

An Exploration of the Spatiotemporal Distribution of Snow Crab in the Eastern Bering Sea: 1982 - 2018

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INTRODUCTION

Snow crab, *Chionoecetes opilio*, is the largest commercially fished crab species in the Bering Sea. Climate change has induced a northern shift in species distributions. Increased variability in the environment adds variance to models of species abundance and distribution patterns and reduces the accuracy of stock assessments used to predict trends and set catch quotas. Fisheries managers are also concerned that as species retreat north, groundfish predation will increase as species such as Pacific cod become more dominant.

Snow crab abundance and distribution in the eastern Bering Sea was explored in space and time using GIS geostatistical methods. Key ecological variables were incorporated from fisheries survey data in a multi-scale regression analysis to quantify the strength and scale of relationships with snow crab.

These GIS techniques support ecosystem-based management approaches which consider climate effects and other relationships in addition to traditional stock assessments and regression modeling, and can help to assess the efficacy of spatially allocated fishery catch quotas.



Figure 1. Study area, the eastern Bering Sea shelf

DATA & METHODS

National Marine Fisheries Service (NMFS) Eastern Bering Sea Bottom Trawl Survey, 1982 to 2018

- Stratified 20x20 nm grid of established fishing station locations across the shelf
- Standardized gear and sampling methods

Attribute Variables

- Location (survey station ID, coordinates)*
- Time (survey year date)
- Depth (m)
- Bottom Temperature (°C)
- Surface Temperature (°C)
- CPUE (catch per unit effort, number caught per nm²)

Snow Crab, Pacific Cod



*Opilio © Bryna Mills, 2017

*Geographic coordinates (latitude/longitude, decimal degrees) were mapped and projected to Alaska Albers Equal Area Conic for analysis and visualization

Spatiotemporal Analysis

- Space time cube (.netcdf) constructed from defined locations of survey stations using ArcGIS Pro
- Spatial neighborhood distance for analysis determined through Global Moran's I measure of spatial autocorrelation: peak z-score detected at 265 nm
- Annual time step
- Spatial and temporal trends in snow crab distribution explored through the Mann Kendall temporal trend test and Hot Spot Analysis

Regression Modeling

- Global scale relationships explored through ordinary least squares (OLS) regression
- Local scale relationships explored through geographically weighted regression (GWR)
- (latest available survey year selected for exploration)
- Dependent variable: snow crab CPUE 2018
- Independent variables: depth, bottom/surface temperature 2018, Pacific cod CPUE 2018
- Gaussian (continuous) model type
- Optimal kernel bandwidth of 45 nm determined via maximizing model performance to extract lowest Akaike's Information Criterion (AIC) score
- Model performance diagnostics compared for global and local regression results, GWR local variable coefficients mapped and explored further

RESULTS

Spatiotemporal Analysis

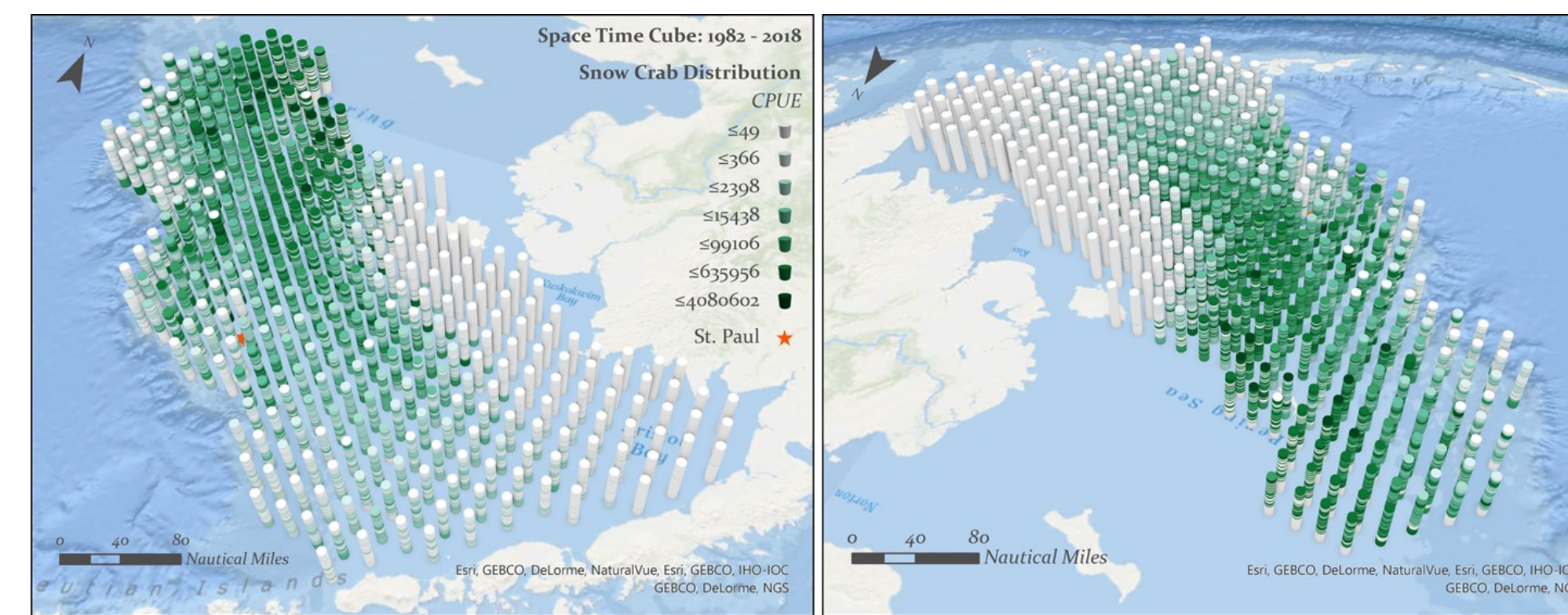


Figure 2. Space time cube showing snow crab CPUE from 1982 to 2018 (left: view to the north along the shelf; right: view to the south)

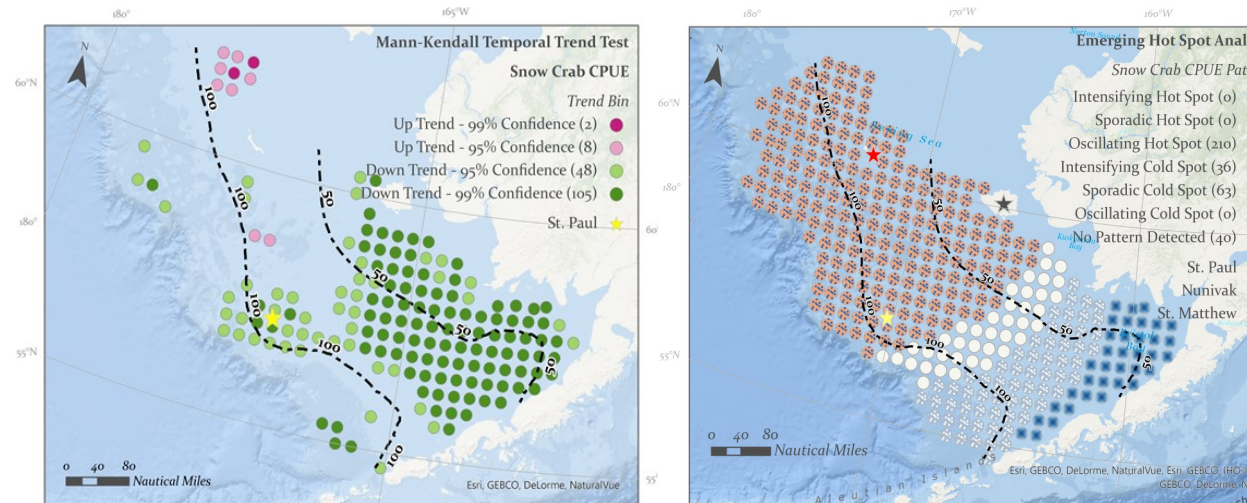


Figure 3. Mann Kendall temporal trends (left) and emerging hot spot analysis (right); both results show decreasing CPUE trends and diminishing abundance across the southern region of the shelf

Space Time Cube Stats

- 349 survey stations x 37 years = 12,913 space time bins

Snow Crab CPUE Trends

- No significant increase or decrease overall from 1982 to 2018 (globally)
- Regional differences detected between southern and northern survey regions masked in the global statistic

Regression Modeling

Global OLS Results

- Depth, bottom temperature and surface temperature were significantly related to snow crab CPUE in 2018, Pacific cod was not

- Bottom temperature showed the strongest (inverse) relationship according to the variable coefficient and the highest coefficient to error ratio (t-statistic)

- No redundancy or multicollinearity in model variables detected, heteroskedasticity or non-stationarity detected in snow crab CPUE, suggesting non-stable relationships

Local GWR Comparison

- GWR model performance and accuracy was improved over OLS according to reduced AIC scores and r² increase from .49 to .83% variance explained
- Neither model resulted in a significant amount of bias, residuals were normally distributed
- The inverse relationship between snow crab CPUE and bottom temperature in 2018 was strongest in the central survey region

Table 1. OLS regression model results (significant if p < .05*)

Variable	Coefficient	Std. Error	t-Statistic	Probability
Intercept	5.5649	3.0341	1.8341	0.0676
Depth	-0.0658	0.0088	-7.4375	0.0000*
Bottom Temperature	-2.6118	0.2627	-9.9405	0.0000*
Surface Temperature	1.8950	0.2685	7.0573	0.0000*
Pacific Cod CPUE	0.2084	0.1998	1.0430	0.2978

Table 2. Regression model performance comparison

Model Statistic	OLS	GWR
AICc	1655	1410
r ²	.49	.83

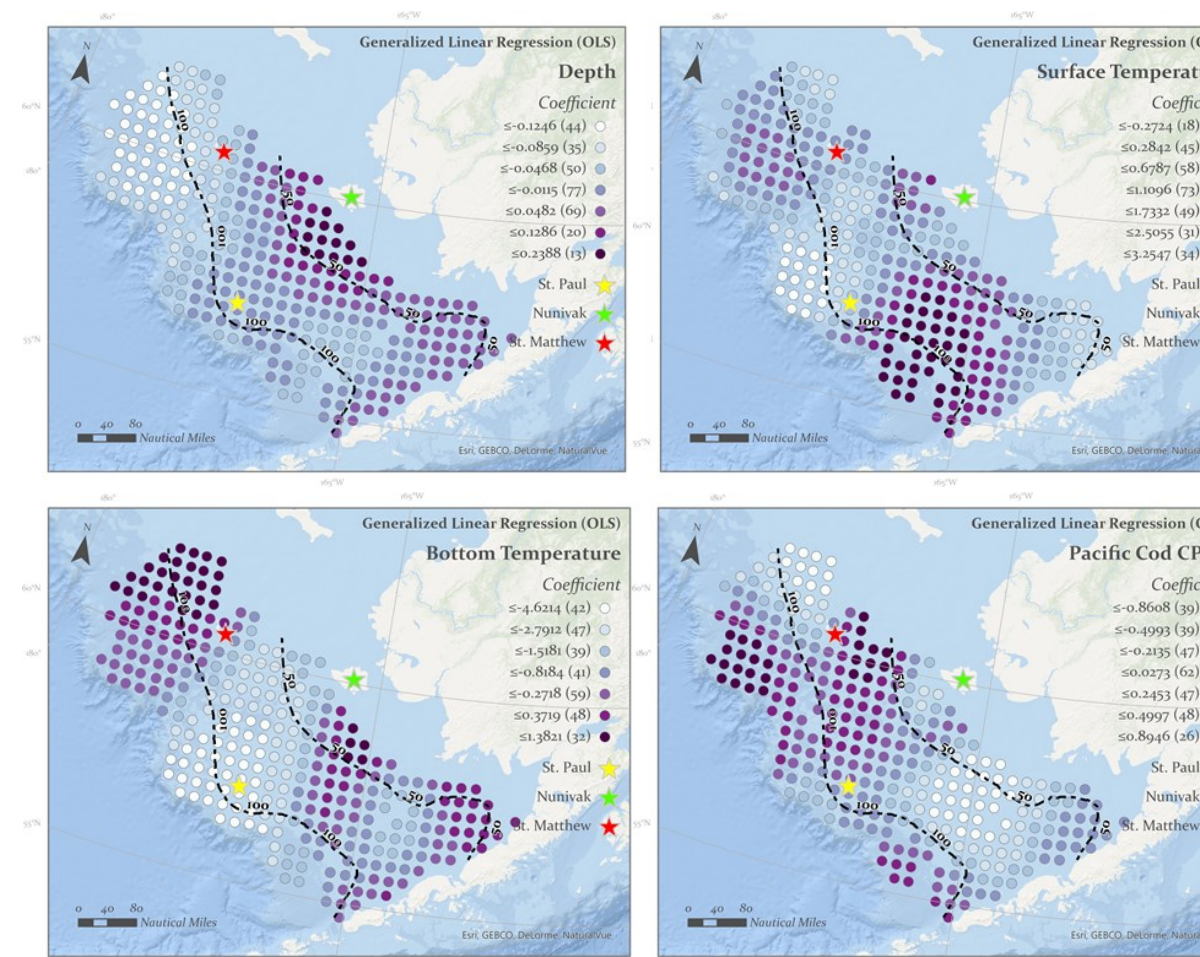


Figure 4. GWR local variable coefficient maps for each independent variable: depth (top left), surface temperature (top right), bottom temperature (bottom left), and Pacific cod CPUE

FURTHER RESEARCH

GWR Development

- Transition zones and impact areas highlighted by the local t-statistic or scaled magnitude of error maps developed from GWR local variable coefficient to error ratios should be further explored
- Test multiple years as the dependent variable and explore how the strength and spatial distribution of the relationships between snow crab CPUE and bottom temperature change over time

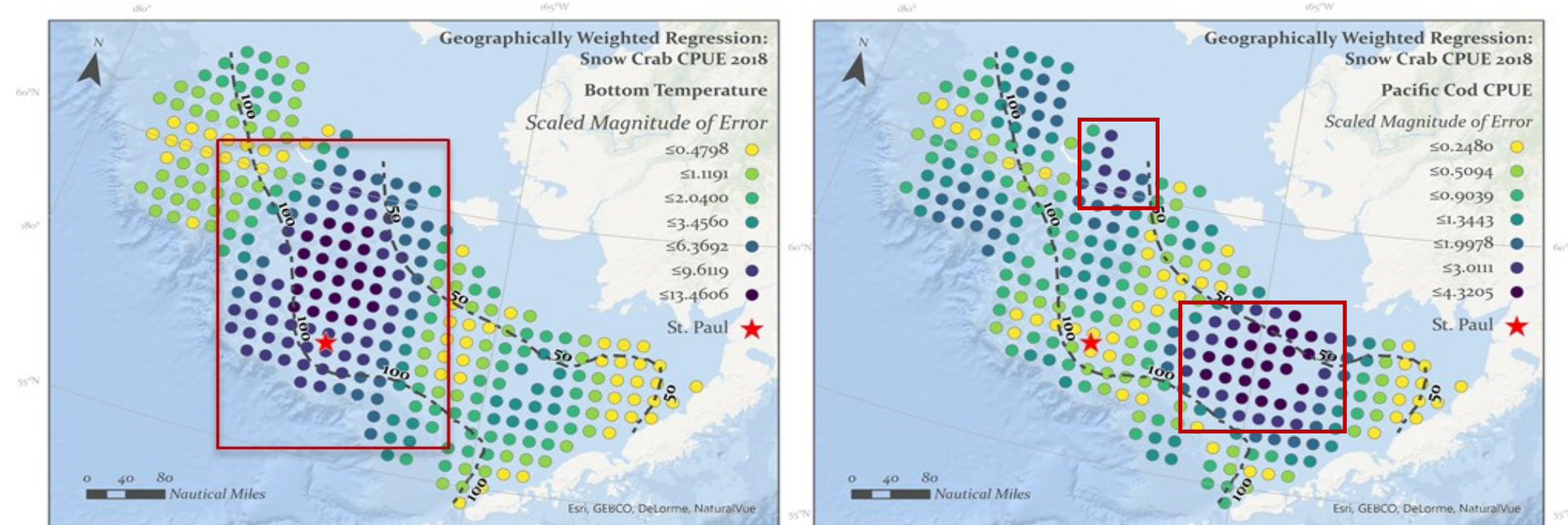


Figure 5. Scaled magnitude of error results or local t-statistics for GWR variables: coefficient to error ratios for bottom temperature (left) and Pacific cod CPUE (right); transition zones in yellow (lowest ratios), surrounding impact areas (highest ratios)

Data and Modeling Development

- Develop interpolation techniques to fill data gaps
- Explore spatial and temporal units of analysis: aggregate data according to trends detected in the spatiotemporal analysis
- Integrate external sources of data to develop model variables (i.e. satellite imagery or other oceanographic survey data, commercial fishery dependent data, conservation and limited take boundaries)
- Snow crab CPUE data distribution was skewed despite the log transformation applied in the regression analysis; box cox or another mode of normalization should be developed to improve regression modeling results and reliability

DISCUSSION

GIS enables customizable visualization of complex fisheries surveys datasets that can be effective communication tools for management and industry stakeholders. The data structure of the space time cube in ArcGIS Pro facilitates data parsing or aggregating as needed, and workflows can be customized and automated to explore the modifiable areal unit problem and test ranges of statistical parameters to fine tune regression models. These techniques can be catered towards any species or regional system assuming available data of adequate spatial and temporal resolution.

Snow crab distribution and abundance patterns are changing in the Bering Sea in response to dynamic environmental conditions. GIS and spatiotemporal analyses can provide context and scale for interpreting the significance of this change to support ecosystem-based management decisions on whether to increase or decrease allowable catch rates in specific areas. These exploratory results provide a strong statistical foundation to build more focused hypotheses and regression testing.

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