



What spatial statistical model is best for predicting fisheries bycatch risk?

BRIAN STOCK

Thank you!

SIO

• Brice Semmens

SWFSC

Tomo Eguchi

NWFSC

- Eric Ward
- Essential Fish Habitat (Blake Feist)
- West Coast Groundfish Observer Program (Jason Jannot)

PIFSC

Hawaii Longline Observer Program (Eric Forney)



XSEDE

Extreme Science and Engineering Discovery Environment

"Target" vs. "bycatch"

Longline





"Target" vs. "bycatch"

Longline



Trawl

Introduction

Oceana (2014)

Bycatch is a big (spatial) issue

Protected species



Competing fisheries



Recovering species



Unmarketable species



Difficult when they move so much...



Introduction

Block et al. (2011)

Static vs. dynamic management

Dynamic

Static



Introduction

Oceana (2012)

Static vs. dynamic management

Dynamic

1. Effectively protected?

2. Huge loss of fishing area

Static



Introduction

Oceana (2012)

Static vs. dynamic management

Dynamic

EXPERIMENTAL PRODUCT

Avoid fishing between solid black 62.6°F and 65.3°F lines to help reduce leatherback and loggerhead sea turtle interactions Avoid fishing between solid black 72.3°F and 74.1°F lines or east of 140°W to help reduce leatherback sea turtle interactions



Introduction

Howell et al. (2008, 2015)

Static

Tools for dynamic management

Need map of bycatch risk



Tools for dynamic management

Need map of bycatch risk



Tools for dynamic management

Need map of bycatch risk



- temperature
- depth
- substrate
- spatial field





The data (fisheries observers)



West Coast Groundfish Trawl

- 2002-2013
- 55,835 tows



Hawaii Longline

- 1994-2014
- 16,714 sets (swordfish only)













"Species distribution models"

Fundamental ecological question: where are they?



- temperature
- depth
- substrate
- spatial field

More zeros than expected



Methods

Zuur et al. (2009)

Approach 1: Zero-inflated distributions

- ZI-Poisson
- ZI-Neg Binomial



Zuur et al. (2009)

Approach 2: Delta (hurdle) model



Methods

Zuur et al. (2009)

Approach 2: Delta (hurdle) model

Binomial

Pr(some bycatch)

$$logit(p_i) = log\left(\frac{p_i}{1 - p_i}\right) = X_i \beta$$
$$Y_i \sim Bernoulli(p_i)$$

Approach 2: Delta (hurdle) model



Pr(some bycatch)

Positive

E(bycatch | some bycatch) $log(\mu_i) = X_i \beta$ $Y_i \sim Gamma(\mu_i, \nu)$ for $Y_i > 0$

Approach 2: Delta (hurdle) model



Pr(some bycatch)

E(bycatch | some bycatch)

E(bycatch)





Goal: prediction

5-fold cross validation repeated 10x



Goal: prediction

5-fold cross validation repeated 10x

Binomial

AUC



RMSE, R^2 (pred – obs)

$$\sqrt{rac{\sum_{i=1}^n ({\hat y}_i-y_i)^2}{n}}$$



Simulate management:

1. Predict bycatch risk at test locations



Simulate management:

- 1. Predict bycatch risk at test locations
- 2. Remove X% of fishing effort with highest bycatch risk



Simulate management:

- 1. Predict bycatch risk at test locations
- 2. Remove X% of fishing effort with highest bycatch risk
- Calculate "prevented" bycatch and target catch (bycatch:target ratio)











obs ~ environmental predictors (temp, depth, ...) $Y_i \sim Bernoulli(logit^{-1}[X_i\beta])$ Binomial $Y_i \sim Gamma(e^{X_i\beta}, v)$ Positive

How much variability can we explain?

- with covariates
- without spatial locations









Why does spatial correlation matter?

- 1. Valid statistical inference
 - Observations not independent
 - Lower effective sample size (i.e. CI should be wider)




2. Get the temporal trend right



Methods

2. Get the temporal trend right



Methods

2. Get the temporal trend right



Methods

3. Effect of habitat vs. schooling





Agostini et al. (2008)

3. Effect of habitat vs. schooling



Methods

Agostini et al. (2008)

3. Effect of habitat vs. schooling



Methods

Agostini et al. (2008)





Wood (2006)

Methods



Methods



Gaussian Markov random field

• Models *covariance* as function of spatial locations obs ~ environmental predictors + $MVN(0, \Sigma)$





Gaussian Markov random field

• Models *covariance* as function of spatial locations obs ~ environmental predictors + $MVN(0, \Sigma)$

Problem...

- Σ has O(N²) elements
- $\,\circ\,$ Computations scale as O(N^3) from $|\Sigma|$ and Σ^{-1}

Methods

GLM

GAM

Gaussian Markov random field

• Models *covariance* as function of spatial locations obs ~ environmental predictors + $MVN(0, \Sigma)$

Solution:

RF

GMRF

• correlation = 0 for "far away" points \rightarrow sparse matrix





Methods



Lindgren, Rue, & Lindstrom (2011)

Methods



Gaussian Markov random field

Models *covariance* as function of spatial locations
obs ~ environmental predictors + MVN(0, Σ)

Increasing adoption in fisheries



Methods

GLM GAM	Gaussian Ma • Models <i>cova</i> obs ~ env	rkov random riance as funct ironmental pre	n field ion of sp edictors	patial loca + <i>MVN</i> (ations (0, Σ)	
GMRF	GMRF • Increasing adoption in fisheries					
	GITHUD This repo	geostatistical_delta-GLMM	Explore Features	Enterprise Pricing		
	Tool for geostatistical a	Tool for geostatistical analysis of survey data, for use when estimating an index of abundance				
	T45 commits	ا 1 branch و	> 8 releases	ক্টি 2 contributors		
	🐧 🛛 Branch: master 🗸	geostatistical_delta-GLMM / +		E		
	📛 James-Thorson fixed	bug in mean_D_tl computation	Latest cor	mmit 6c99fa7 11 hours ago		
	🖿 R	fixed bug in V3i		a day ago		
	🖬 data	adding South African grid		7 days ago		
	examples	aqqeq v31		a day ago		

Methods

Thorson et al. (2015)



Methods

Breiman (2001)

GLM	

RF

- Machine learning, designed for prediction
- "Black box"
 - Predictor-bycatch relationships not modeled
 - No spatial field (add LAT, LON)



Breiman (2001)

Methods

Bycatch risk maps



Results B

Binomial

Generally: GLM < GAM < GMRF < RF



Generally: GLM < GAM < GMRF < RF

Less clear for rarer species



Generally: GLM < GAM < GMRF < RF



Results

Positive

Q3: How much bycatch can they prevent?



Results

Conclusions

Q1: Which spatial model best predicts bycatch?

Q2: Does the answer depend on species?

No, **RF** had consistent advantage

(larger for species with higher bycatch rates)

Q3: How much bycatch can they prevent?

Enough to consider using them in management

Results

Discussion

If the goal is purely *prediction*:

...but if we care about *inference on processes* affecting bycatch:

Discussion

Covariate effects



Discussion

Palczewksa (2013), Welling (2016)

Covariate effects

Are random forests really "black boxes"?





Discussion

Palczewksa (2013), Welling (2016)

Can random forests do *better*?

Identifying covariate interactions

0.1^{R^2= 0}:2² 0.4 0.3 Û 0.4 0.2 Û -0.2 -1 Day Pred Occ PHLB -2



Discussion

Thank you!

SIO

• Brice Semmens

SWFSC

Tomo Eguchi

NWFSC

- Eric Ward
- Essential Fish Habitat (Blake Feist)
- West Coast Groundfish Observer Program (Jason Jannot)

PIFSC

Hawaii Longline Observer Program (Eric Forney)



XSEDE

Extreme Science and Engineering Discovery Environment



Research opportunities in applied math/statistics and fisheries science

We can easily harvest too many fish



McCauley et al. 2015

We use models in management

1. Sustainable harvest \rightarrow need to assess populations

We use models in management

1. Sustainable harvest \rightarrow need to assess populations

2. Primarily, how many and where





Build & test population models

- 1. Stock assessment
- 2. Simulate alternative harvest strategies



Work with physics/climate modelers

What are the effects on fish of:

1. Ocean productivity?



Work with physics/climate modelers

What are the effects on fish of:

- 1. Ocean productivity?
- 2. Dispersal of eggs and larvae?



Work with physics/climate modelers

What are the effects on fish of:

- 1. Ocean productivity?
- 2. Dispersal of eggs and larvae?
- 3. Range shifts?



How to gauge model performance?

Goal: prediction

5-fold cross validation repeated 10x

Binomial

ROC curve (AUC)



RMSE

Methods
West Coast Groundfish covariates

Binomial \sim sst + sst² + Positive depth + depth² + distance to rocky substrate + size of rocky patch + in Rockfish Conservation Area + predicted occurrence (survey) + day of year + spatial field

Chapter 2: Bycatch prediction

Shelton et al. (2014)

Hawaii Longline covariates



spatial field

Chapter 2: Bycatch prediction

Shelton et al. (2014)

RF

- + Better at prediction
- + More complex covariate relationships (incl. interactions)
- + Much quicker to set up and run (~2 min vs. 5-15 hours)
- + Not just a "black box"?

GMRF

- + Statistical inference, marginal posteriors for covariate effects
- + Ability to include observation error

Discussion

Covariate effects



RF



Results

Palczewksa (2013), Welling (2016)

Covariate effects



 $Prediction_i = 0.11 = 0.18 - 0.06 (Depth) - 0.01 (Temp)$

Results

Palczewksa (2013), Welling (2016)