**Groundfish paper title goes here**

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**Abstract**

**Introduction**

Major environmental disasters such as oil spills are a persistent concern to marine ecosystems worldwide, with major oil disasters striking coastal seas with regularity throughout the past century affecting all oceans. Particularly well known spills include the Santa Barbara, CA oil spill of 1969 (Squire 1992), the Amoco Cadiz spill off France in 1978 (Conan et al. 1982, Gundlach et al. 1983), and the Deepwater Horizon spill of 2010 (Camilli et al. 2010, White et al. 2012). Oil spills is associated with significant impacts on the marine environment, including insults to ecological systems from the intertidal to the deep sea and from plankton to fish to marine mammals (Conan et al. 1982, Paine et al. 1996, Peterson et al. 2003).

The impacts of petroleum contamination on marine species are varied and complex. Documented effects range from the acute and direct (e.g. toxicological effects that cause serious injury or immediate death (Piatt & Ford 1996)) to the gradual and indirect (modifications to physiological pathways and reproductive characteristics (Collier et al. 1992, Hicken et al. 2011, Monson et al. 2011) ). In recent years, a consensus has developed indicating that even relatively low levels of exposure can have considerable fitness consequences for individuals (Collier et al. 1993, Hicken et al. 2011, Incardona et al. 2015, Sørhus et al. 2016). While detailed laboratory studies have repeatedly found negative consequences of petroleum related contaminants, connecting these excellent individual level studies to population or community level effect in natural populations has proven difficult

(Peterson 2001, Peterson et al. 2003, Awkerman et al. 2016) primarily because of the presence of natural environmental variation and sparse biological sampling may interfere with the detection of any signal of an oil spill (Paine et al. 1996).

Significant and enduring challenges complicate efforts to identify and understand the ecological effects of oil spills on marine communities. In many cases, information on important components of the ecosystem from before oil spills are lacking, restricting direct before-after comparisons of specific species or communities. Additionally, a substantial amount of spatial and habitat-driven variation of species and communities that confound direct comparison of oil exposed and unexposed areas.

The Exxon Valdez oil spill (hereafter “EVOS”) in March 1989 spilled approximately 257,000 barrels (36,000 mt) of crude oil into Prince William Sound, Alaska (Paine et al. 1996) [check this number].

In the weeks and months following the spill, oil was advected by wind and currents to the southwest, spreading into the Gulf of Alaska. While the exact dispersal path and final distribution of oil in water and sediments remains uncertain, the approximate distribution and extent of surface oil is documented (Wolfe et al. 1994) as are beaches that were contaminated with oil (Fig. 1). Furthermore, multiple lines of evidence suggest that oil from EVOS reached a wide range of habitats; oil was observed both directly in some deep water trawls (Armstrong et al. 1995) and a range of elevated petroleum metabolites were detected in a wide range of invertebrate and fish species from a wide spatial area (Krahn et al. 1992, Collier et al. 1993, Short & Heintz 1997, Sol et al. 2000, Peterson 2001, Marty et al. 2003). Estimates by (Wolfe et al. 1994) suggest about 20% or the oil reached the sediments in Prince William Sound and the Gulf of Alaska. Furthermore, in at least some habitats EVOS oil remains in the environment to the present day: oil has been documented nearly 30 years after the spill along shorelines (Peterson et al. 2003, Short et al. 2007).

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Despite undisputed evidence that oil spills have negative consequences for marine ecosystems and that EVOS was a widely dispersed and disruptive event in the Gulf of Alaska (Peterson et al. 2003), it has been difficult to quantify ecosystem wide consequences of EVOS. Direct mortality to charismatics species such as marine mammals (Garrott et al. 1993) and birds (Piatt et al. 1990, Piatt & Ford 1996) is well documented and some longer-term signals of oil impacts have been described for some species and habitats(Short et al. 2007, Monson et al. 2011). However, ecological systems are extraordinarily complex and theory suggests that many ecosystem level consequences of an event like EVOS are the result of indirect interactions and complex species-by-environment interactions (Peterson 2001, Peterson et al. 2003). Thus, a retrospective examination of the ecological consequences of EVOS 35 on is warranted.

Here we focus an understudied community in the context of EVOS - demersal fish communities of the central and western Gulf of Alaska to explore community responses to the EVOS spill over a broad spatial extent and long time periods. Demersal fish communities were exposed to EVOS as oil swept west out of Prince William Sound (Fig. 1, Collier et al. 1993, Sol et al. 2000). While the extent and exposure of fish communities to oil is almost wholly unknown, it is clear that some areas were exposed to significant amounts of oil while other, similar habitats in other areas were left unexposed. We leverage this spatial gradient in exposure to contrast demersal fish communities over the past 30 years (1984-2015) to compare groundfish communities in areas across a gradient of EVOS exposure. Specifically, we develop and apply a suite of spatio-temporal models to a fishery-indepent groundfish survey and calculate a range of community metrics to describe demersal fish communities. Then we compare both spatial and time-series patterns of areas that experienced a range of exposure to EVOS to identify any potential EVOS related signal in changes to the groundfish community. Rather than focus on a detailed analysis of individual species as has been done previously ((but see Wiens et al. 1996, Rice et al. 2001, Deriso et al. 2008, Monson et al. 2011), we assess aspects of the entire demersal fish community and examine available information for signals of EVOS…. SOMETHING MORE HERE.

**Methods**

*Data*

To assess spatial and temporal patterns in groundfish communities we used fisheries independent surveys conducted by the Alaska Fisheries Science Center (AFSC) between 1984 and 2015. This AFSC dataset has used the same methodology over the time series (stratified random sampling design, with the same bottom trawl sampling gear throughout the time series (Armistead & Nichol 1990, Stauffer 2004)). The average latitude and longitude of survey tows were used to represent the spatial locations of each sample, and these values were converted to ALBERS PROJECTION which is appropriate for the Gulf of Alaska (need to dig out methods for Albers projection). We focus on shallow waters and restrict our analysis to trawls conducted shallower than 600m. In total, we included 7601 individual hauls between 1984 and 2015.

We applied our models to 53 species groups. These groups represent species that were observed in at least 3% of the tows (>230 tows). 53? represent individual species and YY represent species complexes that were not identified to species separately during field sampling throughout the survey extent (supplementary TABLE). For brevity, we refer to these species and species groups simply as “species” subsequently. We provide the full species list and number of tows in which each species was observed in the supplement.

*Statistical modeling*

We constructed separate models for each groundfish species to understand the spatial and temporal patterns of occurrence and abundance. We estimated a model for each species independently and subsequently combined the model outputs to generate a suite of multi-species metrics of the groundfish communities. We first present the statistical model and then describe the spatio-temporal metrics groundfish communities.

In all models, we used catch per unit effort (kg∙hectare-1) observed on each trawl as the response variable. Because most species were absent from a large number of observed trawls, we separately modeled the presence and distribution of species density, adopting a delta-GLM approach with two sub-models (Maunder & Punt 2004, Shelton et al. 2014). Probability of occurrence, ***π****it*(***s***), of the *i*th species in year *t* for a set of locations ***s***, was modeled using a binomial GLMM with logit link,

(1)

where represents a matrix of fixed effect covariates at locations ***s*** in year *t*, represents a vector of coefficients for species *i*, and represents a vector of spatial random effects that follow a first-order autoregressive process:

(2)

where ***ρ*** represents the degree of autoregression in encounter probabilities and ***Σ*** represents spatial covariation in random effects (discussed below). Random effects were assumed to be autoregressive to account for variation not explicitly included in our model (e.g., variation due to the environment or population processes such as density dependence). Note that because trawl surveys are not conducted annually but triennially (1984-1999) or biennially (1999-2015) the autoregressive term refers to the date of the previous survey year, not the previous calendar year.

The second groundfish sub-model describes the distribution of CPUE conditional on the occurrence of at least one individual. We assumed that for this “positive” sub-model that groundfish CPUE was Gamma distributed and used a log-link,

(3)

where is a matrix of covariates corresponding to each haul location, represents the estimated species-specific coefficients, represent spatial random effects that again follow an autoregressive process (analogous to eqn 2, but with an independently derived covariance matrix). Then represents the mean and *σi* the scaleparameter of the Gamma distribution. Again this model incorporates only hauls in which the species was observed and so describes the CPUE of each species conditioned on the species presence.

For all models we used available haul level information about bottom depth (m) and included both linear and quadratic terms for log(depth) in the occurrence and positive models (Shelton et al. 2014, Tolimieri et al. 2015). We centered log(depth) by subtracting the mean log(depth) across all tows. We also considered two models for fixed year effects: i) we estimated a single intercept, and ii) we allowed for a distinct intercept for each year. As the intercept scales the occurrence or conditional CPUE, respectively for the entire region, models with variable intercepts allow for spatially uniform, region wide changes in occurrence or CPUE.

Covariance for spatial random effects was modeled as a function of distance using the Matérn function in the occurrence and positive models. The covariance between location *sj* and *sk* distance in the Matérn function is

(4)

where *τ*2 is the spatial variance, *Γ*() and *Kν()* represent the Gamma and Bessel functions, respectively, *djk* is the Euclidian distance between locations *sj* and *sk*, and *κ* is an estimated scaling parameter (Lindgren et al. 2011). The parameter *ν* controls the smoothness of the Matérn function and is usually fixed rather than estimated from data (when *ν*  = 0.5, the Matérn reduces to the exponential covariance function). Following previous work, we chose *ν* = 3/2; this allows the Matérn to be more flexible than the exponential, but also allows the function to be differentiable (Rasmussen & Williams 2006, Ward et al. 2015). The covariance matrices for the presence-absence and positive models for each species have separate parameters *τ*2 and *κ*, reflecting the assumptions that each model component may have a different variance or rate at which correlations decline as a function of distance. Further details can be found in (Ward et al. 2015, Ono et al. 2016).

We estimate the model using the integrated nested Laplace approximation as implemented in the R package INLA (www.r-inla.org,(Martins et al. 2013)). INLA approximates the inverse of the spatial variance-covariance matrix of fixed locations using three large sparse matrices using stochastic partial differential equations (Rue et al. 2009, Ruiz-Cárdenas et al. 2012). Estimation of the fixed effects is then done via marginal maximum likelihood using the Laplace approximation to approximate the integral across random effects, and random effects are estimated via Empirical Bayes. Using these estimates and non-informative priors on fixed effects, INLA allows Monte Carlo samples to be generated from the posterior distribution, as the Laplace approximation to the marginal likelihood.

Four models were estimated for each species: two occurrence models and two positive models. For each submodel, we estimated one model with a single intercept and one with a year-specific intercept. We compared single and year-specific models using posterior predictive plots and deviance information criterion (DIC) to then identifed preferred models for each species.

***Generating predictive densities for each species***

After estimating the two sub-models for each species, we used the estimated models to generate predicted densities for Gulf of Alaska. We projected our model estimates to the center of 2x2 km grid created for the entire Gulf of Alaska (add details of the projection to a supplement). We generated 1,000 Markov Chain Monte Carlo (MCMC) samples from the joint approximate posterior density for each species and for each MCMC sample we predicted a density for each sub-model to the 2x2km grid. We then combined the occurrence and positive models to generate an unconditional expectation for CPUE for each grid cell. Using MCMC samples from the full posterior distribution maintains the spatio-temporal correlation structure of the estimated parameters and random effects and properly accounts for uncertainty in these estimates. Because the occurrence and positive models are estimated independently, we can calculate the unconditional expectation for CPUE of species at time *t* and location *s* by multiplying each MCMC sample from the occurrence and positive model. Specifically, for the *g*th MCMC sample, the unconditional CPUE estimate is and has units kg∙hectare-1.

***Defining areas for comparison across the Gulf of Alaska***

We identified eleven areas across the Gulf of Alaska to compare groundfish communities through time (Fig. 1). Each area represents habitat between 50 and 150m deep divided by natural bathymetric breaks (canyons) resulting in irregularly shaped areas that range in size from 1,352 to over 8,000 km2 (Table 1). Due to the irregular bathymetry, some focal areas are divided by narrow channels while others are separated by large distances. This is an unavoidable aspect of the Gulf of Alaska bathymetry. The focal areas span a range of habitats with differing exposures to EVOS (Fig. 1; Wolfe et al. 1994, Niebauer et al. 1994, Short & Heintz 1997). The east-most area (Area 1) was almost wholly unexposed to EVOS oil as currents and wind drove EVOS oil west out of Prince William Sound. Areas 3, 4, and 5 were exposed to main flow of oil, as evidenced by both direct observation of surface sheens (REF) as well as shorelines documented to be oiled during EVOS (Fig. 1) (NOAA 1997). Areas 2 and 6 received some oil, but the majority of oil is thought to have traveled down Shelikof Straight, inside of Kodiak Island. Areas 7 to 11, may have been slightly exposed to EVOS, but direct observations of oil and oceanographic models suggest minimal impact for these areas (Wolfe et al. 1994, Niebauer et al. 1994, Short & Heintz 1997). Thus our comparison areas bracket the spill spatially and provide areas with more and less exposure to EVOS. We do not consider areas further east in the Gulf of Alaska due to a general agreement that Cape Suckling (144° W longitude) is a major biogeographic break separating the eastern and western Gulf of Alaska (REF).

***Community metrics***

For each area, we summarized the groundfish community by constructing four community metrics from the single-species spatio-temporal models. As we expect the effect of EVOS to manifest differentially across species with multiple life-history and functional attributes, we focused on community metrics that reflect species groups with different characteristics. For each metric, we summarize the predicted CPUE for each species in each year in each region using the MCMC draws for each 2x2 km grid cell. We combined information across grid cells within each area to generate an index-standardized mean estimate (and uncertainty) for CPUE (Shelton et al. 2012, 2014, Ward et al. 2015) . Thus for each metric in each area, we have a time-series for each species for 1984 to 2015. We combined these species-specific metrics to generate multi-species community metrics for each area in each year. We describe the multi-species metrics and how they map onto expected EVOS impacts in turn.

*Total biomass*. This is the simplest attribute and reflects the sum of all 53 fish species estimated by the spatio-temporal model. We hypothesized that total biomass would exhibit an overall decline if EVOS initiated a decrease in productivity as a result of persistent, low level toxicity, that negatively affected reproduction, growth, or survival at the community scale.

*Feeding Guild.* We definedguilds for Gulf of Alaska groundfish based on the categorization of species primary feeding habitat: pelagic (P) or benthic (B) foragers (Aydin et al. 2007, Gaichas et al. 2009). In addition, we categorized the eight largest and most voracious fish predators in the system as apex (A) predators (including Lingcod, *Ophiodon elongates,* and Pacific halibut, *Hippoglossus stenolepis;* Table XX*).* As the majority of EVOS oil in these habitat is thought to be present in benthic sediments, we hypothesize that benthic feeders would be most likely to exhibit a response to EVOS, though Apex predators may respond indirectly via foodweb connections.

*Diet classification.* We classified species based on their published dietary preferences. We use published diet data for each species (Aydin et al. 2007) to classify the dominant prey type for each species. We defined species diet as predominantly invertebrate (>80% of diet is invertebrates; I), predominantly fish (>80% of diet is fish; F), or generalist (diet is between 20 and 80% for both fish and invertebrates). We hypothesize that species with diets based heavily upon invertebrates will exhibit a greater population decline…

*Recruitment interval.* Hydrocarbons pollution effects are documented to be particularly detrimental to early life-stages of fish ((Hicken et al. 2011, Incardona et al. 2015, Sørhus et al. 2016). However, as the trawl survey only catches species that are generally longer than 15cm standard length, the lag between the exposure of larvae to the oil and when juvenile fish are observed in the survey will vary among species. Therefore we divided species into three groups by the number of years expected between parturition and achieving a size of 20cm (a size at which survey capture efficiency is close to one; REF). We categorized this interval as short (<2 years), medium (2 to 4 years), or long (>4 years). We defined the interval using published parameters for the Von Bertalanffy growth curve and generated a predicted age to reach 15cm. For species with multiple estimates of *k* and *L∞* we used the median estimate. For a few species, we could not find published growth parameter. In these cases we used available estimates from similar species in the same family. We hypothesize that shorter recruitment interval species will exhibit an immediate effect of EVOS while longer recruitment interval species will exhibit delayed effects.

We initially considered additional groupings based upon the reproductive characteristics of fish (e.g. oviparous versus ovoviviparous) but discovered that classification by reproductive characteristics produced groups the coincided almost identically with guilds and produced virtually identical results. Therefore we omit detailed results for reproductive characteristics.

For all community metrics, we present four summaries to describe their change over time. First we present the raw time-series for each focal area to visually examine the time-series for evidence of a shock provided by EVOS. Second, to compare among areas exposed to we calculate a linear trend for each area post-spill (1990-2015). Ideally, we would compare trends before and after the spill but with only two surveys occurring before EVOS, breakpoint analysis is not statistically feasible. Third, we compare the variability of each metric during the post-spill period using the coefficient of variation (CV = standard deviation/mean). We calculated the CV using the deviations from the linear trend to estimate the standard deviation and the overall mean abundance from 1990 to 2015.

Finally, we calculated matrics of synchrony across the entire 53 species community

Box car correlations, etc.

**Results**

We successfully estimated spatio-temporal models for 53 species (Table 2) and generated predictions for each of the 2x2 km grid cells in the Gulf of Alaska. We then combined predicted densities into our multi-species metrics for each of the focal areas. Our analysis revealed substantial variation among areas across all community metrics (Fig. 2). For example, areas varied more than three fold in total biomass and in general the relative rank of individual areas tended to be stable through time; low biomass areas tended to remain low biomass areas and high biomass areas tend to remain high biomass areas. In general, the raw time-series from three focal areas most exposed to EVOS do not appear notably different than other areas in the GOA. This is true for total biomass as well as all guilds, diet types, and recruitment categories (Fig. 2).

However, examining raw time-series by eye can be difficult, so examine both linear trends (Fig. 3) and temporal variability (as measured by CV; Fig. 4) for each metric in each region. Here, we do see an association between negative linear trends in total biomass and EVOS exposure with the three most exposed areas having strongly negative trends while control regions had zero or positive trends. Of the two areas with moderate EVOS exposure, one had a strong negative trend and the other had no trend. While the total biomass trend was not driven by a single species or group, the negative trend in EVOS regions total biomass was associated with a negative trend in the apex predator guild (Guild A) and near lower (near zero) trend in the pelagic forager guild (Guild P) in areas most exposed to EVOS. There was not an obvious pattern in trend for diet types and the trend for recruitment categories; species with short times to recruitment and long times to recruitment showed an inclination toward more negative trends.

In contrast to linear trends, there were no obvious patterns of temporal variability in response to EVOS. Values for CV were relatively similar across all areas in all metrics, though there were two categories, pelagic foragers (Guild P) and invertebrate consumers (Diet type I), that exhibited a general decline in CV from east to west (Areas 1 to 11).

Estimates of community-wide synchrony for the entire were low across all areas ( and permutation tests found no significant difference at any area between estimated synchrony and simulated communities in which species undergo uncorrelated fluctuations (*p* > 0.10 for all areas). Sliding window analysis of community synchrony also showed no obvious changes in synchrony across the time series. There is a suggestion of a slight decline in synchrony for EVOS areas relative to Control areas (Fig. 5) but any difference is very minor if it exists.

Finally, we did find evidence of find evidence of a time-varying signature in the cross correlation in total biomass among EVOS-affected areas and among Control areas (Fig. 6). At the beginning and end of the time-series, correlations among EVOS-affected, among Control, and between EVOS and Control, are indistinguishable. Both peaked during the 1990-1999 window before both declined gradually over the next 20 years. Interestingly, during this period the cross-correlation between EVOS-affected and Control areas decreased to become negative, indicating that biomass fluctuated in opposite directions between EVOS-affected and Control areas during these periods (Fig. 6).

**Discussion**

Identifying signatures of oil spill impacts in marine ecosystems is both easy and difficult. It is well documented that petroleum contamination can causes massive mortality of some species {e.g. Piatt:1996wa, Monson:2011ft} and can affect a range of physiological processes that affect growth and development in a range of other species {e.g. Hicken:2011is, Sorhus:2016cw, Incardona:2015id, Rice:2001if}. But how such effects translate from individuals and focal populations to full communities remains poorly understood. We focused on an ecologically and economically important component of the marine community, demersal groundfish, to attempt to detect a signature of EVOS over 35 years after the spill. EVOS contaminated substantial portions of the Gulf of Alaska as evidenced by both direct observations of oil, and evidence of exposure from sampled fish {Collier:1993ey}. {Armstrong:1995kf} concluded that there was likely minimal effect on groundfish populations was entirely based upon the assessment that a relatively small proportion of groundfish populations were exposed to acutely toxic densities of oil. Since Armstrong’s work, however, many researchers have shown that relatively low levels of petroleum contamination can lead to substantial physiological and fitness consequences for a range of fish species.

Unfortunately, we lack direct measurements of

: direct mortality of groundfish from EVOS

Uncertainty in biology

Data Limitations

Obscured by natural variability.

Given that EVOS did not produce mass, directed mortality of fish from petroleum toxicity (Armstrong et al. 1995), and that the effects of petroleum contamination are frequently non-lethal but affect long-term growth, reproduction, and survival (REFS), the effect of oil on demersal fish communities is expected to be indirect and complex. We adopted a community-level approach to detecting the signature of EVOS in demersal groundfish, constructing spatio-temporal models to determine the abundance of 53 groundfish species and then comparing time-series of discrete spatial areas with different levels of exposure to EVOS. Our approach showed that while EVOS and Control areas were indistinguishable in term of temporal variability (CV) and synchrony, we did show that EVOS-affected areas showed a decreasing trend in total biomass relative to Control areas. This signal appears to be driven largely by declines of apex predators in the EVOS-affected areas which include important fisheries species such as Lingcod (*Ophiodon elongatus*), Pacific cod (*Gadus macrocephalus*), and Pacific halibut (*Hippoglossus stenolepis*) and pelagic foragers such as Pacific hake (*Merluccius productus*) and multiple rockfish species in the genus *Sebastes.* In contrast to our expectations that benthic foragers would be most exposed to any oil toxicity, we observed no clear signal between EVOS and Control regions among benthic foragers.

As with any large scale and long-term study, it is impossible to control all possible covariates to isolate the effects of an oil spill. However, we have utilized a major fishery-independent data set and identified discrete areas within a standardize depth range and divided by natural breaks. Additionally, as our areas are contained within a single biogeographic region, all areas share major oceanographic drivers such as the Pacific Decadal Oscillation (PDO; Hare & Mantua 2000).

(Mueter & Norcross 2002)

variation persisted throughout the time series

areas had persistent variation in biomass across the entire time-series, indicating standing stock biomass varied greater than 3-fold among areas

focal area in each survey year. We assess the trends for the fish community in each of the focal spatial areas (Fig. 1).

We highlight the mean for

Plots:

Plot time series for each area (highlight areas expected to be most influenced by oil), look for change around 1989.

Each of the numbered circles is a shallow area that should have approximately similar fish communities based on physical parameters (50 to 150m) and they were all surveys before the exxon spill (1984 and 1987) and after the spill (1990 and on). They experienced different levels of direct exposure to the oil spill, though. We would expect that oil spill effects would be most intense near the oil (in space and time) and decline as a function of both distance from the spill and time since the spill. So we would expect to see the largest changes at the site number 3,4,5, somewhat less at 2,6,7, and much less at 1,8-11.

How do we measure changes among these areas to look at the effect of the spill?

First we estimate a model for the CPUE observed in the AFSC survey for each of 55 species for each year we have data (1984-2015; every 3 years, switch to every other year in 1999). We then generate a predictive density for each species on a 2x2km grid in each year. So we have a stack of 57 species distribution models for each location in each year. Using these predicted densities we can calculate all sorts of community metrics for each spatial location.

In this paper we focus on one metrics analyzed in several different ways:

· Total biomass

o By Taxonomy

§ Fish only (top 54 species)

§ Fish + common crabs (55 species)

§ Within Fish

· Sharks and allies vs. all others

o By life-habits

§ Pelagic vs. Benthic.

§ Functional feeding Groups

· there is some evidence that different groups have different exposure and susceptibility to oil.

After we have calculated a metric for each location, we can aggregate the predictions across all of the locations within a specified area to come up with a spatial mean or median for that metric in that year-area combination. I’d propose looking at each metric in three ways.

1. Treat each area as a univariate time-series for the metric.

a. Ask if there is a trend in the metric, or any notable changes at the dates that bracket the spill (1987 vs 1990 or 1993).

b. Ask if particular metrics return or diverge from pre-spill values

a. Any pattern with sites based on their proximity to the spill

2. Look at all areas simultaneously. Do the aggregate properties across all areas change with the spill

a. Is there a change in variance among sites

b. Does the pairwise correlation between site change in some way?

c. Are areas becoming more similar or more distinct post-spill?

**What is done so far:**

Work Completed (except where noted)

1. Identified the most common fish and mobile invert species

a. 52 fish

I. also did 6 species of abundant fish divided into “large” and “small” categories (20 cm break for all based on EcoPath model).

b. 3 crab

2. Fit several occurrence and abundance model for each.

a. Compared several models, picked a favorite.

I. Only used depth as a fixed covariate (bottom temperature proved inconvenient)

b. Saved model objects

3. Resampled from these estimated models to generate predictions for locations on a 2x2km grid in the Gulf of Alaska for each species (with uncertainty)

a. Made maps for each species

b. Made maps for aggregate quantities

i. Total biomass

1. All

2. Fish only

3. Cartilage vs. Boney

4. Pelagic vs. Benthic

5. To do:

a. Feeding categories.

b. Other functional traits.

4. Identified 11 areas with similar attributes to calculate index-standardized measures of abundance of each species.

a. Started creating univariate summaries of each site through time for aggregate measures.

b. Need to work up true portolio metrics

i. Variance, other metrics

c. To Do:

Assess whether we like the areas I chose or should add some.

In addition,

several fish species encountered during this study

have protracted pelagic larval stages, such as grena

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diers (Stein 1980; Stein and Pearcy 1982; Endo et al.

1993), Pacific flatnose, rockfishes,

deep-sea sole and

sablefish (Matarese et al. 1989).

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Details for the projection areas

|  |  |  |  |
| --- | --- | --- | --- |
| Focal area | km2 | Qualitative exposure to EVOS |  |
| 1 | 8364 | Zero |  |
| 2 | 2136 | Medium |  |
| 3 | 1820 | High |  |
| 4 | 1352 | High |  |
| 5 | 2100 | High |  |
| 6 | 4572 | Medium |  |
| 7 | 7064 | Low |  |
| 8 | 5280 | Low |  |
| 9 | 2792 | Zero |  |
| 10 | 3732 | Zero |  |
| 11 | 7840 | Zero |  |

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Appendix A:

Guilds

Classification based on

* guilds by Aydin & Gaichas
* REEM diet database for GoA samples only, for all years that stomachs are available (I’ve used % weight to classify) <http://access.afsc.noaa.gov/REEM/WebDietData/DietTableIntro.php>

A = Fish apex predators

Lingcod

Sablefish

Grenadier

Bigmouth sculpin

Chinook salmon

Arrowtooth flounder

Pacific cod

Pacific halibut

P = Pelagic Foragers

Searcher

Chum salmon

Pacific hake

Atka mackerel

Pacific ocean perch

Redbanded rockfish

Silvergray rockfish

Northern rockfish

Redstripe rockfish

Harlequin rockfish

Sharpchin rockfish

Shortraker rockfish

Rougheye/Blackspotted rockfish (“Sebastes group 2)

Dusky/Dark rockfish (“Sebastes group 1)

Prowfish

Lanternfish

Pollock

Capelin

B = Benthic Foragers

Big skate

Longnose skate

Aleutian skate

Sandpaper skate

Rex sole

Yellow irish lord

Kelp greenling

Flathead sole

Spotted ratfish

Butter sole

Rock soles

Yellowfin sole

Shortfin eelpout

Watted eelpout

Slender sole

Dover sole

English sole

Starry flounder

Alaska plaice

Sturgeon poacher

Rosethorn rockfish

Shortspine thornyhead

Dogfish

Spinyhead sculpin

Darkfin sculpin

Great sculpin

E = Motile epifauna (crabs, starfish)

S = Structural epifauna (corals, sponges)

N = Infauna (clams, worms)

Sometimes there's a slope box broken out from apex predators:  ex: sablefish, grenadier, turbot in Bering.

Diets

I = invertebrate prey

F = fish prey

B = demersal prey

C = pelagic prey

G = generalist (I called something a generalist if it consumes both Invert & Fish prey (threshold = 20% diet by weight))

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