**=Focal questions for groundfish**

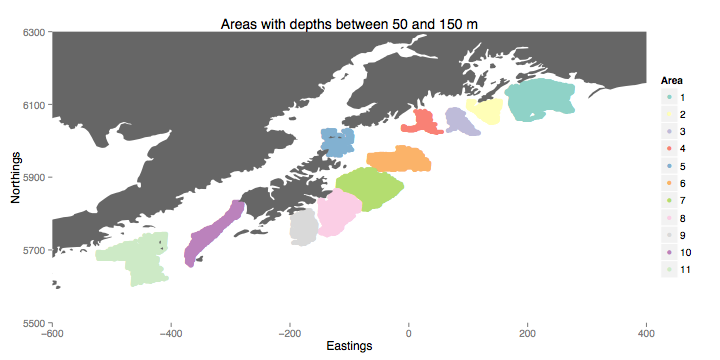
**1. Have there been detectable changes in spatial distribution of groundfish related to oil spill (space/time)?**

**a. Different responses depending on life history characteristics?**

**b. Shifts in diversity in groundfish assemblages.**

**Paper 1 (there is a lot here right now. Prob need to trim.)**

Divide the gulf of Alaska in to a number of discrete chunks. Like so:



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 (1984-2011; 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 I want to focus on these metrics

Total biomass

1. By taxonomy

-Fish only (top 54 species)

-Fish + common crabs (55 species)

-Within Fish

-Sharks and allies vs. all others

2. By life-habits

-Pelagic vs. Benthic.

-Functional feeding Group (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

c. 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.

ii. 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:

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

**Writing.**

**Introduction:**

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

Here we overcome both of these general limitations by applying spatio-temporal models to groundfish communities sampled in the Alaska Fisheries Science Center. We do THIS, then we do THAT.

Need to include:

· Oil stuff

o Evidence that the oil got to deep water

o Effect of oil is likely not direct mortality, rather reduced performance (reproductive success, growth, etc) from exposure to low levels of oil-derived toxics. (mostly very recent pubs)

o Fish far away from exxon had detectable oil metabolites

· Ecological theory also suggests that effects of a stressor may be lagged and indirect.

o So we focus on community metrics, not single species.

**Groundfish 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 2011 (AFSC survey REF).

The average latitude and longitude of survey tow 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.)

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; BEST REF?). As our interest was primarily in the waters likely most affected by the Exxon Valdez oil spill, we restricted our analysis to trawls conducted shallower that 600m. In total we included 7601 individual hauls between 1984 and 2011.

We applied our models to 55 species groups. These groups represent species that were observed in at least 270 survey tows. 53? represent individual species and YY represent species complexes that represent were not identified to species separately during field sampling throughout the survey extent (TABLE). For brevity, we refer to these as species and species groups simply as “species” subsequently. We provide the full species list and sample sizes for each species in the supplement.

For 6 abundant species, we used the size distribution data to divide our groundfish data into two components…. Big individuals and small individuals. We follow some ecopath models developed by Kerim and friends and use a 20cm cutoff to divide individuals into juvenile and adult size classes. Something about how the cutoff size was identified (chat with Mary H.) [not sure even if we will include

**Things to do for Data:**

Make map of trawl locations for each year.

· Write detailed methods for how I separated out the different sizes

o Dealing with no observed size data.

o Converting observed length to weight using allometric equations.

o Determining which fraction are “big” versus “small” and applying that to the CPUE data to generate CPUE for each size class.

**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 range of multi-species metrics of the groundfish communities. We first discuss the spatio-temporal statistical model before describing spatio-temporal metrics of community change.

In all models, we used catch per unit effort (kghectare-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 eulachon 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,*** *,* 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). Spatial random effects were assumed to be autoregressive to account for variation not explicitly included in our model (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 (1999-2011) the autoregressive term refers to the date of the previous survey year, not the previous calendar year.

For the second groundfish sub-model (hereafter positive model), we assumed that groundfish CPU was gamma distributed and used a log-link,

**(3)**

where is a matrix of covariates corresponding to each haul location (similar to ), represents the estimated species-specific coefficients, represent spatial random effects that again follow an autoregressive process (similar to eqn 2, but with a independently derived covariance matrix). Then represents the mean of the gamma distribution and represents the **shape** parameter of the gamma distribution. This model only uses the hauls in which the species was observed and so the positive model 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). We centered log(depth) by it’s mean before estimating the model. 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 , is the covariance between location and , is the spatial variance, and represent the gamma and Bessel functions, respectively, is the Euclidian distance between locations and , and is an estimated scaling parameter (Lindgren et al. 2011). The parameter controls the smoothness of the Matern function and is usually fixed rather than estimated from data (when = 0.5, the Matern reduces to the exponential covariance function). Following previous work, we chose = 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 , and , 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) and Ward et al. (2015).

Estimation of latent Gaussian Markov random fields is difficult, and can be

challenging in a Bayesian framework if the dimensionality of the knots or locations is large (Shelton et al. 2014). Recent advances have allowed the spatial covariance matrix to be approximated via stochastic partial differential equations (SPDE) as calculated within INLA (Rue et al. 2009, Ruiz-Cardenas et al. 2012). More specifically, INLA approximates the inverse of the spatial variance-covariance matrix of fixed locations using three large sparse matrices. Estimation of the fixed effects is then done via maximum marginal 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**

After the two sub-models were estimated for each species, we used the estimated models to generate predicted densities for the Gulf of Alaska. We projected our model estimates to the center of 2 x 2 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 sample from the full posterior distribution maintains the spatio-temporal correlation structure and 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* bymultiplying each MCMC sample from the occurrence and positive model. Specifically, for the *g*th MCMC sample, the unconditional CPUE estimate is in units kghectare-1.

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

Identified areas that were between 50 and 150m deep, divided by natural breaks (areas that were deeper (or shallower) than 150 m).

**Calculating community metrics**

There are a lot of ones that could be constructed.