

Modelação Ecológica: será possível ter o melhor dos dois mundos?

Aula 10.12.2019



2002

2007

2011

2012

Estágio: *Utilização das zonas costeiras adjacentes ao estuário do Douro como área de viveiro pela faneca, *Trisopterus luscus**

Use of the coastal areas adjacent to the Douro estuary as a nursery area for pouting, *Trisopterus luscus* Linnaeus, 1758

By S. França, C. Vinagre, M. J. Costa and H. N. Cabral

Instituto de Oceanografia, Faculdade de Ciências da Universidade de Lisboa, Campo Grande, Lisboa, Portugal

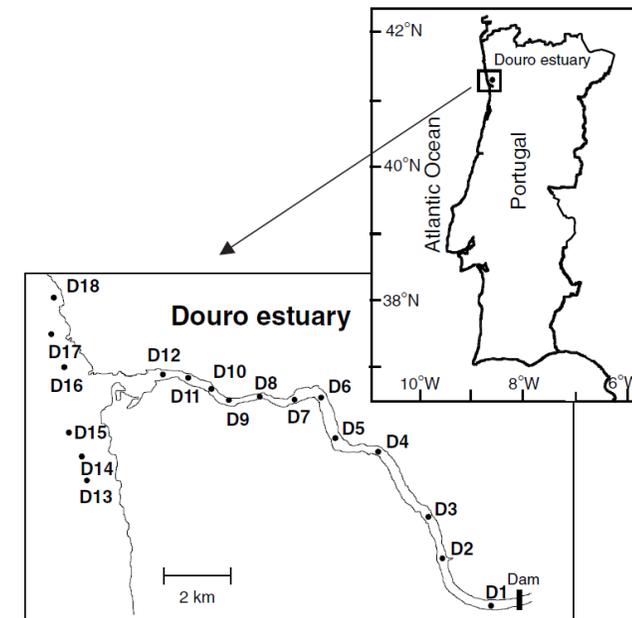


Fig. 1. Location of the sampling stations (D1–D18) in the Douro estuary and adjacent Portuguese coastal areas

2002

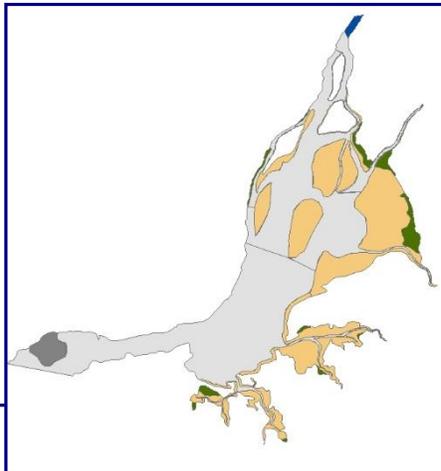
2007

2011

2012



MSc Thesis: *Use of intertidal mudflat habitats in the Tejo estuary by macrozoobenthos and fish communities.*



- Habitat Type**
-  Intertidal soft substratum
 -  Saltmarsh
 -  Subtidal hard substratum
 -  Subtidal soft substratum
 -  Tidal freshwater

Mudflat nekton assemblages in the Tagus estuary (Portugal): distribution and feeding patterns

SUSANA FRANÇA ¹, MIGUEL A. PARDAL ² and HENRIQUE N. CABRAL ^{1,3}

¹ Instituto de Oceanografia, Faculdade de Ciências da Universidade de Lisboa, Campo Grande, 1749-016 Lisboa, Portugal.

Spatial and temporal patterns of benthic invertebrates in the Tagus estuary, Portugal: comparison between subtidal and an intertidal mudflat

SUSANA FRANÇA ¹, CATARINA VINAGRE ¹, MIGUEL A. PARDAL ³ and HENRIQUE N. CABRAL ^{1,2}



2002

2007

2011

2012

PhD Thesis: *Spatial and temporal variation of fish assemblages in estuarine systems: habitat use, dependence and connectivity*



Assessing habitat specific fish assemblages in estuaries along the Portuguese coast

Susana França^{a,*}, Maria José Costa^{a,b}, Henrique N. Cabral^{a,b}



Assessing food web dynamics and relative importance of organic matter sources for fish species in two Portuguese estuaries: A stable isotope approach

Susana França^{a,*}, Rita P. Vasconcelos^a, Susanne Tanner^a, Cristina Máguas^b, Maria José Costa^{a,c}, Henrique N. Cabral^{a,c}



Vulnerability of Portuguese estuarine habitats to human impacts and relationship with structural and functional properties of the fish community

Susana França^{a,*}, Rita P. Vasconcelos^a, Patrick Reis-Santos^a, Vanessa F. Fonseca^a, Maria José Costa^{a,b}, Henrique N. Cabral^{a,b}

Modelos ??



2002

2007

2011

2012



Contents lists available at ScienceDirect

Estuarine, Coastal and Shelf Science

journal homepage: www.elsevier.com/locate/ecss

Inter- and intra-estuarine fish assemblage variability patterns along the Portuguese coast

Susana França^{a,*}, Maria José Costa^{a,b}, Henrique N. Cabral^{a,b}

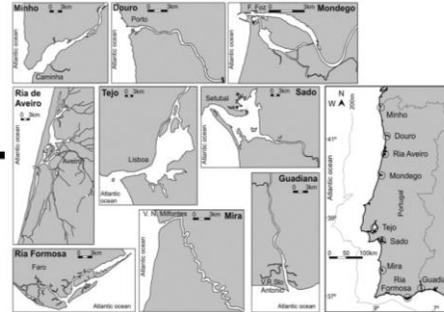


Fig. 1. Estuarine systems sampled in the Portuguese coast.

(i) variação riqueza específica ao longo dos 9 estuários

Variáveis: área estuário; caudal fluvial; profundidade; tempo de residência; volume; índice de pressão; % área intertidal; latitude; % área oligohalina; % área mesohalina; % área polihalina

(i) variação riqueza específica em cada estuário

Variáveis: oxigénio dissolvido; salinidade; temperatura; profundidade; % vasa no sedimento; distância à boca do estuário; densidade de presas; tipo de habitat

- ✓ Perguntas | Variáveis
- ✗ Muitas variáveis (e correlacionadas)
- ✗ Modelos muito complexos
- ✗ Distribuição mal escolhida

Table 3

Analysis of deviance table for the gamma-based GLM fitted to the species richness values for the nine estuaries of the Portuguese coast (values of deviance for each factor, residual deviance (Res. Dev.), percentage of the total deviance explained by each factor (% Expl.) and *p*-values are presented).

	Predictors	<i>p</i> -value	Res. Dev.	Deviance	% Expl.
Species richness	Null				1.59
	Main effects				
	River flow	<0.001	0.590	1.006	63.01
	Anthropogenic pressure	0.002	0.381	1.215	13.12
	Latitude	0.001	0.231	1.364	9.35
	Total explained				85.50

??

copiar ~~X~~ cripts

2002

2007

2011

2019



Predicting fish community properties within estuaries: Influence of habitat type and other environmental features

Susana França*, Rita P. Vasconcelos, Vanessa F. Fonseca, Susanne E. Tanner, Patrick Reis-Santos, Maria José Costa, Henrique N. Cabral

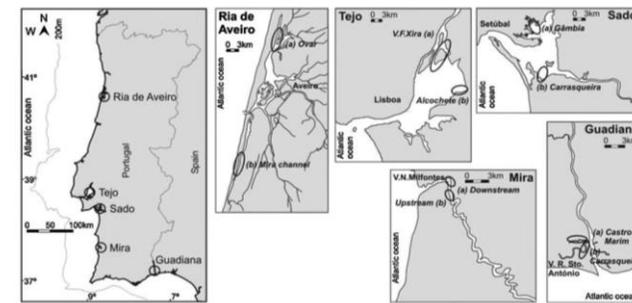


Fig. 1. Estuarine systems sampled in the Portuguese coast. Also shown is the location of sites within each estuary where the three habitats (saltmarsh, mudflat and subtidal) were sampled.

Amostragem: orientado para o habitat, durante todo o ano

GAM

Divisão dos dados para validar o modelo: poucos dados - overfitting

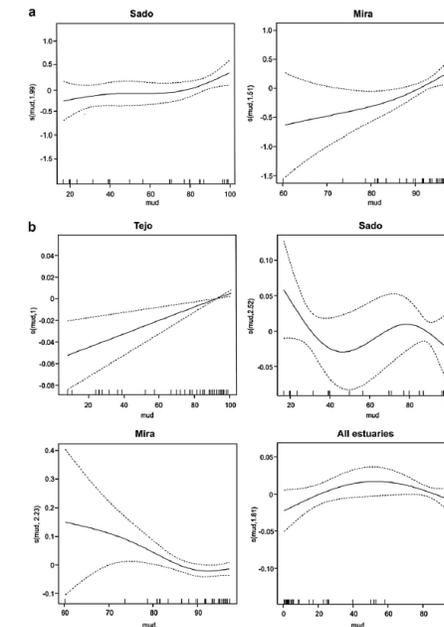
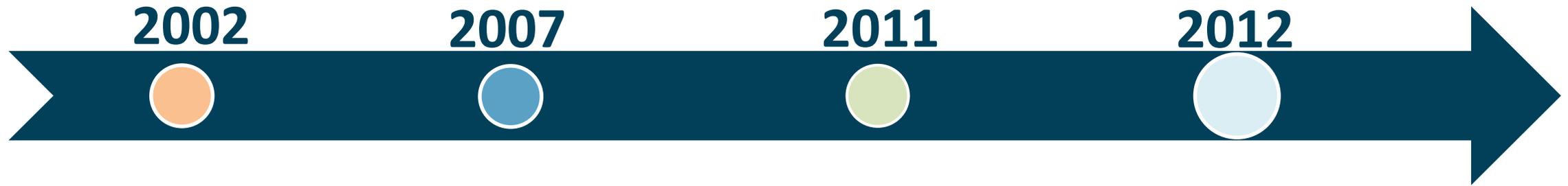
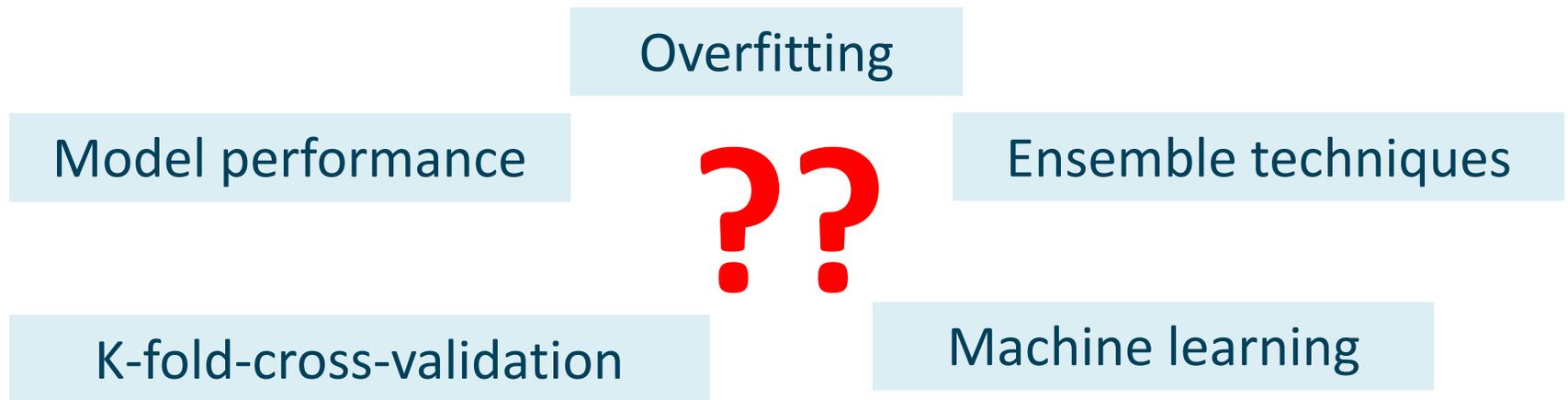


Fig. 3. Partial effect of "percentage of mud in the sediment" on (a) fish species richness and (b) densities, for the estuaries where this predictor was retained in tick marks show the distribution of the predictor values. Y-axes represent the partial effect of the predictor in the response variable.



PosDoc - *Dynamic modelling of estuarine fish populations: an evaluation of different approaches to model species functional traits at a multi-scale level*



Contents lists available at [ScienceDirect](#)
Environmental Modelling & Software
 journal homepage: www.elsevier.com/locate/envsoft

Haverá resposta para isto? →

Predicting fish species richness in estuaries: Which modelling technique to use?

Susana França ^{a,*}, Henrique N. Cabral ^{a,b}



2002

2007

2011

2012

A importância de conhecer a ecologia das espécies

1. Estuários são ecossistemas muito dinâmicos e com grande variabilidade (natural e de origem humana)



2. Espécies com ciclos de vida e usos do estuário muito diferentes

Solea solea



**MARINE
MIGRANTS**

Dicentrarchus labrax



RESIDENT



Pomatoschistus microps



Halobatrachus didactylus



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Estuarine, Coastal and Shelf Science

journal homepage: www.elsevier.com/locate/ecss



Predicting fish species distribution in estuaries: Influence of species' ecology in model accuracy

Susana França^{*}, Henrique N. Cabral

MARE – Marine and Environmental Sciences Centre, Faculdade de Ciências, Universidade de Lisboa, Campo Grande, 1749 – 016, Lisboa, Portugal



2002

2007

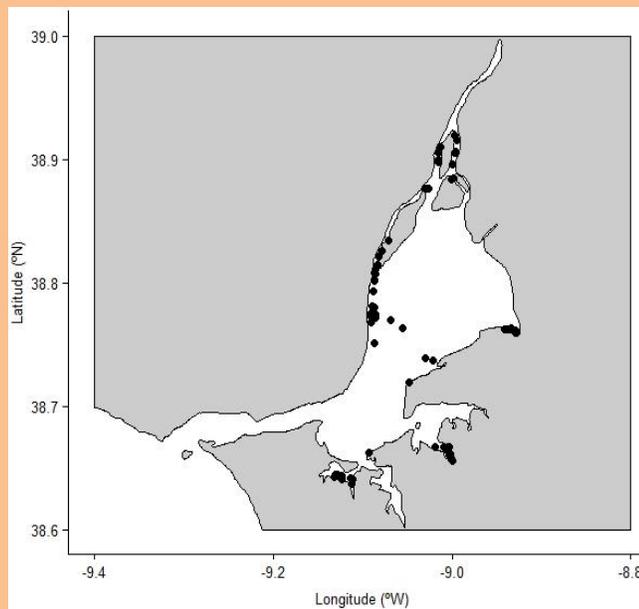
2011

2012

SPECIES DISTRIBUTION MODELS

2006

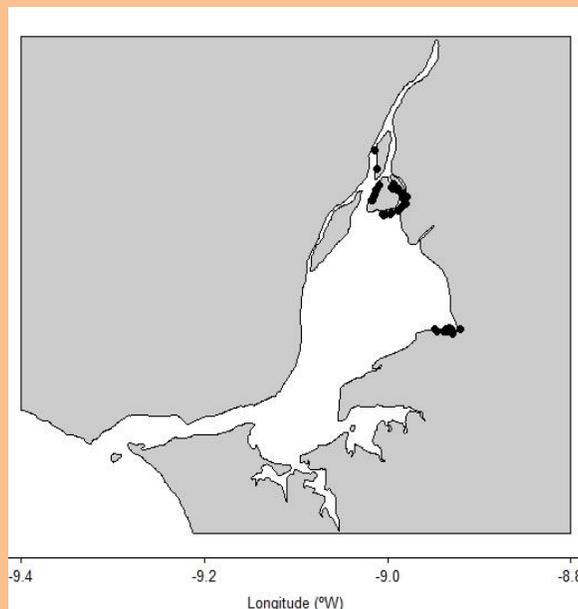
One season
Estuarine gradient



Seasonal bias

2009

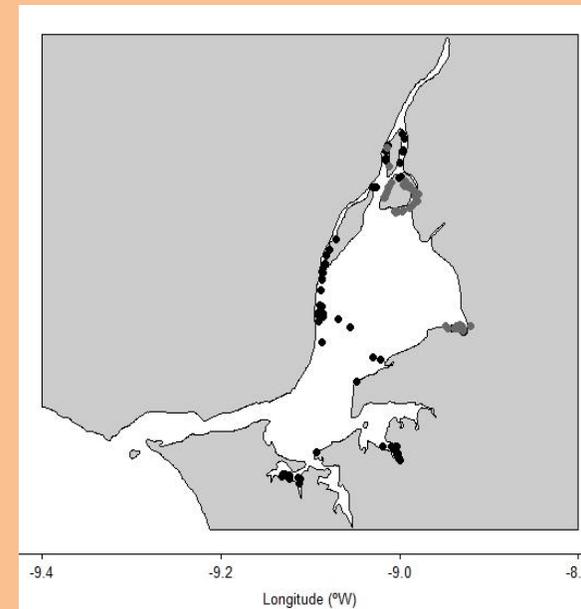
Four seasons
Habitat oriented



Spatial bias

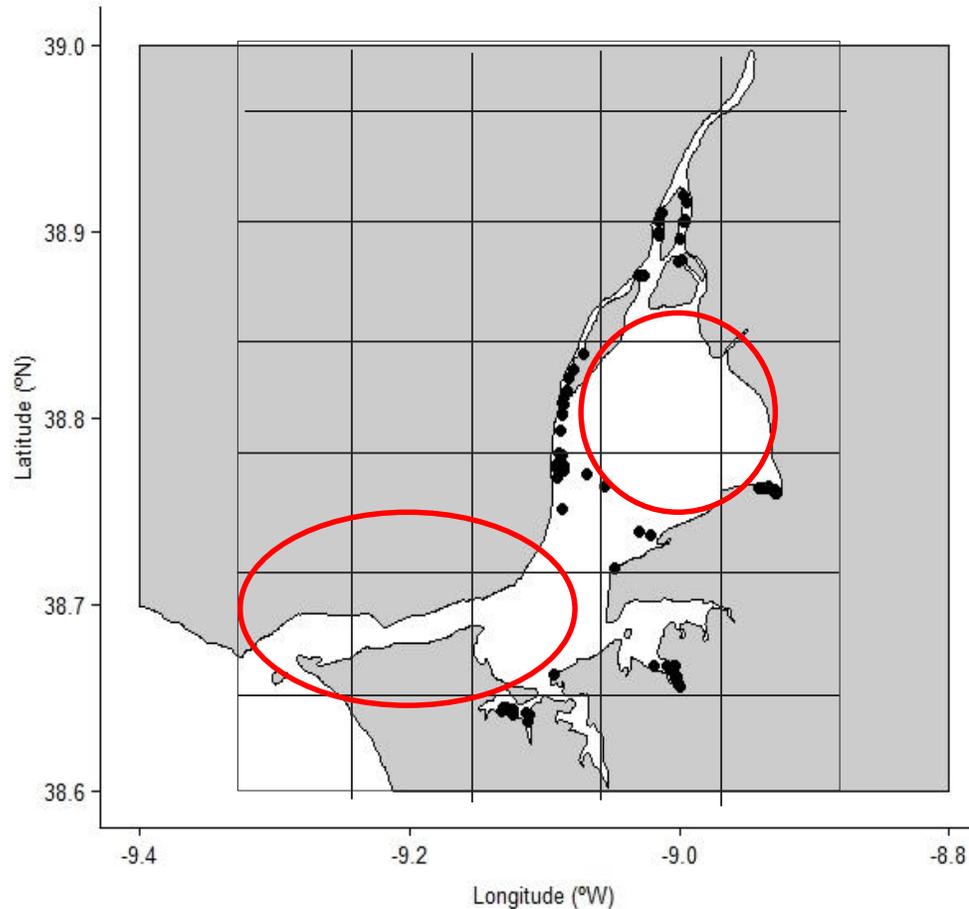
TOTAL

2006 + 2009



Full potential distribution

SPECIES DISTRIBUTION MODELS



1. Boa ferramenta para obter mapas de distribuição futura das espécies;

2. Ajustar/Construir (Training) o modelo com os dados que temos

3. Validar/Testar o modelos com dados novos (por exemplo: dados de temperatura previstos)

4. Outros métodos quando não existem dados novos: k-fold-cross validation e data spliting (75% | 25%- mesma proporção de presenças e ausências)

5. “Species prevalence” a ter em conta (influência o modelo)

6. Independência dos dados – atenção nestes modelos espaciais

SPECIES DISTRIBUTION MODELS

Medidas de avaliação da precisão dos modelos (accuracy | model performance)

Sensitivity and Specificity

Sensitivity :

- proportion of correctly predicted observations of species presence.
- Low when omissions errors are common

Specificity :

- proportion of correctly predicted observations of species absence.
- Low when commissions errors are frequent.

		Observado	
		Presença	Ausência
Previsto	Presença	Verdadeira presença	Falsa presença
	Ausência	Falsa ausência	Verdadeira ausência

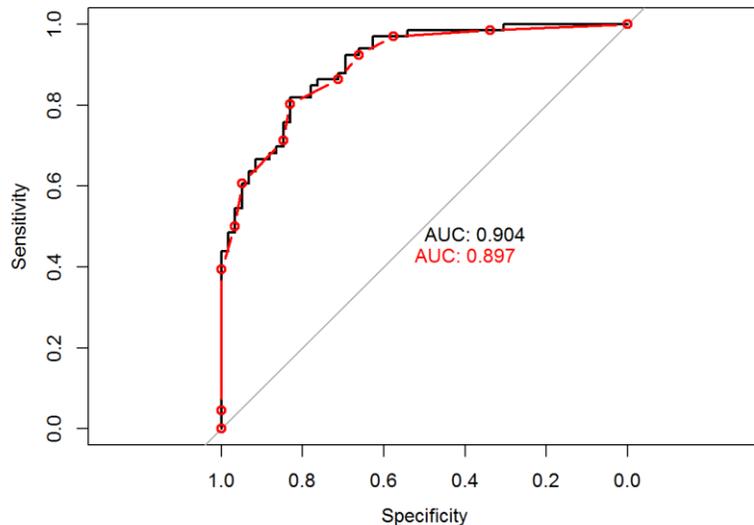
Para calcular estas medidas, as probabilidades da ocorrência da espécie tem que ser transformada em presenças e ausências, sendo necessário um “threshold”.

Como escolher o threshold??

SPECIES DISTRIBUTION MODELS

Medidas de avaliação da precisão dos modelos (accuracy | model performance)

AUC “Area Under de Curve” of the ROC (Receiver Operating Characteristic) plot



- Independente do threshold
- Avalia capacidade do modelo de prever corretamente uma probabilidade maior de ocorrência, onde a espécie está presente, do que nos locais onde está ausente
- < 0.7 – modelo com má capacidade de previsão
- 0.7 – 0.9 – modelo relativamente útil
- > 0.9 – modelo com boa capacidade de previsão

Tem sido fortemente criticado!!!

SPECIES DISTRIBUTION MODELS

Medidas de avaliação da precisão dos modelos (accuracy | model performance)

TSS “True Skill Statistics”

- Prevalence independent
- Considera os dois tipos de erros (commission and omission)
- Ranges from -1 to 1

Kappa

- Measures the proportion of correctly predicted sites after the probability of chance agreement has been removed
- Ranges from 0 to 1

Qual usar????

SPECIES DISTRIBUTION MODELS

Journal of Applied Ecology



Journal of Applied Ecology homepage

Free Access

Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS)

OMRI ALLOUCHE, ASAF TSOAR, RONEN KADMON

Ecology and Evolution

Open Access

Ecol. Evol. 2017 Feb; 7(3): 863–872.

Published online 2017 Jan 12. doi: [10.1002/ece3.2654](https://doi.org/10.1002/ece3.2654)

PMCID: PMC5288248

PMID: [28168023](https://pubmed.ncbi.nlm.nih.gov/28168023/)

Prevalence dependence in model goodness measures with special emphasis on true skill statistics

Imelda Somodi,¹ Nikolett Lepesi,^{2,3} and Zoltán Botta-Dukát¹

CE & DISASTER



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Online ISSN: 2249-460X & Print ISSN: 0975-587X

Measuring

Global Ecology and Biogeography

A Journal of Macroecology

Full Access



ELSEVIER

AUC: a misleading measure of the performance of predictive distribution models

Jorge M. Lobo, Alberto Jiménez-Valverde

Global Ecology and Biogeography

A Journal of Macroecology

Free Access

Review

Ecological relevance of performance criteria for species distribution models

Ans M. Mouton^{a, b, c, d, e}, Bernard De Baets^b, Peter L.M. Goethals^a

Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modelling

Alberto Jiménez-Valverde

Assessing Accuracy Methods of Species Distribution Models: AUC, Specificity, Sensitivity and the True Skill Statistic

By Farzin Shabani, Lalit Kumar & Mohsen Ahmadi

Modelling

September 2008, Pages 48-58



Performance of threshold classification in terms of area under the curve and kappa

SPECIES DISTRIBUTION MODELS



Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf



Distribution models of estuarine fish species: The effect of sampling bias, species ecology and threshold selection on models' accuracy

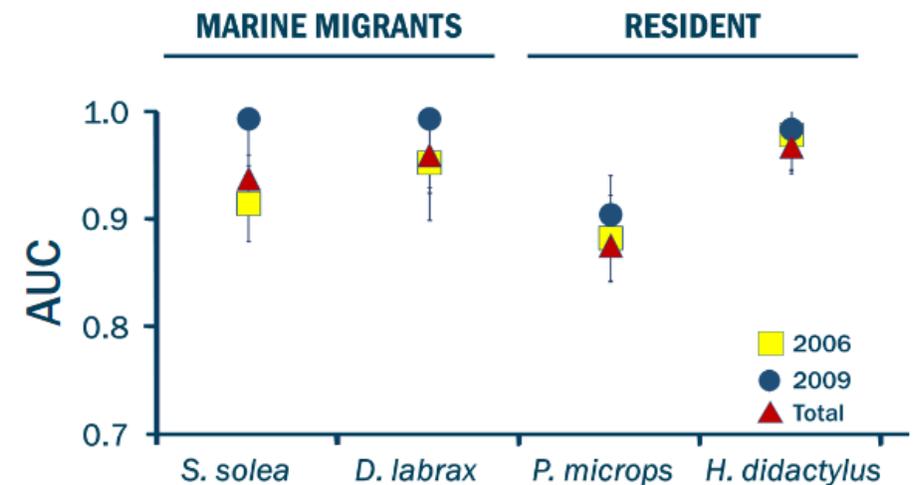


Susana França^{a,*}, Henrique N. Cabral^{a,b}

^a MARE - Marine and Environmental Sciences Centre, Faculdade de Ciências da Universidade de Lisboa, Campo Grande, 1749 - 016 Lisboa, Portugal

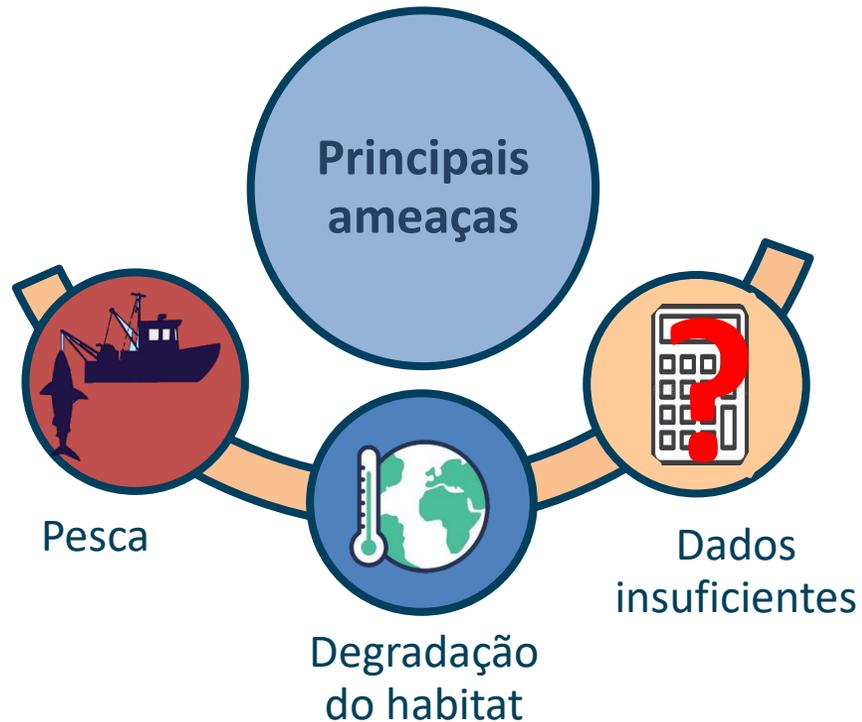
^b Irstea, UR EABX, Centre de Bordeaux, 50 avenue de Verdun, 33612 Cestas, France

SPECIES	
<i>Solea solea</i> 	MARINE MIGRANTS
<i>Dicentrarchus labrax</i> 	
<i>Pomatoschistus microps</i> 	RESIDENT
<i>Halobatrachus didactylus</i> 	



E ainda...

Tubarões e Raias



Superar desafios relativos à conservação de tubarões e raias

Intervenientes com maior impacto nestas populações



Aumento do conhecimento sobre perigos e ameaças



Comportamentos e exploração sustentável



Análise de desembarques de espécies de tubarões e raias

Dados

Informação mais precisa sobre o estado e tendências da pesca de tubarões e raias em Portugal



Sensibilização de pescadores em relação às ameaças e conservação destas espécies

Mitigar

Reunir informação de suporte para sugestão de medidas mitigadoras da mortalidade de tubarões e raias na pesca



Sensibilização do público em relação às ameaças e conservação destas espécies

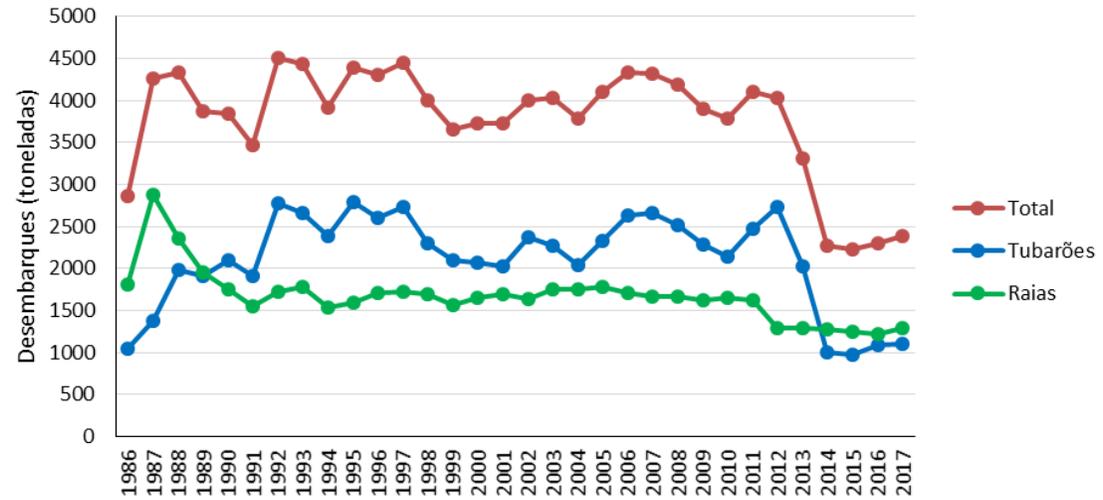
Conscientizar

Mudar perceção de pescadores e público acerca do papel que estas espécies têm no ecossistema



Análise de desembarques de espécies de tubarões e raias

Dados desembarques de espécies de tubarões e raias (DGRM) - 1986 a 2017





COASTNET
COASTAL MONITORING NETWORK

CoastNet - Portuguese Coastal Monitoring Network

CoastNet aims at monitoring important ecosystems of the Portuguese coast through relevant chemical, physical and biological parameters, collected remotely in near real-time.

Learn more [+](#)



EN PT

About

Infrastructure

News & Events

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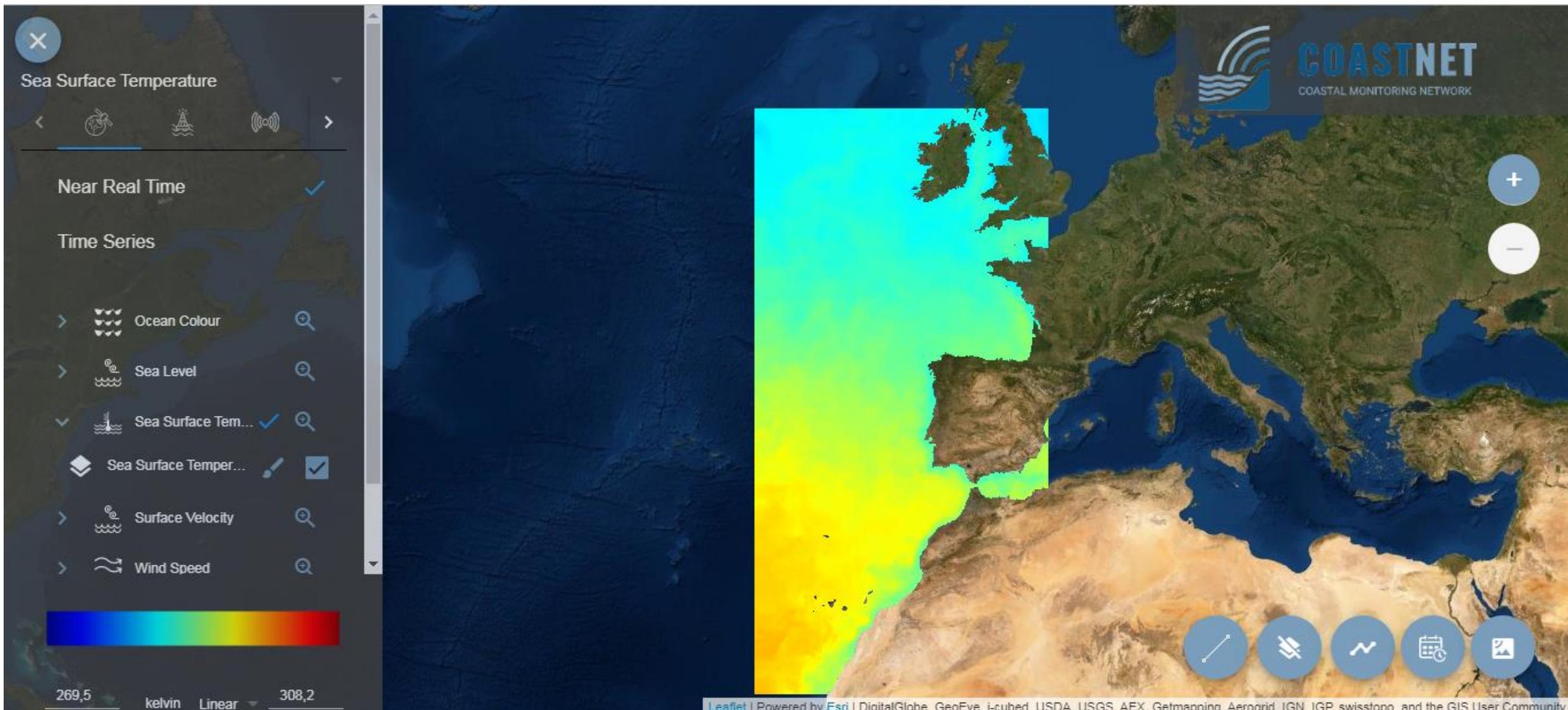
The CoastNet Research Infrastructure

CoastNet will provide raw and processed data obtained through this RI functioning and historical datasets, either for immediate visualization or for download.



Coastal Remote Sensing System

The Coastal Remote Sensing System (CRSS) will provide a range of Earth Observation (EO) products for the Portuguese coastal region. EO-based information for coastal waters includes standard (e.g. Sea Surface Temperature-SST and chlorophyll *a* concentrations) and innovative specific products (e.g. phytoplankton size classes and ocean fronts). The in-house development of novel algorithms (e.g. chlorophyll *a*, turbidity and coloured dissolved organic matter (CDOM)) will, in the long run, be integrated in this platform for remote monitoring of coastal waters.



Sea Surface Temperature



Near Real Time

Time Series

- > Ocean Colour
- > Sea Level
- > Sea Surface Tem...
- > Sea Surface Temper...
- > Surface Velocity
- > Wind Speed



269,5 kelvin Linear 308,2



Master layer

- Mira
- Buoy 1
- Buoy 2
- Buoy 3
- Mondego
- Tejo

COASTNET
COASTAL MONITORING NETWORK

Leaflet | Powered by Esri | DigitalGlobe, GeoEye, i-cubed, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community

Espécie: *Dicentrarchus labrax* (robalo)

Marine migrant (juvenis usam o estuário como zona de viveiro nos primeiros anos de vida.)

	Lat	Long	mes	do	temp	sal	depth	hab	mud	dlt
1	41.8701	8.8585	maio	9.2	16.5	24.6	2.5	sub	20.04	0
2	41.8702	8.8561	maio	9.1	16.6	24.2	2.5	sub	20.04	0
3	41.8799	8.8368	maio	9.0	16.4	19.2	2.5	sub	20.04	0
4	41.8796	8.8333	maio	9.1	15.9	27.5	1.5	inter	20.04	0
5	41.8823	8.8285	maio	8.9	16.2	28.6	1.5	inter	20.04	0
6	41.8806	8.8348	maio	9.1	5.8	32.6	3.0	sub	7.79	0
7	41.8968	8.8444	maio	8.7	16.5	25.4	1.1	inter	7.79	0
8	41.8997	8.8433	maio	8.6	16.8	24.0	1.5	inter	7.79	0
9	41.9035	8.8422	maio	8.0	17.1	21.3	1.4	inter	7.79	0
10	41.9105	8.8295	maio	8.0	17.1	20.0	1.5	inter	7.79	0

Showing 1 to 11 of 574 entries

```
'data.frame': 574 obs. of 10 variables:
 $ Lat : num 41.9 41.9 41.9 41.9 41.9 ...
 $ Long : num 8.86 8.86 8.84 8.83 8.83 ...
 $ mes : Factor w/ 4 levels "abril","janeiro",...: 4 4 4 4 4 4 4 4 4 4 ...
 $ do : num 9.2 9.1 9 9.1 8.9 9.1 8.7 8.6 8 8 ...
 $ temp : num 16.5 16.6 16.4 15.9 16.2 5.8 16.5 16.8 17.1 17.1 ...
 $ sal : num 24.6 24.2 19.2 27.5 28.6 32.6 25.4 24 21.3 20 ...
 $ depth: num 2.5 2.5 2.5 1.5 1.5 3 1.1 1.5 1.4 1.5 ...
 $ hab : Factor w/ 5 levels "fresh","inter",...: 5 5 5 2 2 5 2 2 2 2 ...
 $ mud : num 20 20 20 20 20 ...
 $ dlt : int 0 0 0 0 0 0 0 0 0 0 ...
> |
```

- Parte dos dados da matriz original (não estão completos);
- Não têm a mesma proporção de presenças e ausências entre dados para construir o modelos e para testar (pode ser problemático);
- Mas... São dados reais, para perceberem que podem ser bastante complexos e difíceis de tratar!!

1. Ajustar melhor modelo

```
> d11<-glm(d1t~Lat+Long+mes+do+temp+sal+depth+hab+mud,family=binomial,data=d1tudo)
> summary(d11)
```

```
Call:
glm(formula = d1t ~ Lat + Long + mes + do + temp + sal + depth +
     hab + mud, family = binomial, data = d1tudo)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.6752	-0.6496	-0.3581	-0.1695	2.4922

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.321e+01	1.055e+03	-0.041	0.96734
Lat	6.055e-01	1.362e-01	4.446	8.73e-06 ***
Long	-1.902e-01	3.602e-01	-0.528	0.59755
mesjaneiro	1.626e+01	1.055e+03	0.015	0.98771
mesjulho	1.273e+01	1.055e+03	0.012	0.99038
mesmaio	1.322e+01	1.055e+03	0.013	0.99001
do	3.144e-02	9.891e-02	0.318	0.75057
temp	2.210e-01	7.091e-02	3.117	0.00183 **
sal	-6.008e-02	1.360e-02	-4.419	9.92e-06 ***
depth	3.221e-02	5.726e-02	0.563	0.57375
habinter	9.460e-01	6.545e-01	1.445	0.14838
habsapa1	1.325e-01	7.800e-01	0.170	0.86515
habseagr	-1.274e+01	9.191e+02	-0.014	0.98894
habsub	9.813e-01	6.366e-01	1.542	0.12316
mud	2.587e-02	5.727e-03	4.518	6.25e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 537.14 on 573 degrees of freedom
Residual deviance: 431.14 on 559 degrees of freedom
AIC: 461.14

Number of Fisher Scoring iterations: 16

```
> scstep<-stepAIC(d11,direction="backward")
```

Start: AIC=461.14

```
d1t ~ Lat + Long + mes + do + temp + sal + depth + hab + mud
```

	Df	Deviance	AIC
- do	1	431.24	459.24
- Long	1	431.41	459.41
- depth	1	431.45	459.45
- hab	4	437.90	459.90
<none>		431.14	461.14
- temp	1	441.51	469.51
- mes	3	450.23	474.23
- sal	1	451.54	479.54
- Lat	1	452.22	480.22
- mud	1	454.07	482.07

Step: AIC=459.24

```
d1t ~ Lat + Long + mes + temp + sal + depth + hab + mud
```

Step: AIC=455.85

```
d1t ~ Lat + mes + temp + sal + hab + mud
```

	Df	Deviance	AIC
- hab	4	439.74	455.74
<none>		431.85	455.85
- temp	1	442.45	464.45
- mes	3	450.71	468.71
- Lat	1	455.54	477.54
- mud	1	455.77	477.77
- sal	1	460.49	482.49

Step: AIC=455.74

```
d1t ~ Lat + mes + temp + sal + mud
```

	Df	Deviance	AIC
<none>		439.74	455.74
- temp	1	449.82	463.82
- mes	3	455.88	465.88
- mud	1	467.56	481.56
- Lat	1	468.19	482.19
- sal	1	469.41	483.41

```
> d12<-glm(dlt~Lat+mes+temp+sal+mud,family=binomial,data=d1tudo)
> summary(d12)
```

```
Call:
glm(formula = dlt ~ Lat + mes + temp + sal + mud, family = binomial,
     data = d1tudo)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.6354	-0.6643	-0.3763	-0.1874	2.4612

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-42.077698	652.979852	-0.064	0.94862
Lat	0.600369	0.117138	5.125	2.97e-07 ***
mesjaneiro	14.825451	652.959575	0.023	0.98189
mesjulho	11.632647	652.959962	0.018	0.98579
mesmaio	12.126369	652.959679	0.019	0.98518
temp	0.209825	0.068377	3.069	0.00215 **
sal	-0.060300	0.011371	-5.303	1.14e-07 ***
mud	0.025255	0.005056	4.995	5.88e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 537.14 on 573 degrees of freedom
Residual deviance: 439.74 on 566 degrees of freedom
AIC: 455.74

Number of Fisher Scoring iterations: 15

```
> d12<-glm(dlt~Lat+sal+mud,family=binomial,data=d1tudo)
> summary(d12)
```

```
Call:
glm(formula = dlt ~ Lat + sal + mud, family = binomial, data = d1tudo)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.5853	-0.6570	-0.4076	-0.2588	2.6945

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-19.628015	4.087340	-4.802	1.57e-06 ***
Lat	0.450116	0.098714	4.560	5.12e-06 ***
sal	-0.060991	0.010917	-5.587	2.32e-08 ***
mud	0.027682	0.004827	5.735	9.78e-09 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 537.14 on 573 degrees of freedom
Residual deviance: 456.41 on 570 degrees of freedom
AIC: 464.41

2. Validar modelo com 25% dos dados não usados para construir o modelo (não é o ideal!)

```
> dlval<-glm(dlt~Lat+sal+mud, family=binomial, data=dltodo_val)
> summary(dlval)
```

```
Call:
glm(formula = dlt ~ Lat + sal + mud, family = binomial, data = dltodo_val)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.29741	-0.34222	-0.14132	-0.07545	3.12079

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-55.212324	18.873906	-2.925	0.00344	**
Lat	1.393692	0.465619	2.993	0.00276	**
sal	-0.061728	0.019314	-3.196	0.00139	**
mud	0.006122	0.011277	0.543	0.58722	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 128.965 on 194 degrees of freedom
Residual deviance: 84.175 on 191 degrees of freedom
AIC: 92.175

3. Calcular AUC

```
> library(verification)
> roc.plot(dltodo_val$dlt,fitted(dlval)) → Plot ROC
> roc.area(dltodo_val$dlt,fitted(dlval))
```

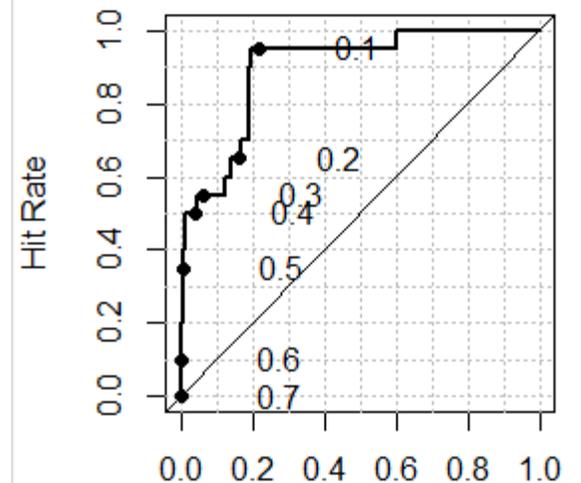
```
$A
[1] 0.896 → Valor AUC
```

```
$n.total
[1] 195
```

```
$n.events
[1] 20
```

```
$n.noevents
[1] 175
```

```
$p.value
[1] 3.421045e-09
```



```

> dl.pred<-fitted(dlval)
> dl.pred
      1      2      3      4      5      6      7
0.003017501 0.003327368 0.003113354 0.002852423 0.006212682 0.006192243 0.006127846
      8      9     10     11     12     13     14
0.006572253 0.006791372 0.006487062 0.005927443 0.005844721 0.005772329 0.008107128
     15     16     17     18     19     20     21
0.006011290 0.006371953 0.005873758 0.006325417 0.004500686 0.005120106 0.005003132
     22     23     24     25     26     27     28
0.257340975 0.272837987 0.270068087 0.491716223 0.512887155 0.499630531 0.486858907
     29     30     31     32     33     34     35
0.365678944 0.209245659 0.158722058 0.016995523 0.012395222 0.012696084 0.015652864
     36     37     38     39     40     41     42
0.014564843 0.019323597 0.019540786 0.021971049 0.019493501 0.014855656 0.020479420
     43     44     45     46     47     48     49
0.017165995 0.056788712 0.056018890 0.054986639 0.062136904 0.060064202 0.061972069
     50     51     52     53     54     55     56
0.062395144 0.059434429 0.059485665 0.101076391 0.103487176 0.101402367 0.108027322
     57     58     59     60     61     62     63
0.122661807 0.080845675 0.056961738 0.064312147 0.002467528 0.002445269 0.002524241
     64     65     66     67     68     69     70
0.002226016 0.001922989 0.002080860 0.001812757 0.002197395 0.002421247 0.002692563
     71     72     73     74     75     76     77
0.002649609 0.002596052 0.002303920 0.002358102 0.002044288 0.006573539 0.006079896
     78     79     80     81     82     83     84
0.006595679 0.006755951 0.006742495 0.006526244 0.004529403 0.005012779 0.004638738
     85     86     87     88     89     90     91
0.436407618 0.428661136 0.196252881 0.251035421 0.188993254 0.181595312 0.262521785

```

Valores previstos pelo modelo, usando os novos dados.



Atenção: são probabilidades da espécie estar presente/ausente, que variam entre 0 e 1

Para transformar em 0s e 1s, precisamos de um threshold. Qual??

```
> dltotal<-data.frame(plotID=1:195,dltudo_val$dlt,dl.pred)
> colnames(dltotal)<-c("plotID","observed", "predicted")
```

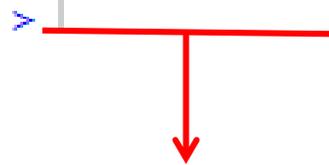


Nova tabela com dados observados e previstos pelo modelo

```
> library(PresenceAbsence)
> error.threshold.plot(dltotal,opt.methods=c(1,2,3))
```

	opt.methods	threshold	PCC	sensitivity	specificity	Kappa
1	Default	0.50	0.9282051	0.35	0.9942857	0.4688716
2	Sens=Spec	0.12	0.8051282	0.75	0.8114286	0.3465608
3	MaxSens+Spec	0.11	0.8205128	0.95	0.8057143	0.4366488

Outras medidas de "model accuracy"



Diferentes métodos de calcular o threshold. Existem 9 neste package!