often function of size and not age

Process model

• Abundance at size (n) for a given size class I, location s and time t+1 is expressed as a product of

$$n_{s,t+1} = g(n_{s,t}) \circ e^{\varepsilon_{s,t}}$$

Function of the previous density and model parameters describing the population dynamics Process error term

 $\circ \epsilon_{s,t}$ accounts for unmodelled spatial and temporal process

✓ movement,

- ✓ spatial variation in biological parameters such as growth and natural mortality.
- Process error considers pairwise covariation between
 - \checkmark any two size classes
 - ✓ any two locations s and si

Model- spatiotemporal size-structured population model of abundance (Cao et al., 2020)

• Population dynamic is described by $g(n_{s,t})$

• Male/female

- Only males are retained in the fishery
- Split into maturity state
- Mature individuals do not molt

 $r_{s,t}$ Vector of recruitment for each of I size classes p_{male} Proportion of male recruitment G Growth transition matrix m_{s,t} Vector of natural mortality at location s, year t $f_{s,t}$ Vector of selectivity at size ν Vector of immature abundance for each of I size classes $n_{s,t}^{immat}$ Vector of mature abundance for each of I size classes $n_{s,t}^{mat}$ Vector of maturity of each size class ω

For Sex == male

$$g(n_{s,t}) = \begin{cases} r_{s,t} * p_{male} + G(n_{s,t-1}^{immat}e^{-m_{s,t-1}-\nu * f_{s,t-1}}) * (1-\omega) & \text{if } n = n^{immat} \\ G(n_{s,t-1}^{mat}e^{-m_{s,t-1}-\nu * f_{s,t-1}}) * \omega + n_{s,t-1}^{mat}e^{-m_{s,t-1}-\nu * f_{s,t-1}} & \text{if } n = n^{mat} \end{cases}$$

Parameters and estimation

- Recruitment
 - ✓ The model allows spatial process error to account for spatial variation in recruitment
 - ✓ The model estimates the annual average recruitment

Model- spatiotemporal size-structured population model of abundance (Cao et al., 2020)

Parameters and estimation

• Recruitment

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- The model estimates the annual average recruitment
- Fishing mortality

 $\log(f_{s,t}) | \log(f_{s,t-1}) \sim N(\log(f_{s,t-1}), \sigma_f^2)$

✓ size specific selectivity

$$f_{l,s,t} = f_{s,t} * v_l$$

Model- spatiotemporal size-structured population model of abundance (Cao et al., 2020)

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• Parameters (input data based on external information)

- Growth transition matrix
- Natural mortality
- Proportion of male at recruitment and achieving maturity at each size

- "Poisson link" delta model (Thorson 2017) fit to observed survey biomass at location s time t
 - Predicted local density of individual
 - Encounter probability

SPECIES DISTRIBUTION MODEL

• Spatially referenced fisheries- dependent data (total amount of fish by size class) is assumed to be lognormally distributed

POPULATION DYNAMIC MODEL

Model validation & evaluation using simulations (Cao et al., 2020)

- Experiment I- How model performance is affected by movement processes that are modelled explicitly when simulating data (Operating Model=OM)
 - $_{\circ}~$ Scenario I- No measurement error and no movement in the OM
 - Scenario 2- Same as scenario 1, except there is movement
 - Scenario 3- Both measurement error and movement in the OM

• Experiment 2- Effect of sample size

- data poor 50 locations
- moderate level 100 locations
- data rich 200 locations

Results- Experiment I- Scenario I-

• The model can generate unbiased and precise estimates of abundance and fishing mortality spatially when data are not subject to measurement error and no movement



Distribution of size class without measurement error and movement

(Cao et al., 2020)

Results- Experiment I-Scenario 2 & 3

• Scenario 2

- The model accounts for movement implicitly via its estimates of process error when the spatiotemporal model fits to data without measurement error but generated given unmodelled (in the Estimation Model) individual movement
- This unmodelled spatial process did not lead to poorer model performance. The model recovers the spatial variation in abundance and fishing mortality over time

• Scenario 3

 The model is able to recover the spatial variation when sampling errors are present (with lower precision)



Fishing mortality without measurement error

(Cao et al., 2020)

Conclusions



• The spatiotemporal model produced unbiased estimates of abundance and fishing mortality spatially

The spatiotemporal model outperformed a spatially-implicit model

 The modeling approach bridges the gap between species distribution and population dynamic models and provides the opportunity to improve natural resource management and conservation

|CHALLENGE| How to implement a spatially-explicit stock assessment model

POPULATION DYNAMIC MODEL

including fisheries process

Fisheries data (Alaska Department of Fish and Game)

SPECIES DISTRIBUTION MODEL

WITHIN A SINGLE STATISTICAL FRAMEWORK

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Survey data (National Marine Fisheries Service)

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VAST as a tool to explore spatial variations in survey data

- VAST (Thorson, 2019) (Vector Autoregressive Spatio-Temporal) is
 - a spatially explicit model that predicts population density for all locations within a spatial domain

• VAST forms the underlying machinery of the assessment model (Cao et al. 2020)

- Stations (Zacher et al., 2019)
 - In 1982: the survey net was changed resulting in a potential change in catchability
 - I 989 : additional survey stations were added



• Stations (Zacher et al., 2019)

- In 1982: the survey net was changed resulting in a potential change in catchability
- 1989 : additional survey stations were added
- Survey selectivity has been historically modeled in two'eras' in the assessment (Szuwalski et al., 2019)
 - I982-1988
 - ✓ I989-present
 - 355-375 stations



- Stations
- Hauls- For few years, several hauls within a station

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2000 2005 2010 2015 2000 2005 2010 2015 2000 2005 2010 2015 2000 2015 2000 2005 2010 2015 2000 2005 2010 2015 2000 2005 2010 2015 AKFIN SURVEY YEAR

• Stations

5000 -



• Hauls- For few years, several hauls within a station

• The standard survey is completed in late July or early August at the western edge of the survey grid, northwest of St. Matthew Island. In some years (i.e., 1999, 2000, 2006-2012, 2017) when the red king crab reproductive cycle is delayed due to colder water temperatures, a small portion of the inner Bristol Bay area is resampled after the conclusion of the standard survey

- Stations
 - **1989-present: 355-375 stations**
- Hauls: early summer
- Spatial distribution



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- Stations (Zacher et al., 2019)
 - **1989-present: 355-375 stations**
- Hauls

Count

- Spatial distribution
- Demographic categories





RUN VAST

• Output are not ecologically or even statistically interpretable because I made a lot of assumptions, like selectivity at length is the same

 \rightarrow How VAST can help to explore data and understand spatial variations in survey data

Density





Density



Eastings



Density



A BUT A



Center of gravity indicating temporal shifts in the mean east-to-west and north-to-south distribution

East to West

 Center of gravity indicated that crab was distributed farther south during the beginning of the time serie

- Perspective
 - Climate change-related distribution changes
 - Link density with covariates generating distribution changes
 - ✓ Cold pool
 - Temperature (bottom or surface)
 - Link recruitment ?



Year

South to North

(km north of equator)

Effective area occupied: indicating range expansion/contraction

• High size classes crab : decrease in area occupied

- Perspectives
 - Habitat loss ? Depending on life stage ?



Index of abundance



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POPULATION DYNAMIC MODEL

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Fisheries data (Alaska Department of Fish and Game)

SPECIES DISTRIBUTION MODEL

Survey data (National Marine Fisheries Service) VITHIN A SINGLE STATISTICAL FRAMEWORK

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RETAINED CATCHES provided by ADFG

• Time-serie : 1985-2019



• Catches are spatially concentrated



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• Catches are spatially concentrated



• Catches are spatially concentrated



175°W170°W165°W160°W155°W150°W 175°W170°W165°W160°W155°W150°W 175°W170°W165°W160°W155°W150°W 175°W170°W165°W160°W155°W150°W

• Catches are spatially concentrated



• Catches are spatially concentrated





• Catches are spatially concentrated



175°W 170°W 165°W 160°W 155°W 150°W 175°W 170°W 165°W 160°W 155°W 150°W 175°W 170°W 165°W 160°W 155°W 150°W

Year	Latitude	Longitude	Number of crabs
2006	56.30	181	503
2002	76	165	25,765
1985	99.99	199	113,082



Next steps

POPULATION DYNAMIC MODEL

including fisheries process

Fisheries data (Alaska Department of Fish and Game) • Fit Data to Cao's model

- Two independent models for male and female
- Any possibility to implement:
 - Movement
 - ✓ survey: summer
 - ✓ fisheries: winter
 - Spatially explicit information on the size composition of the catches
 - Data to estimate parameters which were specified based on external information
 - Proportion achieving maturity at each size/male in recruitment
 - ✓ Natural mortality



Fit Data to Cao's model

• Catchability/Selectivity- trawl efficiency

- "Snow crab survey catchability function is not a logistic function of carapace width as it is assumed in the stock assessment model."
- "Trawl selectivity was greater in sand than mud and greater in shallow water than deep"

SPECIES DISTRIBUTION MODEL

Survey data (National Marine Fisheries Service)



Catchability of snow crab (*Chionoecetes opilio*) by the eastern Bering Sea bottom trawl survey estimated using a catch comparison experiment David A. Somerton, Kenneth L. Weinberg, and Scott E. Goodman 1699

ARTIC



Composition data output



Process

Abundance at size (n) for a given location s and time t

$$\boldsymbol{n}_{s,t+1} = g(\boldsymbol{n}_{s,t}) \circ e^{\boldsymbol{\varepsilon}_{s,t}}$$

 $\Sigma_t \sim \text{MVN}(0, \mathbf{R}_{spatial} \otimes \Theta_L)$

- Hadamard product (entrywise product)
- s location
- t year
- ⊗ Kronecker product

- $\mathbf{n}_{s,t}$ vector of abundances for each of *l* size classes
- g() function representing population dynamic
- $\boldsymbol{\varepsilon}_{s,t}$ vector of random effects (process error)
- Θ_L covariance among size classes (*l* by *l* matrix **L**)
- $\mathbf{R}_{spatial}$ spatial covariance matrix (covariance between 2 locations follows a Matern function)