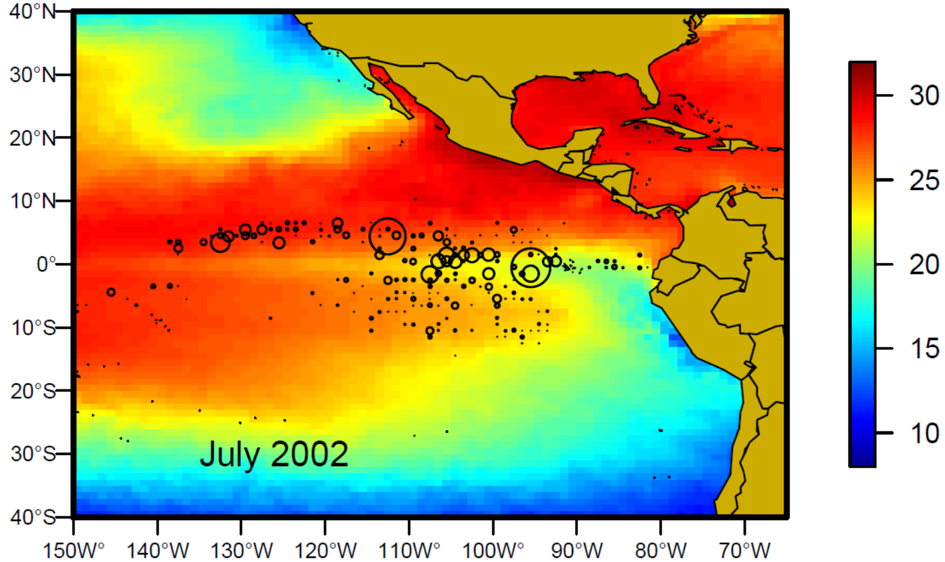
Spatio-Temporal Analysis for Near Real-Time Spatial Management of Large Pelagic Predators in the Eastern Pacific Ocean



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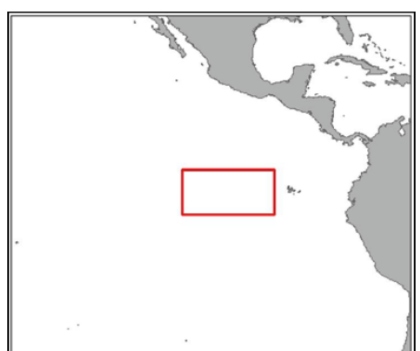
Inter-American Tropical Tuna Commission (IATTC)

3rd Meeting of the Scientific Advisory Committee

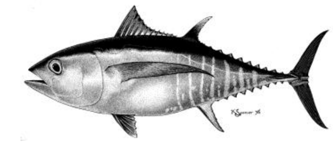
La Jolla, USA, May 15-18, 2012

Background - management

- IATTC management responsibilities in EPO:
  - Tuna (target species)
  - Bycatch species (elasmobranchs, small pelagics, others)
- Management measures:
  - Fishing effort reductions (temporal closures)
  - Static Spatial closures (“el corralito”)



Background – challenges



- Tuna:
  - Skipjack (SKJ) and bigeye (BET) are mixed on floating object (OBJ) sets
  - Reduce BET catch while not decreasing SKJ yields
  - Optimism about use of eco-sounder technologies to guess tuna composition (but experience required)
  - Fishing gear mitigation measures (no solution yet)
- Bycatch species:
  - Avoid large aggregations of juveniles/pregnant sharks (pupping/nursery grounds)
  - Avoid large aggregations of sea turtles

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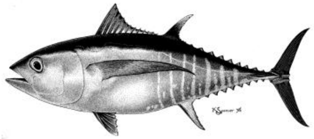
Dynamic spatial management

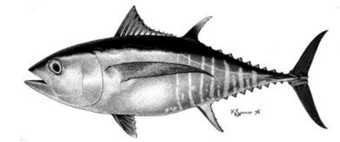


- Species distribution is highly dependent on oceanographic conditions which are dynamic
- Species are highly migratory
- Dynamic (rather than static) spatial closures

Objectives of study

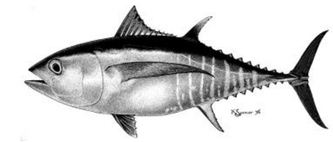
- Develop a spatio-temporal modeling approach which could guide dynamic spatial management in EPO
- Bigeye tuna (BET) as case study species

What do we need?



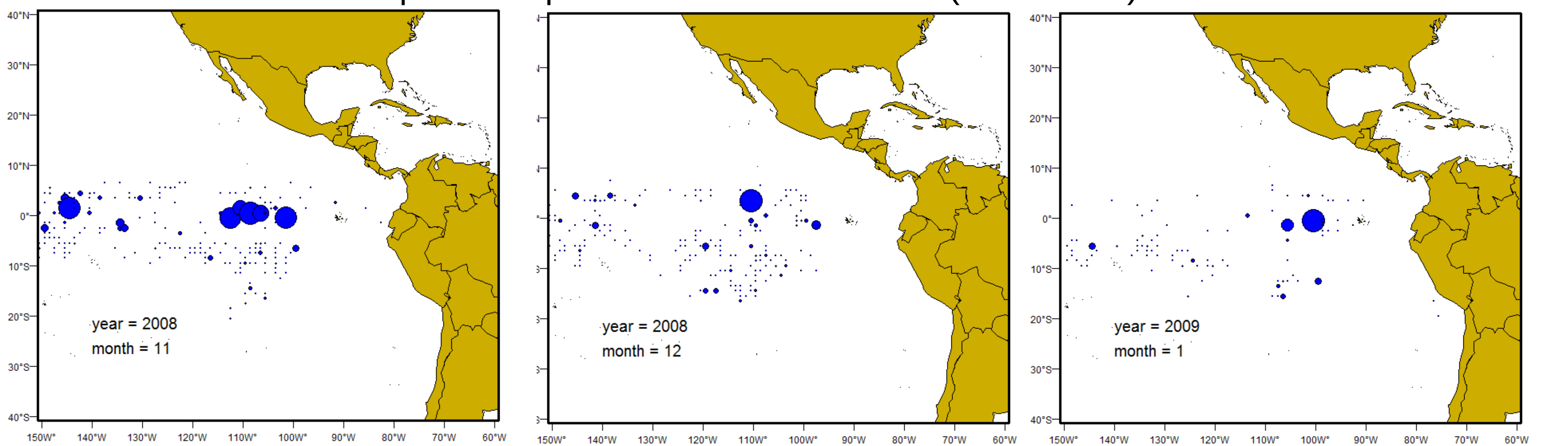
- Near real-time fishery data:
  - IATTC fishery observer program (100% coverage)
  - High spatio-temporal resolution (near real-time!)
- Near real-time oceanographic data
- Spatio-temporal model:
  - We want to predict catch in space over time (forecast)
  - Incorporate spatial structure of catches
  - Use oceanographic data as explanatory variables

Data sources - fishery

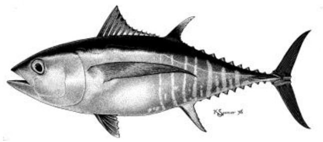


- Fishery data:
  - BET catch per set (from logbook and observer records)
  - Large (class 6) and medium-size vessels (classes 1-5)
  - Monthly aggregates at 1x1 degree squares
  - Training dataset (2005-2008); testing dataset (2009-2010)

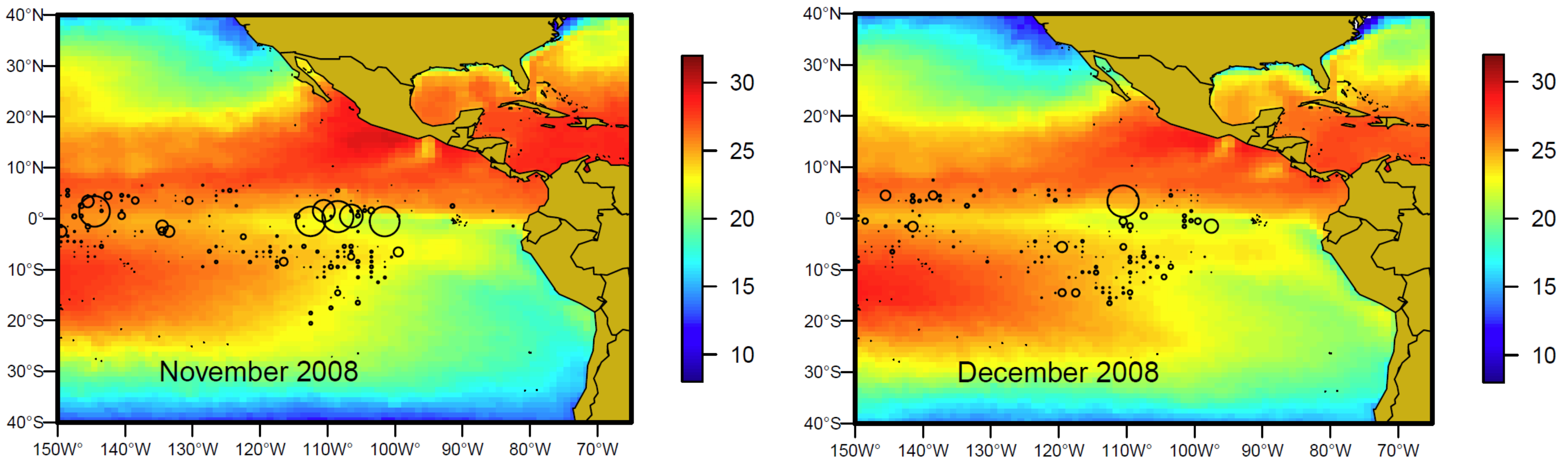
Spatio-temporal series of 48 months (2005-2008)



Data sources



- Oceanographic data:
  - Sea surface temperature (SST), sea surface height (SSH), chlorophyll a (CHLa), bottom depth, distance to land
  - Obtained from NOAA's Coastwatch
  - Monthly aggregates at 1x1 degree squares (2005-2010)



Geostatistical model - Regression kriging

- Hybrid model (2 components)
  - Correlation with auxiliary predictors (regression)
  - Spatial autocorrelation (ordinary kriging)

- Universal model of spatial variation

Spatially correlated component

Target variable

$$Z(s) = m(s) + \varepsilon'(s) + \varepsilon''$$

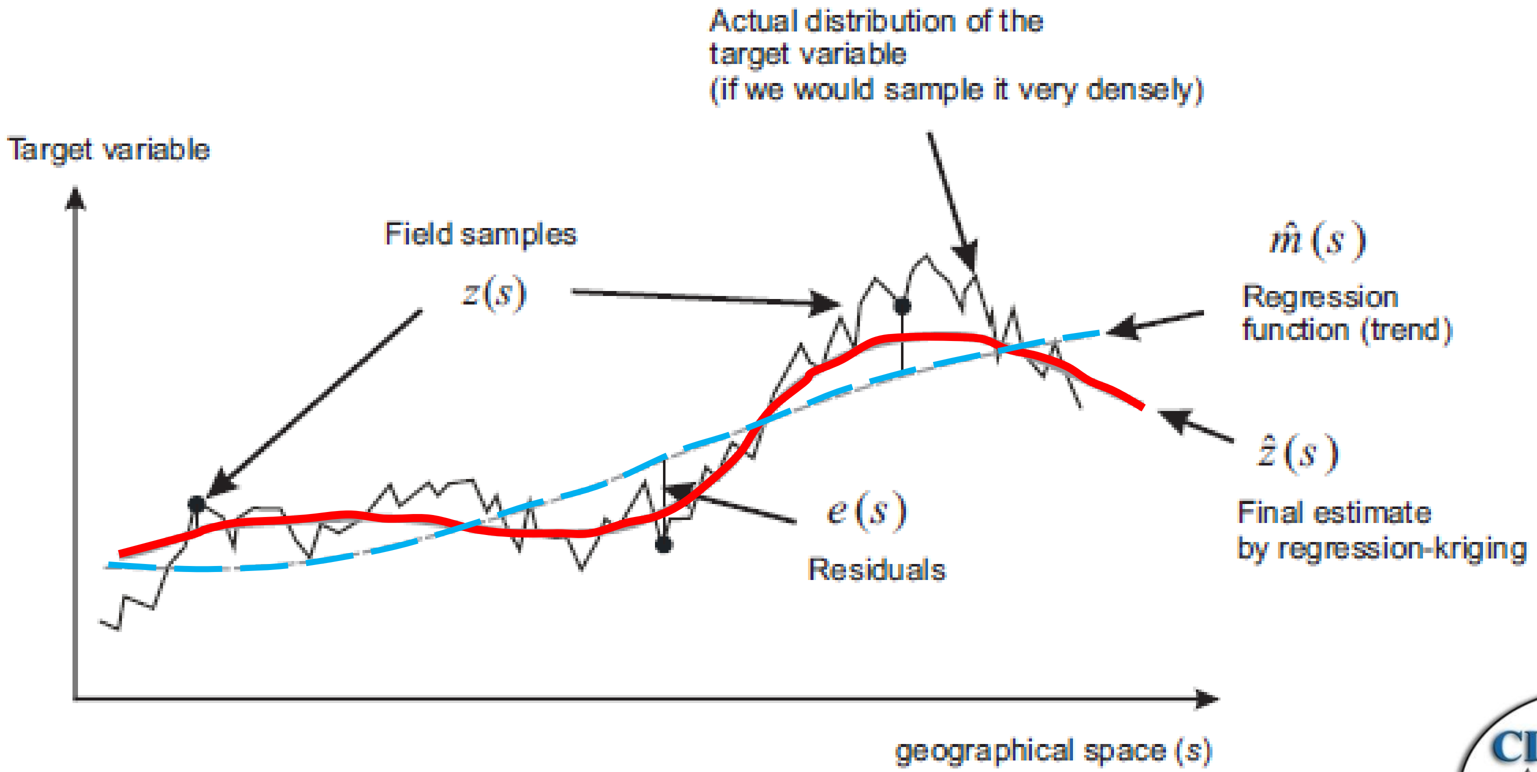
Measurement error

Deterministic component

Matheron (1969)

Geostatistical model - Regression kriging

$$Z(s) = m(s) + \varepsilon'(s) + \varepsilon''$$



From Hengl (2009)

Geostatistical model - Regression kriging

Spatially correlated component

Target variable

$$Z(s) = m(s) + \varepsilon'(s) + \varepsilon''$$

Measurement error

Deterministic component

- Deterministic component (global trend)
  - Generalized additive modes (GAM)
  - Oceanographic explanatory variables: SST, SSH, CHLa, bottom depth, distance to land

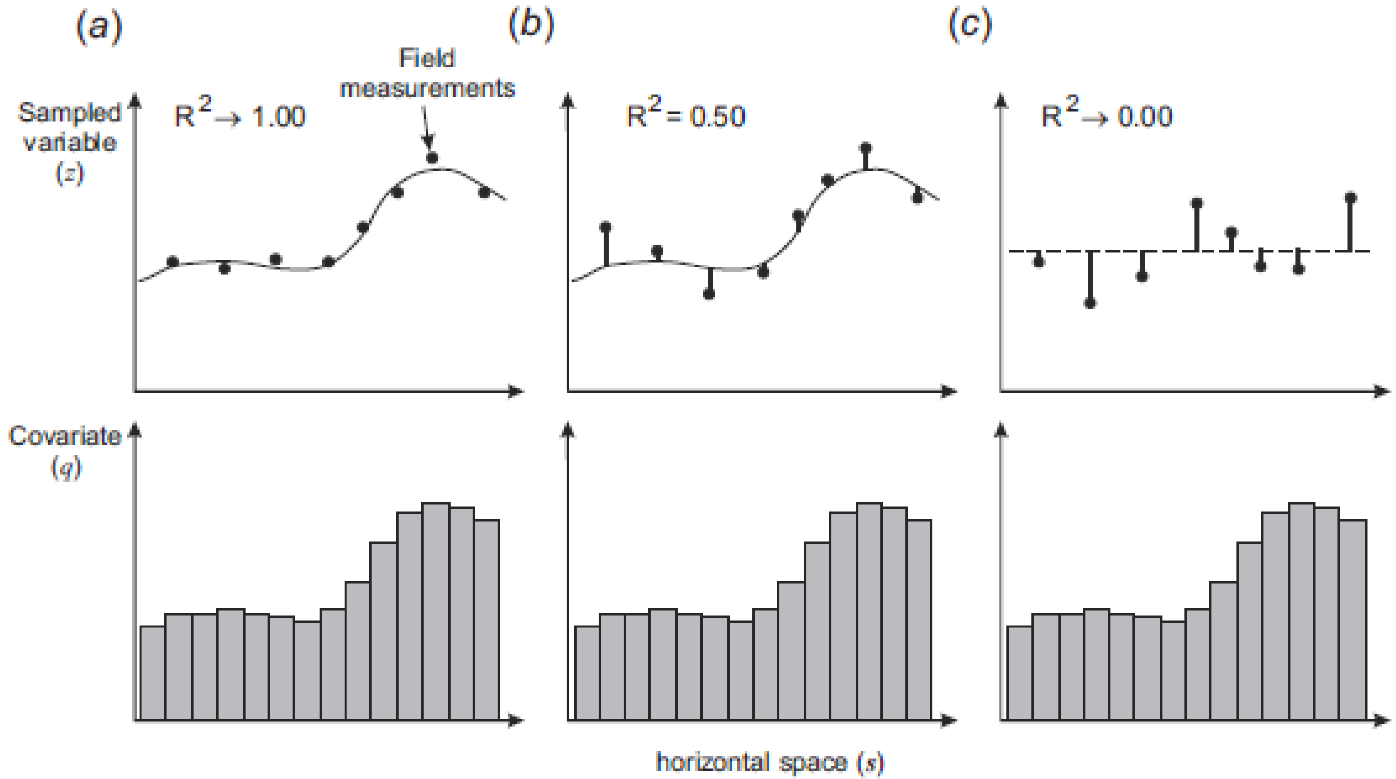
- Spatially correlated component (local trend)
  - Ordinary kriging on GAM residuals

Geostatistical model - Regression kriging

- If R square is high
- Residuals small
- Use pure regression

- If R square is moderate
- Combination of regression and kriging

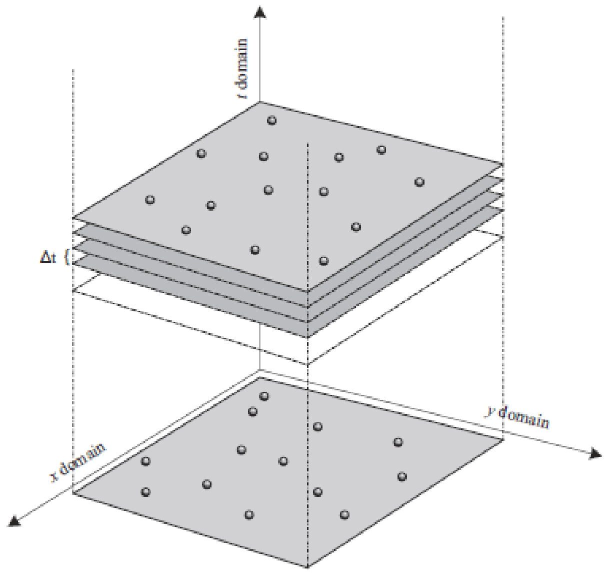
- If R square is small
- Poor correlation with covariates
- Use ordinary kriging



From Hengl (2009)

Spatial-temporal regression kriging

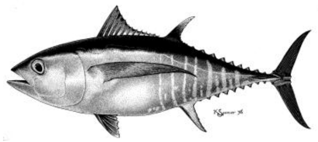
- Time-series analysis is well known, but mixed spatio-temporal processes are still an experimental field of geostatistics (Banerjee et al., 2004)
- A simplification of the space-time models is to make time the 3rd dimension of space (variogram estimated in 3 dimensions)



From Hengl (2009)

Fig. 2.10: Extension of a 2D prediction model to the space-time domain. Note that in the space-time cube, the amount of pixels needed to store the data exponentially increases as a function of: width × height × number of predictors × number of time intervals.

Hurdle model



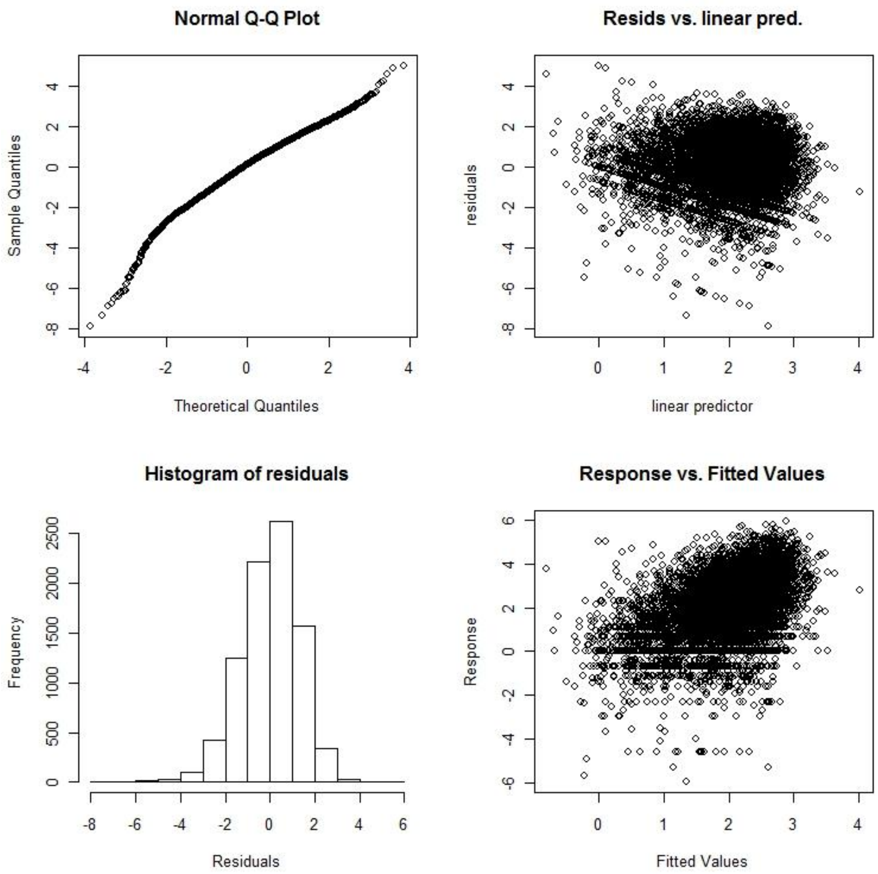
- Hurdle (delta-lognormal) model
  - 2 components (CPUE of positive sets and presence/absence)
  - Each component assumes: mean = large-scale 'trend' + small-scale spatio-temporal process

- CPUE of positive sets
  - lognormal GAM (identity link)
  - log(cpue) ~ s(lon, lat) + month + s(SST) + s(SSH) + s(CHLa) + s(depth) + s(distKM)

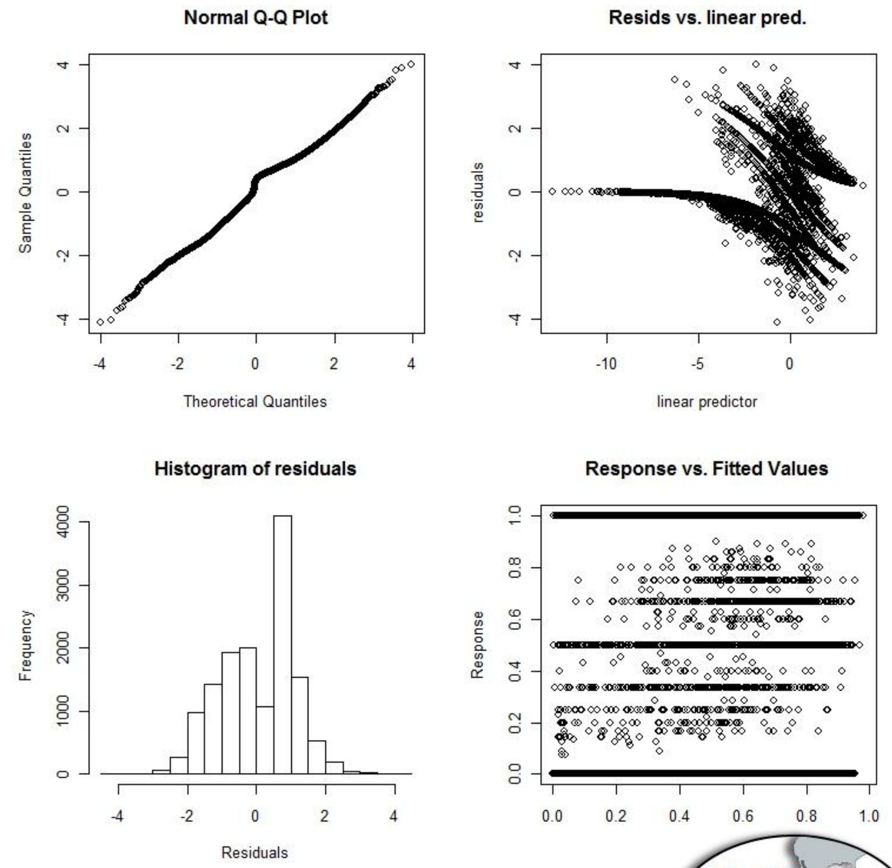
- Presence absence
  - binomial GAM (logit link)
  - PosZeroMat ~ s(lon, lat) + month + s(SST) + s(SSH) + s(CHLa) + s(depth) + s(distKM)

GAMs on global trends - diagnostics

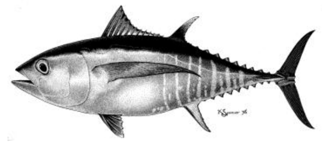
CPUE positive sets - lognormal



Presence/absence - binomial



GAMs on global trends



CPUE positive sets - lognormal

	edf	Ref.df	F	p-value	
s(lon,lat)	26.263	27.844	14.238	< 2e-16	***
s(SST)	6.552	7.726	4.935	5.77E-06	***
s(SSH)	1.543	1.946	8.886	0.000164	***
s(CHLa)	7.538	8.454	7.352	3.16E-10	***
s(depth)	1.907	2.5	1.068	0.354232	
s(distKM)	7.742	8.455	2.706	0.004718	**

R-sq.(adj) = 0.171
Deviance explained = 17.7%

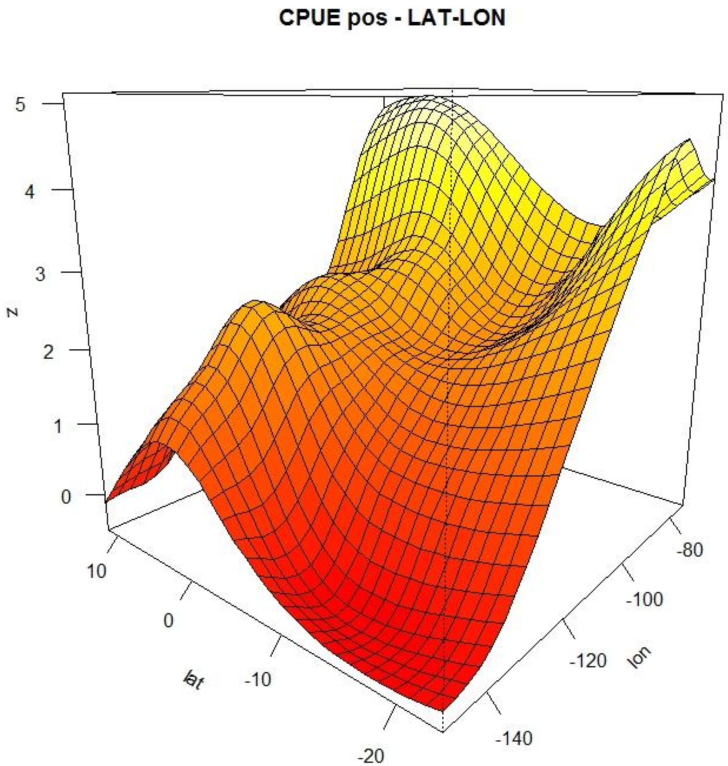
Presence/absence - binomial

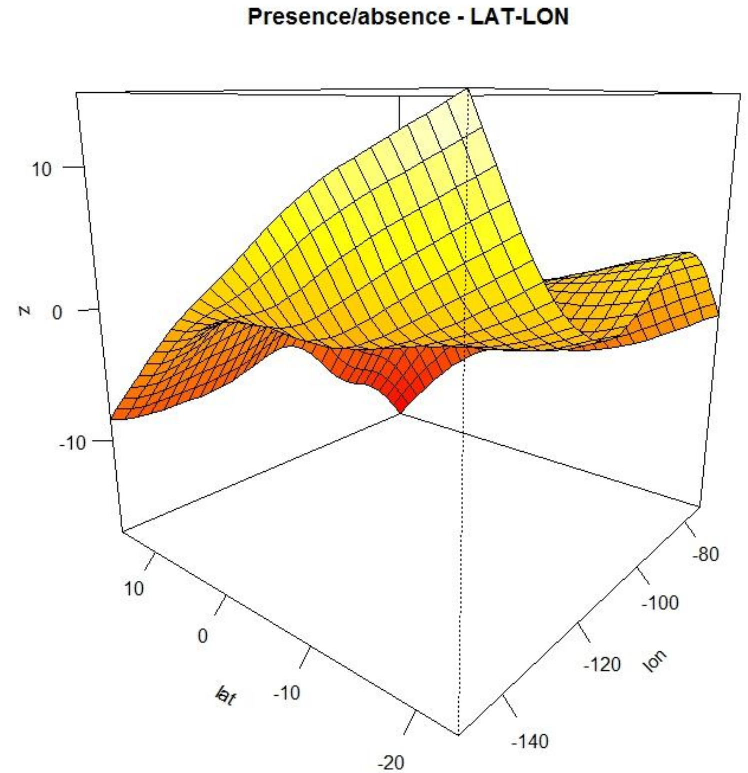
	edf	Ref.df	Chi.sq	p-value	
s(lon,lat)	28.736	28.979	1159	< 2e-16	***
s(SST)	6.65	7.813	80.666	2.85E-14	***
s(SSH)	6.918	8.032	228.119	< 2e-16	***
s(CHLa)	4.158	5.16	6.051	0.319	
s(depth)	7.272	8.341	56.61	3.07E-09	***
s(distKM)	8.804	8.983	59.177	1.90E-09	***

R-sq.(adj) = 0.61
Deviance explained = 36%

GAM cpue positive – spatial effects

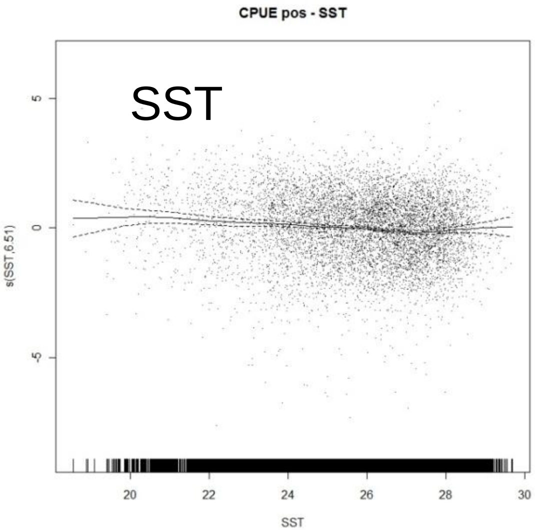
s(lon,lat)

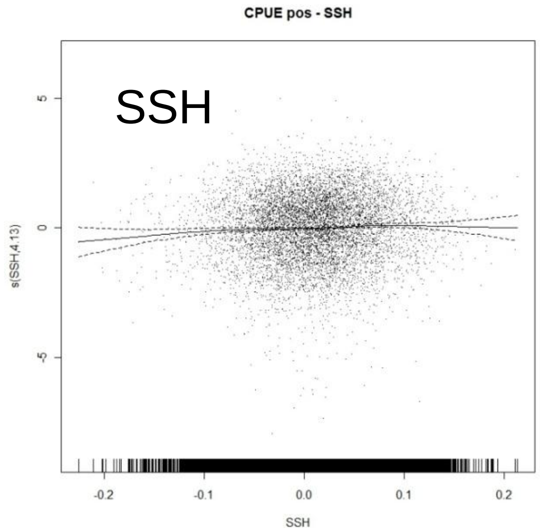


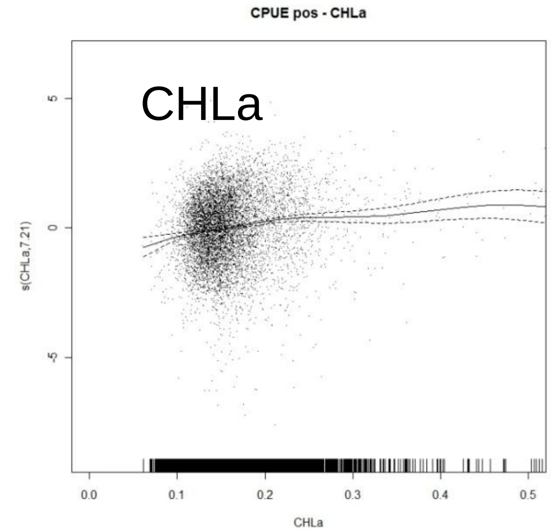


GAM cpue positive – oceanographic effects

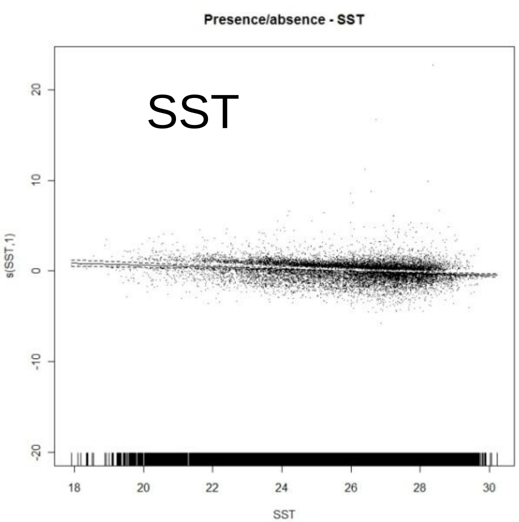
CPUE positive sets - lognormal

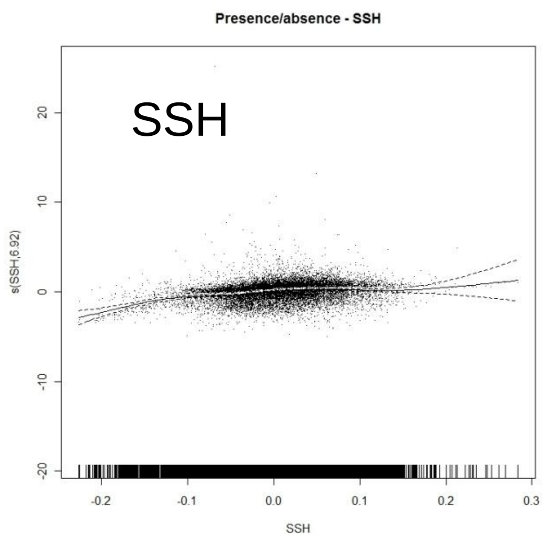


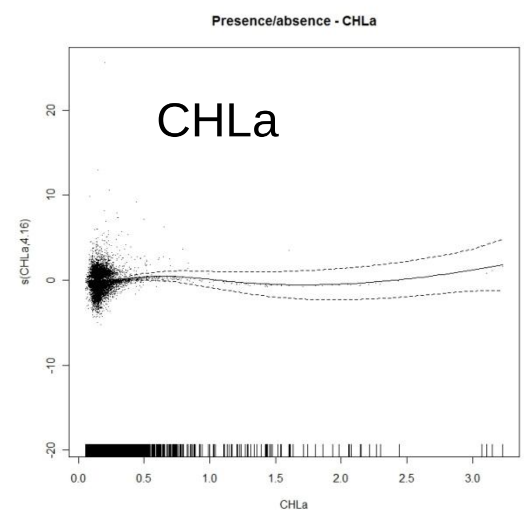




Presence/absence - binomial

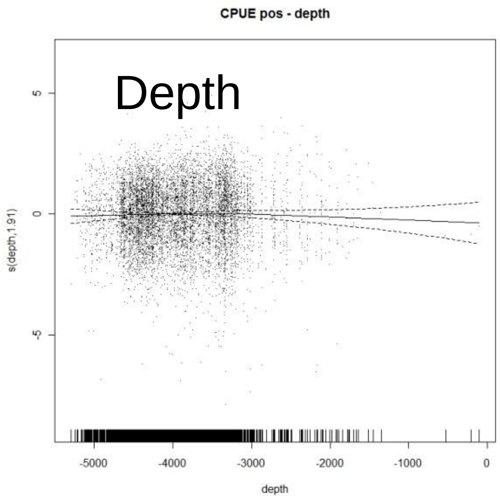


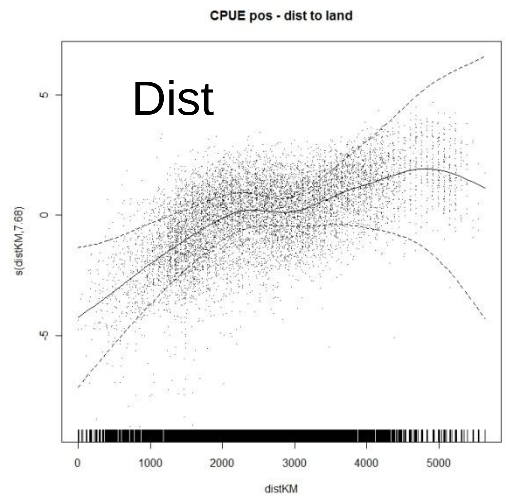




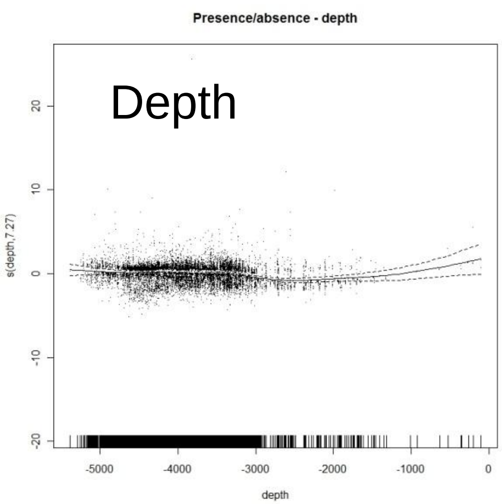
GAM cpue positive – other effects

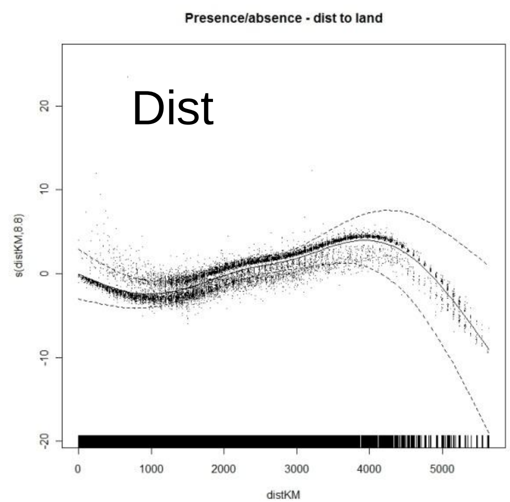
CPUE positive sets - lognormal





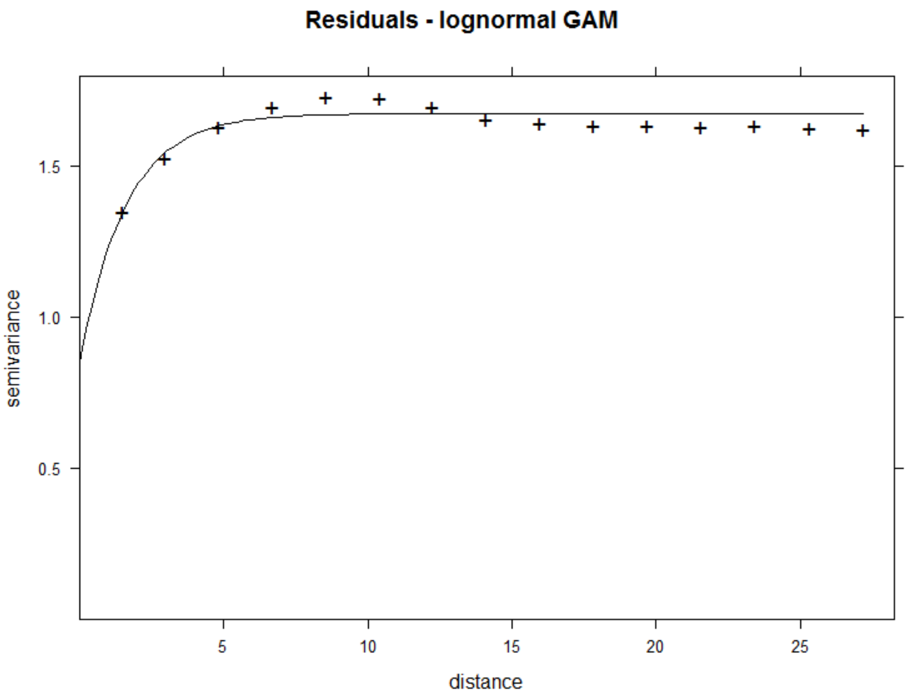
Presence/absence - binomial



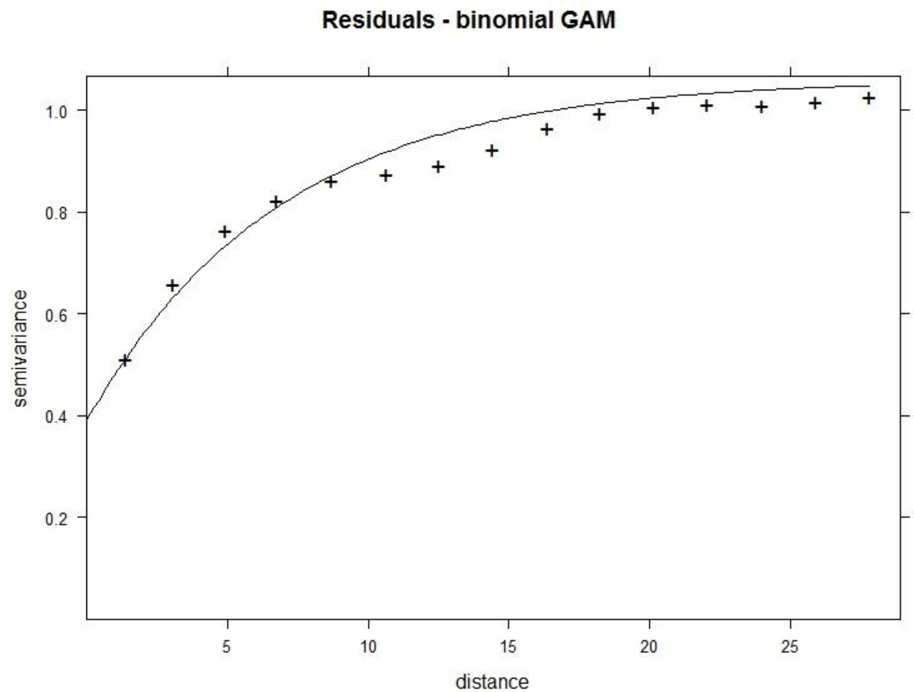


Kriging for local pattern - variograms

CPUE positive sets - lognormal

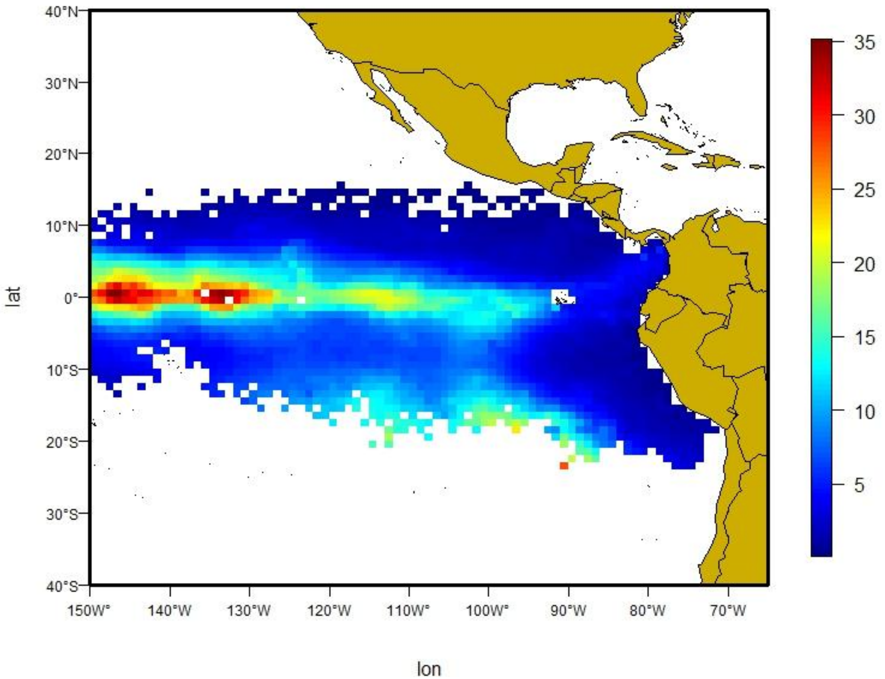


Presence/absence - binomial

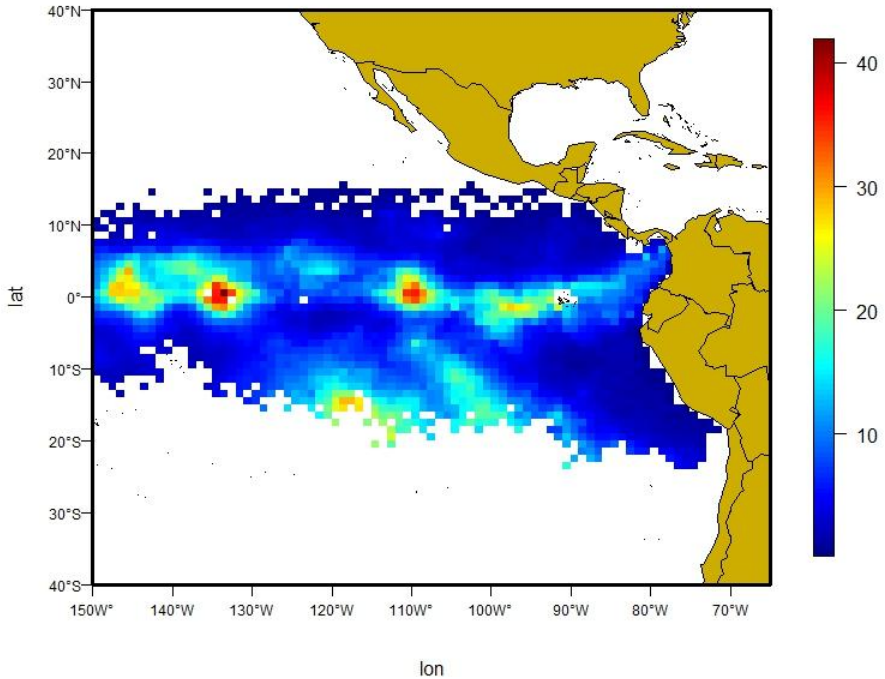


Spatio-temporal prediction – CPUE

Global trend - GAM

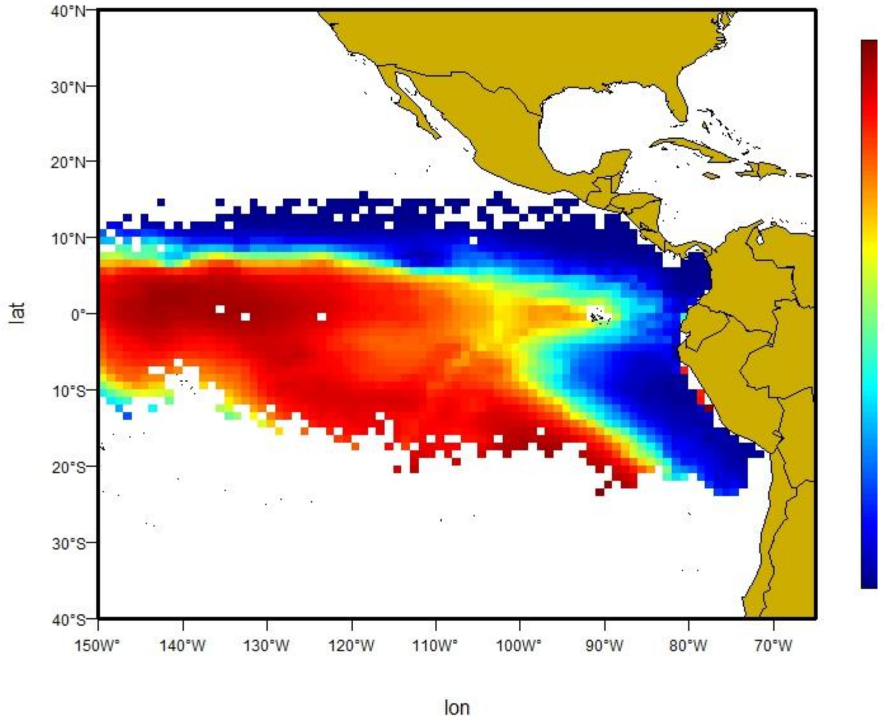


Regression Kriging

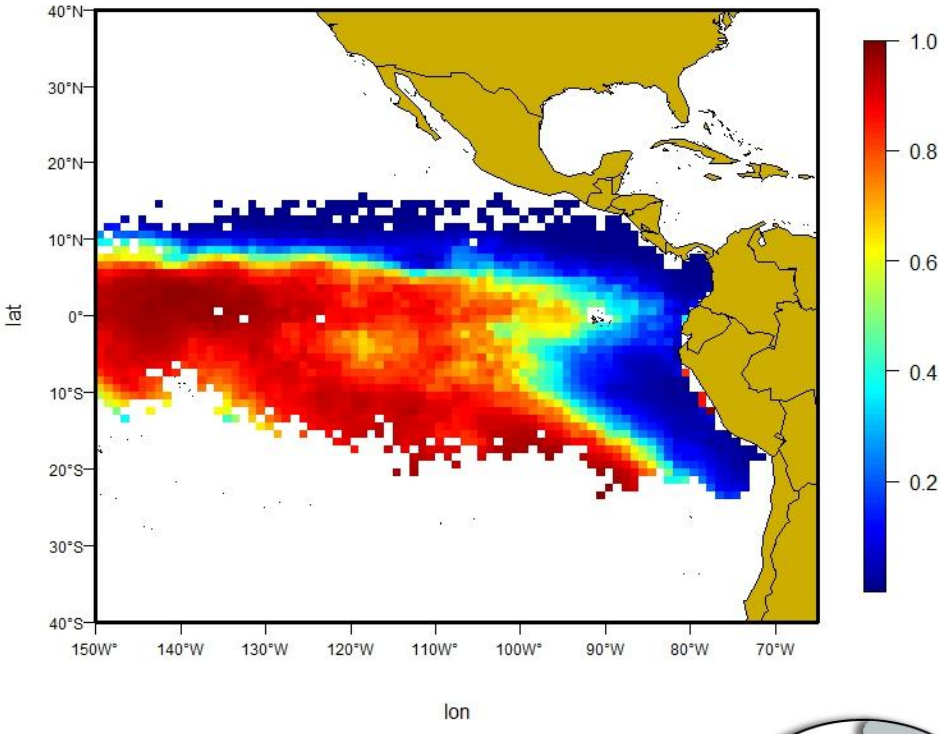


Spatio-temporal prediction – Presence/absence

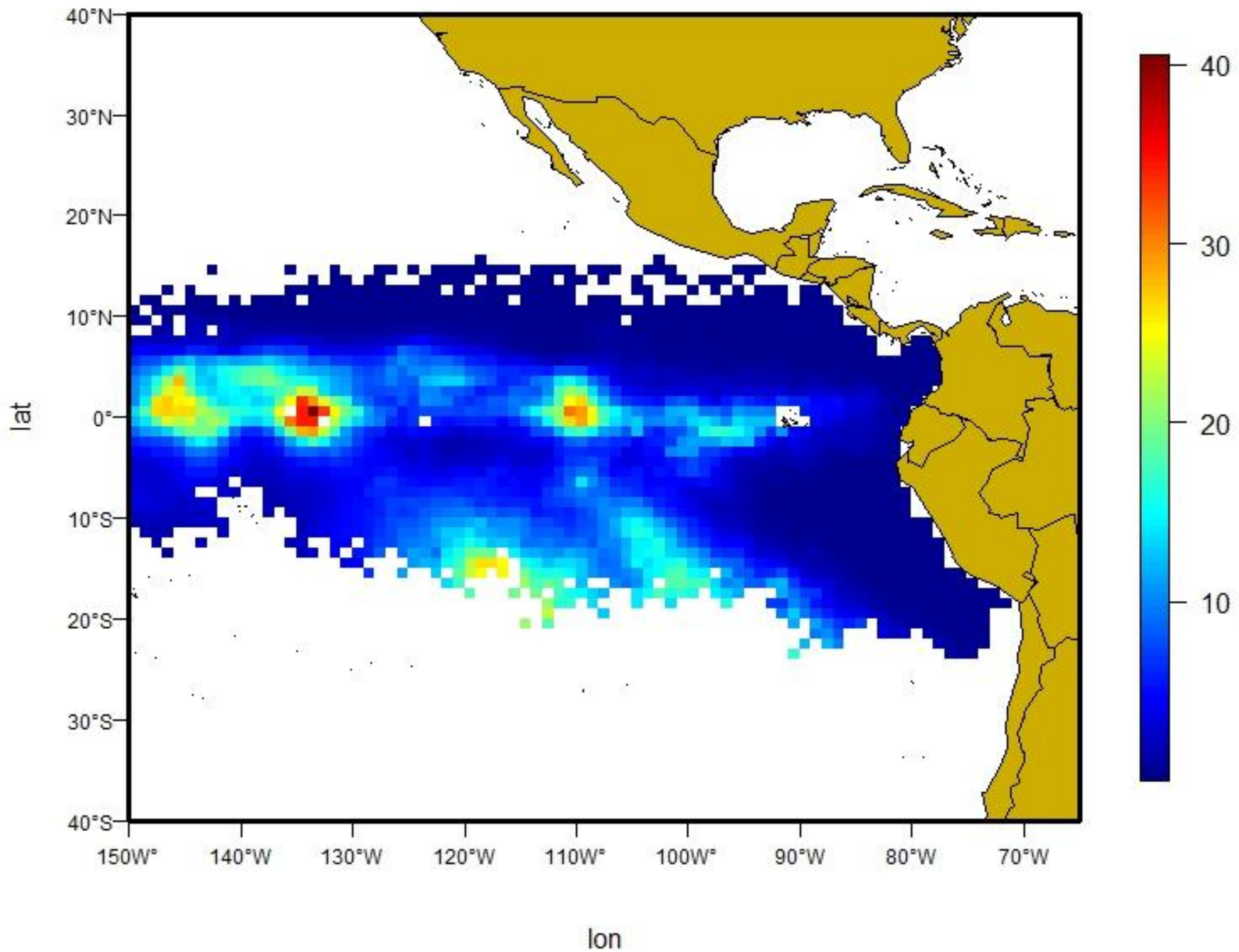
Global trend - GAM



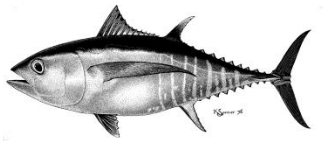
Regression Kriging



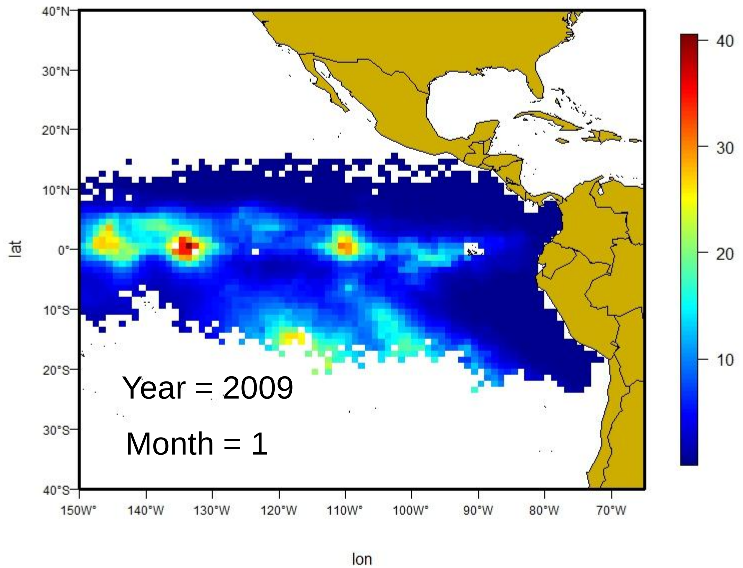
Spatio-temporal prediction – hurdle model

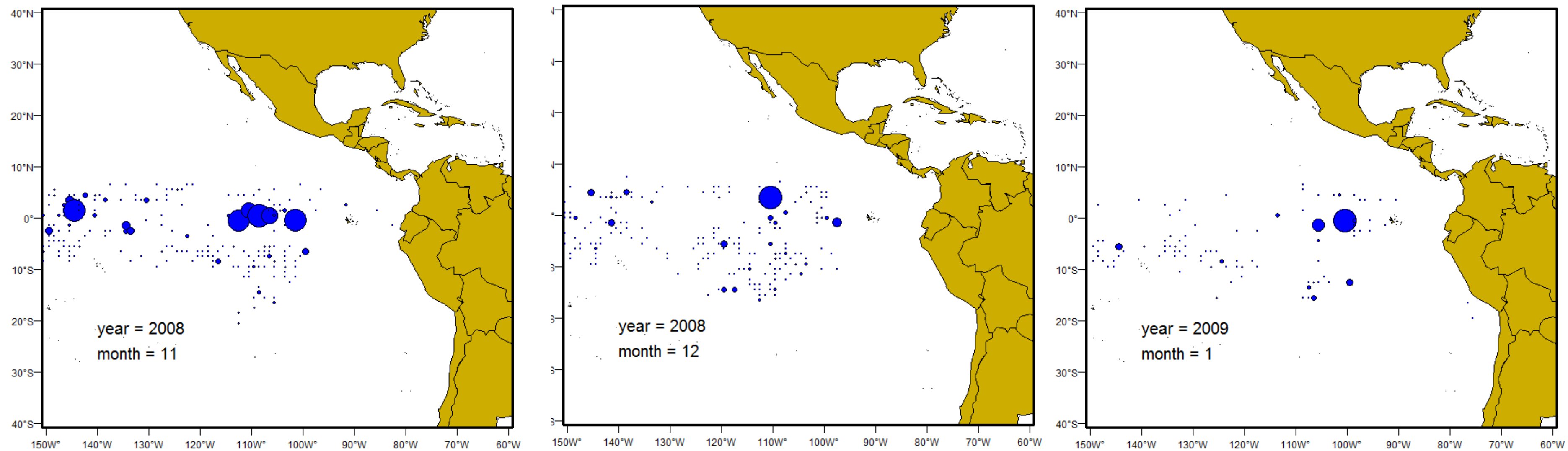


Prediction versus observed



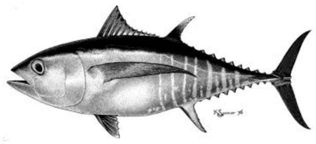
Predicted





Observed

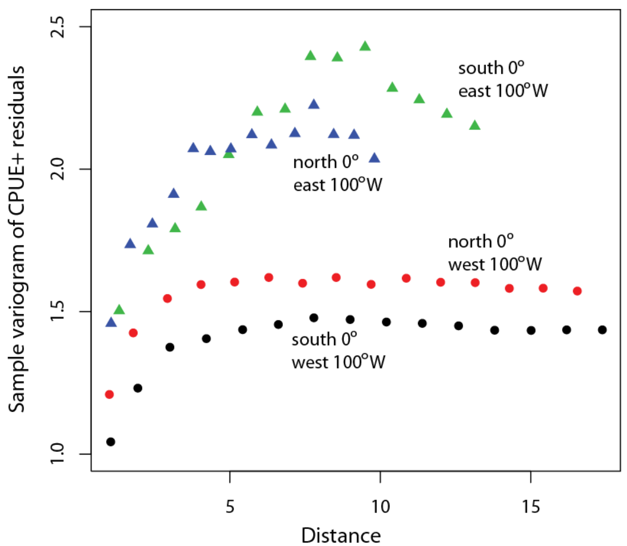
Conclusions



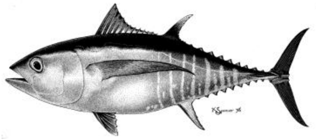
- R-K shows potential as a tool for spatio-temporal modeling of large pelagics in EPO
- Improvements could be made:
  - The % deviance explained is fairly low (~18%) for all trend models of log(CPUE) of positive sets
  - There may be correlation among environmental variables
  - Other environmental variables could be used (e.g., mixing layer depth)
  - Finer spatio-temporal

Conclusions (cont.)

- The assumption of stationary for the small-scale spatio-temporal process is probably not realistic
- Variograms of residuals from both components of hurdle model showed spatial structure:
  - Magnitude of residual variance is greater inshore than offshore
  - “distance” over which residuals are correlated (i.e., practical range) is greater inshore than offshore



Future work



- Global trend (GAMs):
  - Improve choice of oceanographic covariates
  - Different spatio-temporal resolution?
- Local trend (kriging):
  - Challenge the stationary assumption (spatial differences)
- Others species
  - Bycatch, etc…

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Acknowledgements

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