Seasonal ocean forecasts promote dynamic management of the Dungeness crab fishery in Washington and Oregon, U.S.A.

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Background: Dungeness crab fishery is valuable but variable

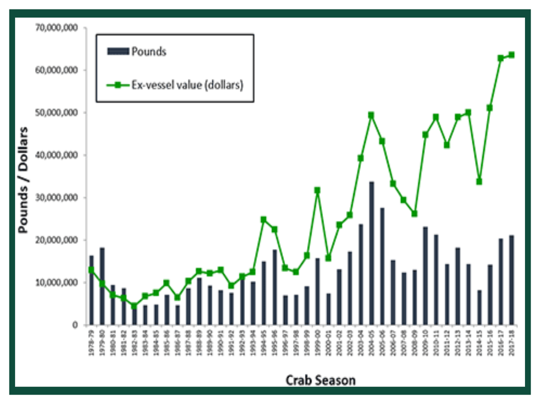


Fig. 1. Oregon commercial Dungeness crab catch.[1]

The Dungeness crab fishery is one of the highest value fisheries in the US Pacific Northwest, but catch rates fluctuate interannually[1] (Fig. 1). Variable environmental conditions are hypothesized to be drivers, though precise mechanisms are not well understood. Abundance of the last larval stage, the megalopal stage, is also correlated to the abundance of fishery catch in Oregon four years later[2] (Fig. 2).

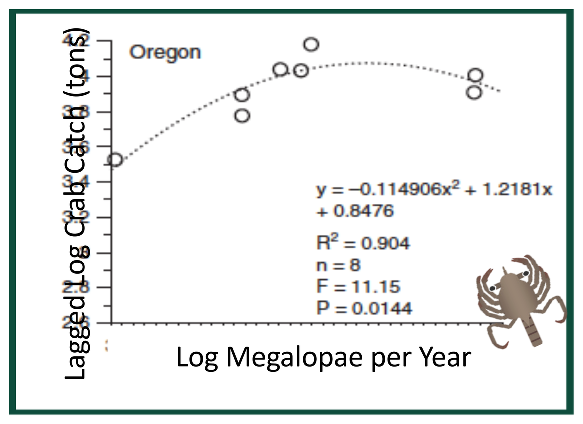
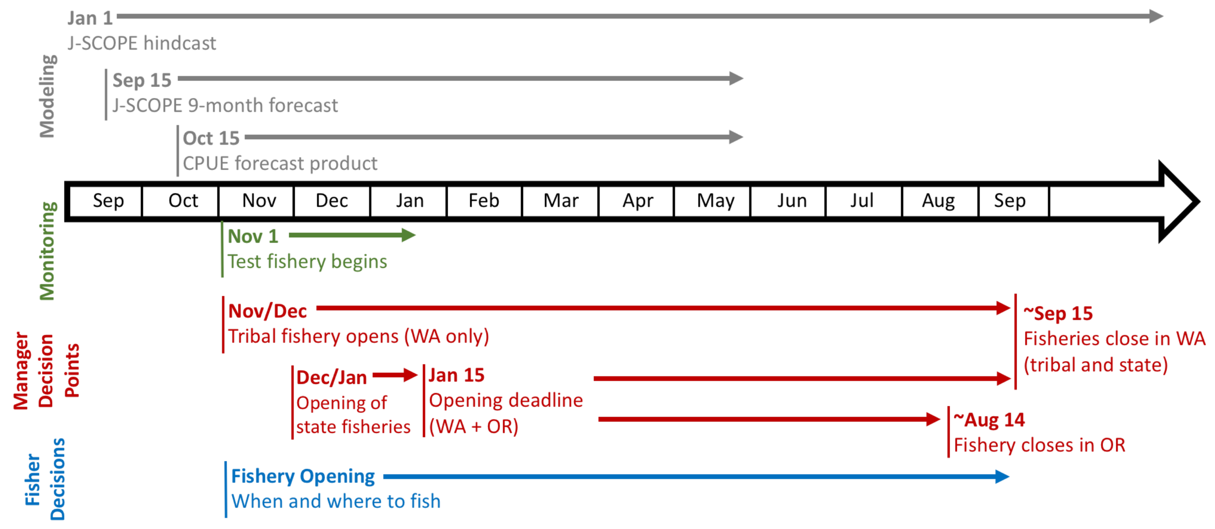


Fig. 2. Correlation of megalopae abundance and adult catch.[2]

Decision context: Annual forecasting cycle



Aim: Use modeled ocean conditions, from past and present, to predict temporal and spatial variability in Dungeness crab catch rates in Washington and Oregon.

Methods: Extract environmental conditions from the J-SCOPE ocean model

J-SCOPE (JISAO's Seasonal Coastal Ocean Prediction of the Ecosystem[3,4]) produces historical ocean simulations ('hindcasts') and seasonal forecasts:

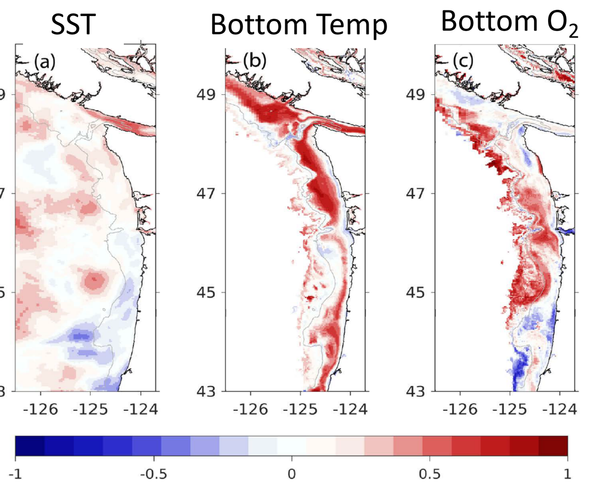


Fig. 4. Anomaly Correlation Coefficient (ACC) for seasonal forecast vs hindcast.[3,4] J-SCOPE has strong forecast skill for bottom conditions, where crabs live.

- NOAA's CFS (coupled air/sea/land model; Fig. 3) provides boundary & atm forcing of ROMS-based regional model with biogeochemistry
- Modeled fields: T, S, O, NO_3, Chl a; derived variables: pH, Ω
- Model skill evaluated[3,4] (Fig. 4)
- Fields applied to habitat models: sardine[5], hake[6], and crab

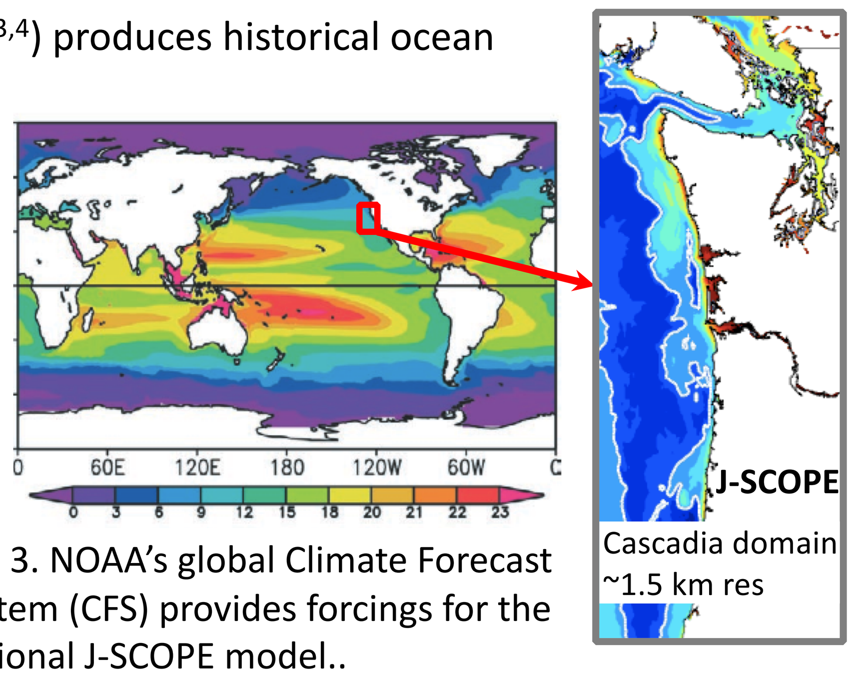


Fig. 3. NOAA's global Climate Forecast System (CFS) provides forcings for the regional J-SCOPE model..

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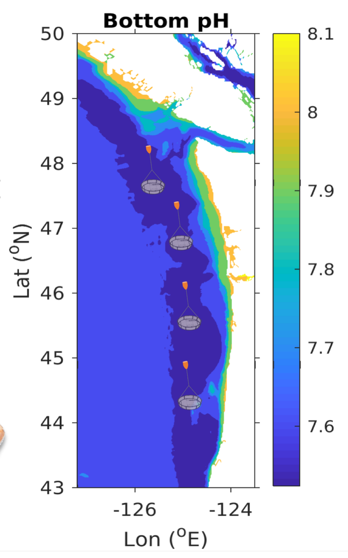
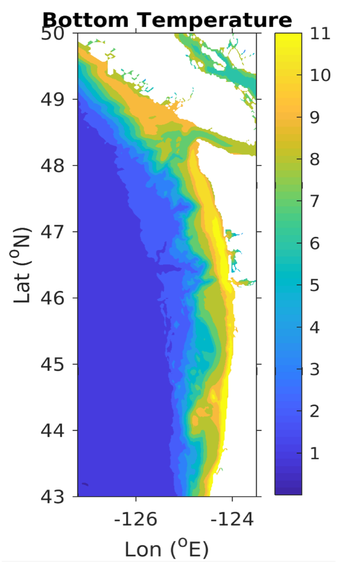
Three types of predictor variables:

1. Static environmental conditions and fishing behavior (i.e., when and where traps were fished; sources: bathymetry layers, fisheries logbooks)

2. Dynamic environmental conditions concurrent with and where crabs were caught (source: monthly-averaged J-SCOPE forecasts)



3. Lagged environmental conditions experienced during earlier life stages (source: 3-4 yr lagged annually-averaged J-SCOPE hindcasts)



Methods: Develop a statistical model to predict crab catch rates

- Generalized additive model (GAM) developed in R (mgcv package):

log link function; smooth functions, k ≤ 3; Normal error

$$g(Y) = \beta_0 + f_1(x_1) + f_2(x_2) + \ldots + f_n(x_n) + e$$

crab catch rates (CPUE); predictor variables (S, D, L)

- GAM trained with fisheries logbook data from 2007/08 – 2015/16 fishing seasons
- Best GAM selected based on minimum Akaike Information Criterion (AIC) score
- GAM validated with fisheries logbook data from 2016/17 – 2018/19 fishing seasons (correlation coefficient (r); anomaly correlation coefficient (ACC))

References: [1]https://www.dfw.state.or.us/MRP/shellfish/commercial/crab/landings.asp. [2]Shanks, A.L., 2013, *Fish. Oceanogr*. **22**:263-272 [3]Siedlecki et al., 2016, *Sci. Rep*. **6**: 27203. [4]http://www.nanoos.org/products/j-scope/home.php. [5]Kaplan et al., 2016, *Fish. Oceanogr*. **25**:15-27. [6]Malick et al., (in prep).

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Result: Best catch model contains static, dynamic, and lagged predictor variables

- The best model (right) explained 56.1% of the deviance and had the lowest AIC score
- Crab catch rates depend heavily on day in the fishing season ("static" condition), but adding dynamic and lagged ocean conditions further improved model skill
- Response of catch rates to individual predictors may be useful for exploring underlying mechanisms and forecasting under particular conditions

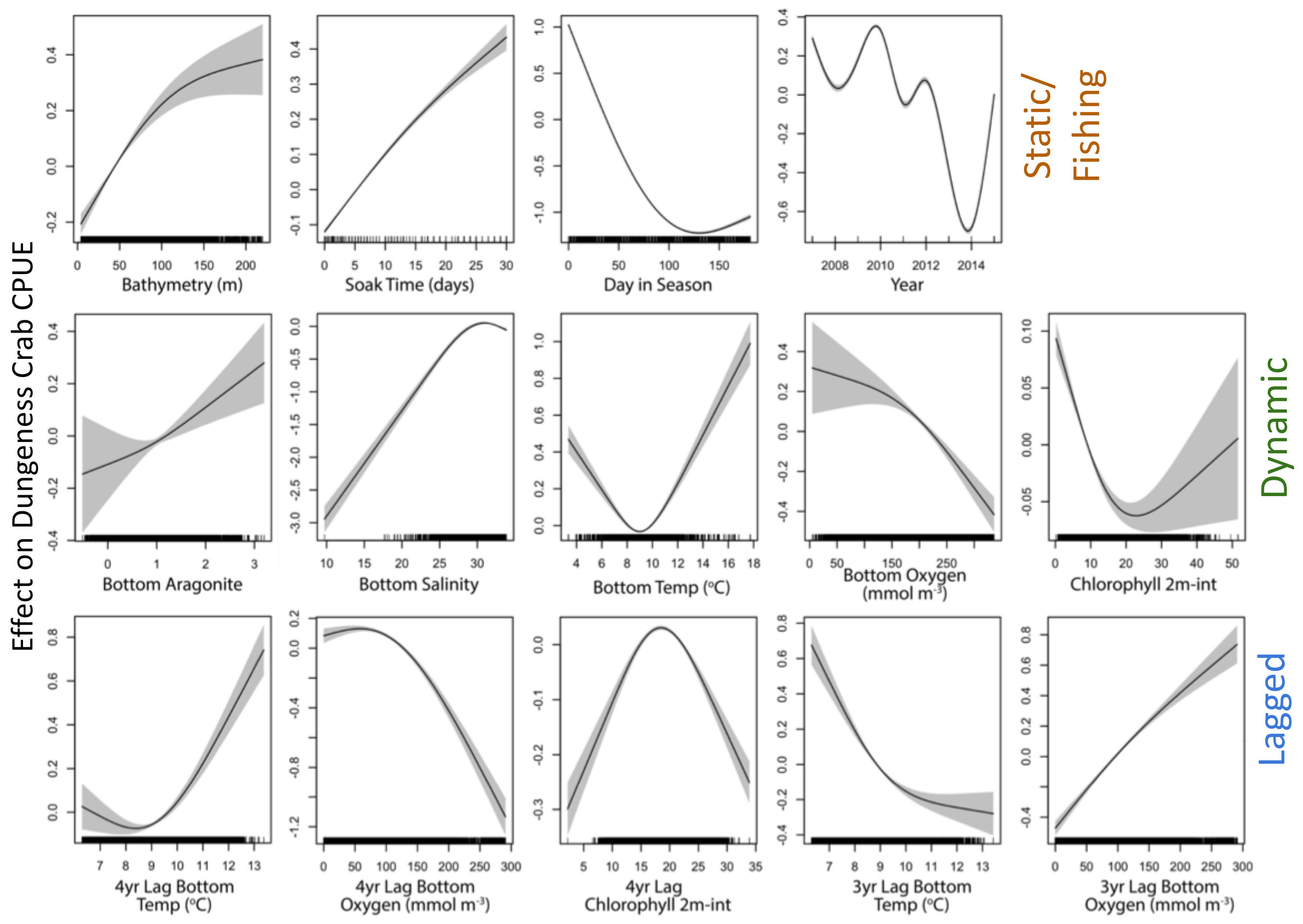


Fig. 4. (right) Effects of individual predictor variables on crab catch rates, when all other variables are held at their average values.

Result: Model reforecasts catch over time and space, when fishing behavior is known

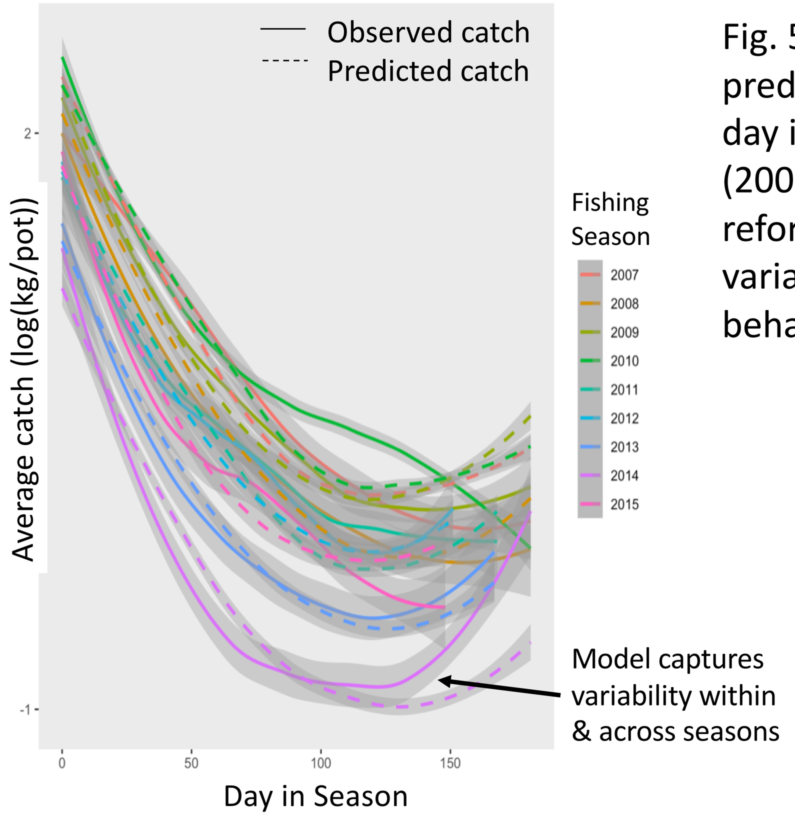
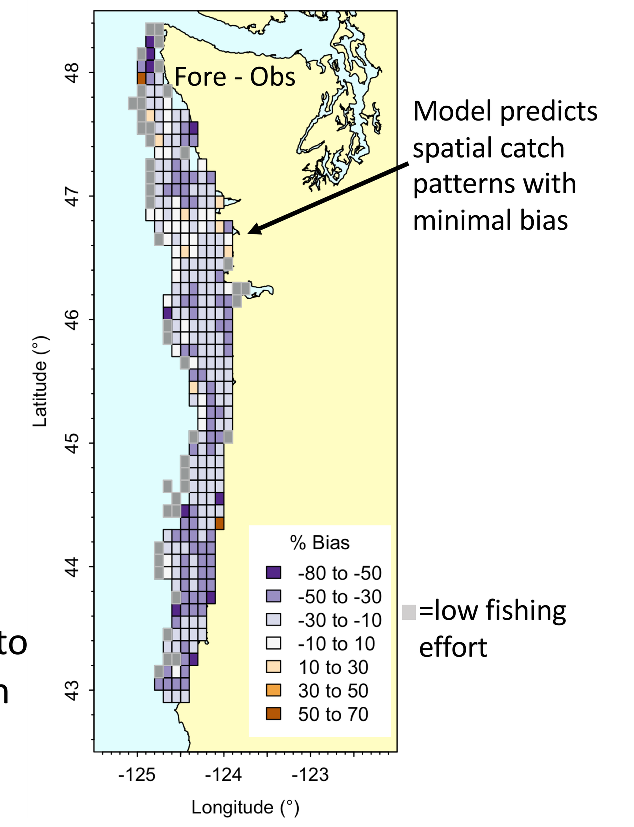


Fig. 5. (left) Observed (solid lines) and predicted (dashed) crab catch rates over day in season for model training years (2007/08 - 2015/16). The model skillfully reforecasts intraseasonal and interannual variability in crab catch rates when fishing behavior is known.

Fig. 6. (right) Average model bias (predicted – observed CPUE) over the entire domain for the training years (2007/08-2015/16). The model tends to underpredict catch rates, though catch is overpredicted in a few areas along the shelf break and nearshore.



Result: Variable fishing behavior complicates true forecasting

-Fishing effort varies widely over time and space (Fig. 7A & B), making it hard to predict for the upcoming season
- Our method sub-samples environmental conditions from the J-SCOPE ocean model at the times and locations where fishing is conducted, so our model is sensitive to this variable fishing behavior (Fig. 10C &D)
- We tried several subsampling schemes for predicting next season's fishing behavior, but model skill always decreased compared to using the observed fishing behavior

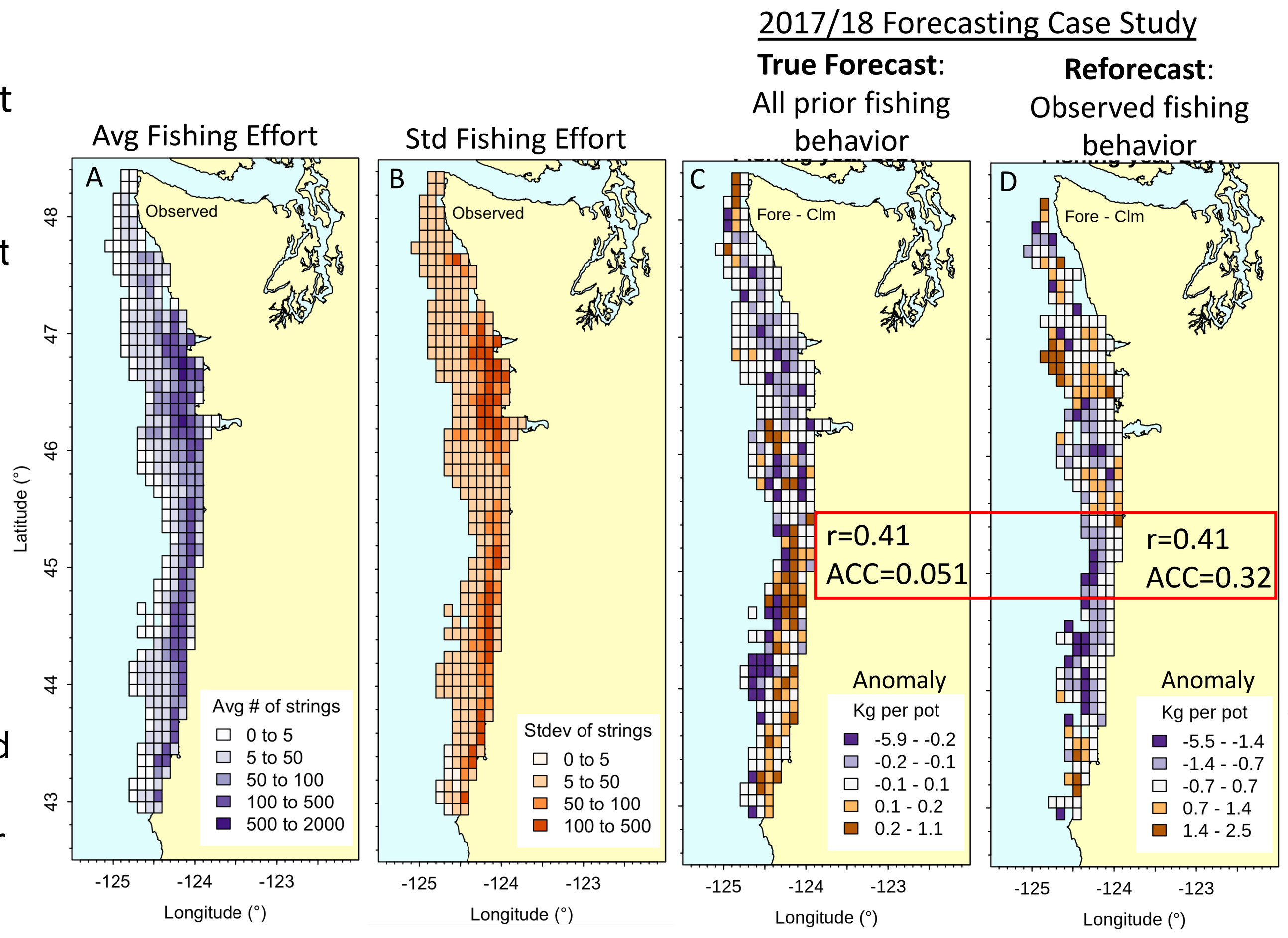


Fig. 7. (right) Fishing effort average (A) and standard deviation (B) for model training period (2007/08-2015/16). True forecast for 2017/18 using fishing behavior from all prior years (C) or observed fishing behavior for that season (D).

Summary and Next Steps

- **Ocean conditions are important drivers of interannual variability in crab catch** because the inclusion of dynamic and lagged ocean conditions, in addition to static conditions, generated the model with the best fit (i.e. lowest AIC)
- The **model skillfully reforecasts crab catch patterns** in space and time
- However, improved **forecasts of fishing behavior are necessary to provide true forecasts of crab catch**
- Currently no stock assessment exists, but **routine crab sampling would remove model uncertainty** associated with variable fishing behavior
- **Predictor variables' relationships to catch are still informative**