Functional Data Analysis for Predicting Landed Fish Abundance per unit effort

Manuel Oviedo de la Fuente^{1,0}

Raquel Menezes² Alexandra A. Silva³

CITIC, A Coruña University, Spain CMAT, Minho University, Portugal Portuguese Institute for the Sea and Atmosphere (IPMA), Portugal

Introduction

Predicting the abundance of landed fish per unit effort (LPUE) is a critical challenge in competitive fish markets (Hilborn & Walters, 1992). Previous research (Maunder & Punt, 2004) has addressed the challenge of modelling species distribution in fisheries using various statistical methods, including time series analysis (e.g., ARIMA models) (Box $\it et$ al., 2015), model-based geostatistics (e.g., SPDE approach, GRFs and kriging) (Lindgren $\it et~al.,~2011$), and regression models (e.g., GLMs) to model complex structures.

This study addresses the challenge of variable selection by employing distance correlation (DC) (Szekely et al., 2007) to investigate the relationships between environmental data (functional data) and other sources of information, such as sale prices, ratio of euros per total catches, calendar variables, and the scalar response, LPUE.

LPUE study

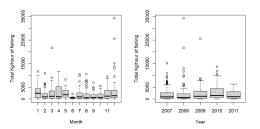
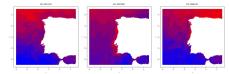


Figure 1: LPUE distribution by month and year

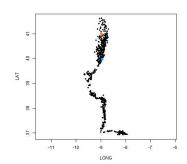
Ocean Monitoring

We use sensor data monitoring, such as chlorophyll-a concentrations (CHL), intensity of ocean currents , Sea Surface Temperature (SST), wind speed and wind direction curves (WS, WD) measured daily during 10 yrs.

SST in 2007/01/01, 2007/07/01 and 2008/01/01



LPUE captures (black) and 2 SST locations





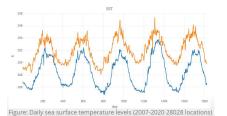








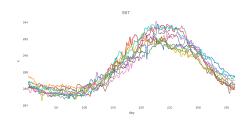




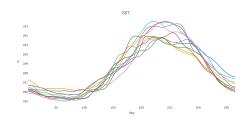
Functional data analysis (FDA)

This study proposes an approach based on FDA (Ramsay et al. 2005). FDA is a branch of statistics that focuses on the analysis of data consisting of curves or anything else that varies along a continuum.

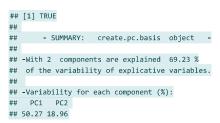
SST raw curves (1 location, 10 years): $\mathcal{X}(t)$



SST smoothing curves: $\hat{\mathcal{X}}(t) = S\mathcal{Y}(t)$



Dimension reduction using functional principal components **(FPC):** $\mathcal{X}(t) = \mu(t) + \sum_k c_k v_k(t), \ c_k$



Functional Additive Model (FAM) with variable selection (VS) using Distance Correlation \mathcal{DC}

We present a step-wise method to select the features based on the calculation of the $\mathcal{D}\mathcal{C}$ between each feature and the response variable (or model residals). \mathcal{DC} is defined for Xand Y random vector variables in arbitrary finite dimension spaces, $\mathcal{DC}(X,Y)=0$ characterizes the independence of Xand Y. For simplicity we use the FAM model as it allows for non-linear estimates of the effects. The covariates can be used from the last observed value, its mean or the principal component PC representation of the curve of the values recorded in the last 30 days (e.g.), etc.

$$LPUE_{h,s} = s_1(LONG)_h + \ldots + s_j(SST(t))_{h,s} + \ldots + \varepsilon_{h,s}$$

where s_i is a smooth function and, $\varepsilon_{h,s} \stackrel{iid}{\sim} N(0,\sigma)$

Results: Train data $h = 1, \dots, 399$, B = 100 replications, $b = h + 1, \ldots, h + B$

per total catches (taxa), ocean current (foclast) and vcomponent (south to north flow) of wind direction (fvlast), bathymetry (bath) and longitude (long) and functional PC of the derivative of: wind intensity curve (dint) and smoothed chlorophyll (sch1).

% of times each variable enters the model

Show entries	Search:
	Percent
rate	100
foclast	56.1
time index	43.9
sstlast	26.5
ssst	20.4
bath	17.3

Showing 1 to 6 of 28 entries



Table 1: Example of a model fit						
Component	Term	Estimate	Std Error	t-value	p-value	
A. parametric coefficients	(Intercept)	7.011	0.076	92.095	0.0000 ***	
Component	Term	edf	Ref. df	F-value	p-value	
B. smooth terms	s(taxa)	6.013	6.659	5.598	0.0000 ***	
	s(bath)	1.000	1.000	5.450	0.0203 *	
	s(foclast)	1.000	1.000	7.740	0.0058 **	
	s(fvlast)	1.000	1.000	2.387	0.1235	
	s(long)	1.966	2,493	3.080	0.0437 *	
	s(dint.PC1)	1.000	1.000	6.919	0.0090 **	
	s(dint.PC2)	1.863	2.377	2.723	0.0567	
	s(dint.PC3)	1.000	1.000	3.459	0.0640.	
	s(dint.PC4)	1.000	1.000	0.789	0.3752	
	s(schl.PC1)	1.000	1.000	1.928	0.1660	
	s(schl.PC2)	1.000	1.000	3.681	0.0561	
	s(schl.PC3)	1.000	1.000	1.243	0.2659	
	s(schl.PC4)	4.928	5.835	2.446	0.0311 *	
	Signif. code	s: 0 <= '***	< 0.001 <	'**' < 0.0	1 < '*' < 0.05	

Adjusted R-squared: 0.240, Deviance explained 0.300

GCV: 1.901, Scale est: 1.745, N: 301

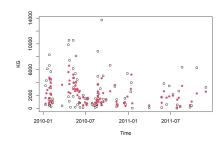


Figure 2: Observed (black) and predicted values (red)

Conclusion

The proposed functional approach has demonstrated promising results when applied to a real dataset LPUE of juvenile sardine along the northern Portuguese coast. These findings present decision makers with a valuable tool to advance marine sustainability and conservation efforts by enhancing our understanding of the factors influencing LPUE.

References

- Febrero-Bande, M, González-Manteiga, W, Oviedo de la Fuente, M. Variable selection in Functional Additive Regression Models. Comput. Stat., 34, 469-87,
- Lindgren, F, Rue, H, Lindström, J. (2011). An explicit link between Gaussian fields and Gaussian Markov random fields.J. R. Stat. Soc. Ser. B Methodol,
- Rodríguez-Climent, S, Angélico, M, Marques, V, Oliveira, P, Wise, L, Silva, A. Essential habitat for sardine juveniles in Iberian waters, Sci. Mar., 81(3), 351-
- Székely, G J, Rizzo, M L, Bakirov, N K. (2007). Measuring and testing dependence by correlation of distances. Ann. Statist. 35(6): 2769-2794.