**Groundfish paper title goes here**

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**Abstract**

**Introduction**

Significant and enduring challenges have complicated efforts to identify and understand the ecological effects of the Exxon Valdez oil spill on marine communities. These include i) a general lack of pre-spill data that restricts direct before-after comparisons of specific species or communities and ii) a substantial amount of spatial and habitat-driven variation of species and communities that confound direct comparison of oil exposed and unexposed areas.

It is well known that exposure to petroleum contamination can have wide-ranging effects on marine species. Documented effects of petroleum range from the acute and direct (e.g. toxicological effects that cause serious injury or immediate death) to the gradual and indirect (modifications to physiological pathways and reproductive characteristics). 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). 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

(Awkerman et al., 2016; Peterson et al., 2003).

The Exxon Valdez Oil Spill (hereafter “EVOS”) in March 1989 spilled approximately 257 thousand barrels (36,000 mt) of crude oil into Prince William Sound, Alaska (Paine, Ruesink, Sun, & Soulanille, 1996).

Over the following weeks and months the 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 received oiling. 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 (Collier et al., 1993; Krahn et al., 1992; Marty, Hoffmann, Okihiro, Hepler, & Hanes, 2003; Peterson, 2001; Sol, Johnson, Horness, & Collier, 2000). In at least some habitats EVOS oil persists in the environment: oil has been documented nearly 30 years after the spill along shorelines (Peterson et al., 2003; Short et al., 2007)

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, Eberhardt, & Burn, 1993) and birds (Piatt & Ford, 1996; Piatt, Lensink, Butler, & Nysewander, 1990) is well documented. However, ecological systems are extraordinarily complex systems 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 (BEST REFS). Thus, a retrospective examination of the ecological consequences of EVOS 35 years later is warranted.

Add in some ref to (Wolfe et al., 1994) which states that about 20% or the oil reached the sediments in PWS and in GOA.

Here we focus on demersal fish communities of the central and western Gulf of Alaska and use available information to explore community responses to the EVOS spill. 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 oiling while other, similar habitats were left unexposed. We leverage this spatial gradient in exposure to contrast demersal fish communities over the past 30 years (1984-2015). Specifically, we develop and apply a suite of spatio-temporal models to a fishery-indepent groundfish survey, assess multiple metrics of demersal fish communities, and compare areas that experienced a range of exposure to EVOS to identify any potential EVOS related signal in changes to the groundfish community.

**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; Stauffer (2004) andArmistead (1993).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). As our interest was primarily in the waters most likely affected by EVOS, we restricted 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 spatiotemporal 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 spatio-temporal statistical model and then describe the spatio-temporal metrics of community change.

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 (Pennington 1983, Maunder and Punt 2004, Shelton et al. 2014). Probability of occurrence of the *i*th species in year *t* for a set of locations ***s***, ***π****it*(***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* represents the **shape** parameter 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, Thorson, Ward, & Feist, 2014; Tolimieri, Shelton, Feist, & Simon, 2015). We centered log(depth) by subtracting the mean. We also considered two models for fixed year effects: in one model we estimated a single intercept while in the other we allowed for a distinct intercept for each year. As the intercept scales the occurrence (or CPUE, respectively) for the entire region, models with variable intercepts allow for spatially uniform, region wide changes in occurrence or CPUE.

For the spatial random effects in the occurrence and positive models, we used the Matern function to model covariance as a function of Euclidian distance, so = *τ*2/*Γ*(*ν*)2ν-1 (*κdjk*)ν *K*ν(*κdjk*), is the covariance between location *sj* and *sk*, *τ*2 is the spatial variance, *Γ*() and *K*ν() 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, Rue, & Lindström, 2011). The parameter *ν* controls the smoothness of the Matern function and is usually fixed rather than estimated from data (when *ν*  = 0.5, the Matern reduces to the exponential covariance function). Following previous work, we chose *ν* = 3/2; this allows the Matern 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 (Ono et al., 2015; Ward et al., 2015).

We estimate the model using the integrated nested Laplace approximation as implemented in the R package INLA (www.r-inla.org,(Martins, Simpson, Lindgren, & Rue, 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, Martino, & Chopin, 2009; Ruiz-Cárdenas, Krainski, & Rue, 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 Bayesian priors on fixed effects), INLA allows Monte Carlo samples to be generated from the posterior distribution, as the Laplace approximation to the marginal likelihood.

For each species, we estimated two occurrence models and two positive models. For each submodel, we estimate one model with a single intercept and one with a year-specific intercept. We compare single and year-specific models using posterior predictive plots and deviance information criterion (DIC) and then identified 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). This results 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 Alaska coastline. The focal areas span a range of habitats with differing exposures to EVOS (Fig. 1). The east-most area (Area 1) was wholly unexposed to EVOS oil. 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). 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 contemporary accounts suggest minimal impact for these areas. 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 of that Cape Suckling (144° W longitude) is a substantial biogeographic break.

***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 focuse on community metrics that reflect species groups with different characteristics. For each of the metrics, 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 construct combine information across grid cells within each area to generate an index-standardized mean estimate (and uncertainty) for CPUE (Shelton et al., 2014; 2012; Ward et al., 2015) . Thus for each metric in each area, we have a time-series for each species for 1984 to 2015. We combine 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. Total biomass would be hypothesized to respond if EVOS initiated an overall decline in productivity as a result of persistent, low level toxicity to fish negatively affecting 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, Gaichas, Ortiz, Kinzey, & Friday, 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 expect this…

*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). 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 the juvenile fish will be observed in the survey will vary among species. Most fish species spawn SPRING-SUMMER (REF). 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 virtually all fish are captured; 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.

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 for each 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 survey before the spill, using a breakpoint analysis is not practicable. Third, we compare the variability of each metric during the post-spill period using the coefficient of variation (CV = standard deviation  mean-1). 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.

**Results**

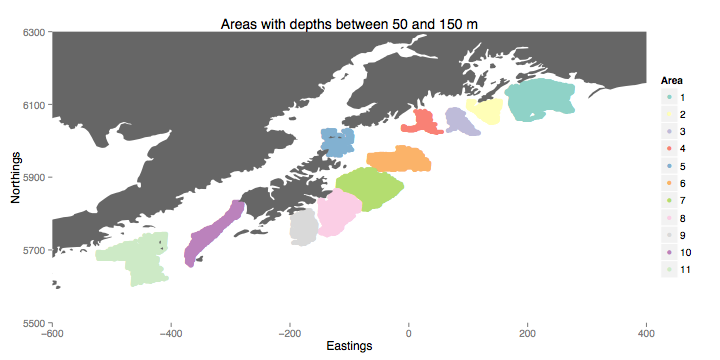
We successfully estimated spatio-temporal models for 53 species (Table 2) and generated density predictions for each of the 2x2 km grid cells in the Gulf of Alaska. We then combine predicted densities into our multi-species metrics for each of the focal areas. First we

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.

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

Magister armhook squid

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

Tanner crab

Pacific lyre crab

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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