The importance of environmental exposure history in forecasting Dungeness crab megalopae occurrence using J-SCOPE, a high-resolution model for the US Pacific Northwest

**Emily L. Norton<sup>1\*</sup>,** Samantha Siedlecki<sup>2</sup>, Isaac C. Kaplan<sup>3</sup>, Albert J. Hermann<sup>1,4</sup>, Jennifer L. Fisher<sup>5</sup>, Cheryl A. Morgan<sup>5</sup>, Suzanna Officer<sup>6</sup>, Casey Saenger<sup>1</sup>, Simone R. Alin<sup>4</sup>, Jan Newton<sup>7</sup>, Nina Bednaršek<sup>8</sup>, and Richard A. Feely<sup>4</sup>

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J-SCOPE





## Dungeness Crab Fishery: Valuable but Variable

#### Historical Catch in Oregon



I-SCOPE

- One of the most valuable fisheries in the Pacific Northwest
- Interannual fluctuations
  - Driven by environmental variability
- Co-managed by State and Tribes
- $\rightarrow$  Managers are interested in

forecasting tools



#### Megalopae Abundance Correlated with Adult Crab Fishery 4 Years Later



#### Dungeness Crab Life Cycle: Benthic and Pelagic Stages



# Exposure History is Important for Some Pelagic Organisms: Pteropod Survival





- > Particles initialized at sampling locations with vertical migration behavior
- Dispersal simulations run forward and backward for 30 days to estimate undersaturation days

Photo: R. Hopcroft

Fig. 3 in Bednaršek et al., 2017. Sci. Rep. 7, 4526

# Project Overview

#### Hypothesis:

Including environmental exposure history will improve our ability to predict megalopae occurrence and habitat compared to using only cooccurring environmental conditions (*'in situ'*).





#### GLM = Generalized Linear Model

Develop

#### Dungeness Megalopae Occurrence Data



- 13 surveys from nine years
  - 2009-2016: develop GLMs
  - 2017: test GLM performance
- 37 sampling locations
- May + June surveys
- Oblique bongo tows 0-30m
- Dungeness megalopae identified and counted

Thanks to C. Morgan for providing data; sampling conducted by Bonneville Power Administration and Northwest Fisheries Science Center (NOAA)

#### J-SCOPE (JISAO's Seasonal Coastal Ocean Prediction of the Ecosystem) I-SCOPE Forecasts Seasonal Coastal Marine Conditions for PNW



#### **Currently forecasting:**

•T, S, O, NO<sub>3</sub>, Chl a, pH,  $\Omega$ 

•Sardine Habitat (Kaplan et al., 2016) • in prep: OA specific indices for adult crab, shellfish, pteropods; and

hake habitat (Malick et al., in prep)

- NOAA's Climate Forecast System (CFS) global coupled air/sea/land model – used for boundary and atm forcing of ROMS-based regional model with biogeochemistry (Cascadia domain, ~1.5 km res)
- Empirically-derived relationships applied to modeled fields to predict additional quantities (e.g. pH and fish)



Anomaly Correlation Coefficient for seasonal forecast vs. hindcast

Next talk: Skill and uncertainty of environmentally **Check out our websit** driven forecasts of Pacific hake distribution

http://www.nanoos.org/products/j-scope/home.php

Siedlecki et al., 2016.



#### Jevelop in situ *model*

J-SCOPE

# "in situ" Variable Extractions



- From J-SCOPE at times and locations concurrent with megalopae sampling (37 stations, 2009-2016)
- Averaged over sampling depth (0-30m depth)



Estimating exposure history is more complicated...

# Exposure History: Particle Dispersal Tracked Backward for 30 Days with LTRANSv2b<sup>1</sup>



EH models

J-SCOP

Develop

 Advection and environmental conditions from J-SCOPE



<sup>1</sup>North et al., 2008; 2011; Schlag and North, 2012

## Exposure History: Particle Dispersal Tracked Backward for 30 Days with LTRANSv2b<sup>1</sup>





EH models

Develop

# Environmental Conditions Extracted Along Particle Trajectories

EH models

Develop



## Calculated Two Types of Exposure Histories Variables



Norton et al., 2019 (submitted, Front. Mar. Sci.)

EH models

Develop

# Exposure History Models Show Better Fit and Performance Than *in situ M*odel

Relative Model Fit (0 is best)									
Experiment	Predictor Variables (bold p<0.05)	ΔAIC	$\begin{array}{c c} \text{in-sample} & \text{Model Performance} \\ \text{AUC} & (0 \rightarrow 1 \text{ higher is better}) \end{array}$						
in situ	-N	11.8	0.602						
EH-P1	+S, +O	0.0	0.658	Worst model fit and performance					
EH-P30	+Ρ, - <b>SI Ω</b> ar	1.9	0.625						
EH-DVM30	+0	4.7	0.644	4 EH models have good fit and					
EH-DVM60	+S, +O	5.3	0.650	performance					
EH-S1	-T, - <b>N, -</b> SI Ωca	7.9	0.645						
→Assemble " <b>biological ensemble</b> "									
Predictor(s) in GLM with									
direction (-/+) of correlation to									
megalonae occurrence									



I-SCOF

# Biological Ensemble Skillfully Forecasts Megalopae Occurrence

- Biological ensemble represents multiple behaviors
- 94% agreement with 2017 megalopae survey
- Predicts habitat on outershelf and northern areas





#### Conclusions

- Prediction of pelagic habitat for Dungeness megalopae is possible with a combination of tools: ocean conditions model, particle tracking, statistical modeling
- Models that include exposure history outperform those that solely rely on *in situ* conditions
- Simulated behavior affects depth habitat and ultimately drives environmental exposure
- Best prediction was the result of a biological ensemble that includes multiple behaviors



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NOAA

For more information, check out our website: http://www.nanoos.org/products/j-scope/home.php

J-SCOPE

Photo Credit: R. Norton

# Ocean Condition Observations for J-SCOPE Skill Assessment

- Surface, seafloor, and water column measurements
- Moorings and cruises
- 2009-2017



## Select Environmental Variables to Consider for Occurrence Model

Criterion 1: Reported as important for megalopae in the literature

1b: Critical thresholds exist to calculate severity indices

Criterion 2: Modeled by J-SCOPE (or could be derived from modeled variables)



Motivation: Variable skill will influence performance of occurrence models  $\rightarrow$  investigate patterns of J-SCOPE skill

• Paired modeled and observed variables within specific depth habitats and seasonal windows: 1) Pearson's Correlation Coefficient (r>0.5)

2) Normalized Root Mean Square Error (-1<NRMSE<1)



Experiment	Depth Habitat (m)	Temperature (°C)	Salinity	Oxygen (mmol m <sup>-3</sup> )	Nitrate (mmol m <sup>-3</sup> )	Phytoplankton (mmol m <sup>-3</sup> )	pН	$\Omega_{ar}$	$\Omega_{ca}$
EH-P1	40-50	0.87	0.66	0.71	0.75	0.04	0.72	0.73	0.77
		-0.59	-0.85	-0.94	2.63	-1.14	-0.90	-0.84	-0.77
		(2403)	(2403)	(2348)	(33)	(2353)	(2165)	(2165)	(2165)
EH-P30	55-70	0.89	0.61	0.54	N/A	0.09	0.58	0.56	0.72
		-0.51	-0.92	-1.25	11/21	-1.57	-1.13	-1.13	-0.88
		(2729)	(2729)	(2665)	(0)	(2689)	(2409)	(2409)	(2409)
FH-DVM30/	0-30	0.88	0.76	0.71	0.61	0.10	0.71	0.75	0.78
in situ		0.58	-0.66	0.79	1.01	1.56	-0.77	-0.70	0.67
		(8391)	(8391)	(8189)	(860)	(8105)	(7516)	(7516)	(7516)
EH-DVM60	0-60	0.91	0.79	0.75	0.62	0.09	0.75	0.77	0.80
		0.51	-0.63	0.82	1.19	-1.30	0.78	0.73	0.68
		(14832)	(14832)	(14482)	(906)	(14398)	(13287)	(13287)	(13287)
EH-81	0-5	0.82	0.74	0.50	0.62	0.50	0.56	0.72	0.76
		0.76	-0.70	-0.92	-0.84	2.71	-0.88	-0.72	-0.69
		(1335)	(1335)	(1302)	(625)	(1255)	(1195)	(1195)	(1195)

→ Significant skill for most variables; skill increases subsurface

# **Results: Particle tracking simulations** Passive Dispersal DVM Behavior





#### Behavior and Initialization Depth Affect Dispersal Trajectory

EH model

Develop



# Environmental Exposure Influenced by Depth Habitat



1. Averages: **Depth habitat** drives exposure patterns – shallow (EH-S1) and deep (EH-P30) habitats are most divergent

2. Severity Indices: Severe conditions experienced in deep habitats (EH-P30, DVM60)



Develop

## Develop GLMs Using *in situ* and Exposure History Variables

Recall Aim: Model megalopae occurrence using in situ vs. exposure history variables

• Binomial distribution ('present' or 'absent') requires logit link function

Probability of Presence = 
$$log\left(\frac{\mu}{1-\mu}\right)$$

where

$$\mu = \frac{e^{X_b}}{1 + e^{X_b}}$$

X<sub>b</sub> is linear combinations of predictor variables

- Considered all variables as potential predictors
  - Selected best combination of variables based on lowest AIC score

### Biological ensemble – 2017 performance

Ever view ant	Fountion (hold n < 0.05)	2017		
Experiment	Equation (bold p<0.05)	AUC		
EH-P1	-11.0 + 0.248* <b>S</b> + 0.0111* <b>O</b>	0.914		
EH-DVM30	-3.01 + 0.109* <b>0</b>	0.814		
EH-DVM60	-6.42 + 0.132* <b>\$</b> + 0.00988* <b>0</b>	0.936		
EH-S1	1.77 - 0.157*T - 0.0994* <b>N</b> - 79.5*(SI Ωca)	0.757		
Biological Ensemble:				

#### 11:50a – 12:10p: 15 min talk + 5 min Q