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main text

Sampling Designs for Bottom Trawl Surveys: The Portuguese Autumn Survey Field Experience

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Abstract

This study presents the results of a field test of four sampling designs for the Portuguese Bottom Trawl Survey. The main objective was to test three new proposals and compare their performance with the design in use at the moment. We aimed at exploring new spatial configurations and possible increases on sample size which could be achieved by e.g. reducing the hauling time from 1 hour to 1/2 hour. A secondary objective was to propose a new statistical approach to analyze and compare the results obtained. We used yield in kg/hour of Hake (Merluccius merluccius) and Horse Mackerel (Trachurus trachurus). The analysis was carried out using model-based geostatistics to estimate the model parameters and predict abundance on the area. The performance statistics, mean abundance, 95th percentile, coverage of the prediction confidence interval and a generalized cross validation index were computed. The main results showed that the design that perform consistently better should mix a random component with a systematic basis. In the case of small designs the best approach is to use a random design that covers all the area, somehow mixing both characteristics. The methods proposed covered a large area of the bottom trawl surveys statistical characteristics and could easily be extended for other variables if necessary, constituting a consistent set of tools to analyze bottom trawl survey data.

Key-words: bottom trawl surveys; geostatistics; hake; horse mackerel; sampling design; field experience.

1 Introduction

Bottom trawl surveys (BTS) have been carried out for a long time mostly following spatial stratified random designs (e.g. Fogerty, 1985; ICES, 2004b). The survey design usually relies on previous knowledge of the target species spatial distribution and population structure and on statistical analysis of preliminary data (e.g. Ault et al., 1999; Hata and Berkson, 2004) or simulation procedures (e.g. Schnute and Haigh, 2003; ICES, 2005b). These results are combined with operational issues (trawlable grounds, vessel availability, etc) to define a protocol for the BTS. Most surveys use sampling statistics (Cochran, 1960; ICES, 2004b) to estimate abundance although several analysis were carried out in order to obtain more precise abundance estimates (e.g. Petrakis et al., 2001; Chen et al., 2004; Dingsor, 2005; Dressel and Norcross, 2005; Mendes et al., in press). The survey sampling design is often reviewed across the years with the aim of improving the estimates of abundance. The most common changes in survey designs are related with stratification (e.g. Smith and Gavaris, 1993; Folmer and Pennington, 2000), tow duration (e.g. Cerviño and Saborido-Rey, 2006; Wieland and Storr-Paulsen, 2006) and technical issues such as gear changes (e.g. Zimmermann et al., 2003; Cooper et al., 2004). However, the choice of the type of design is rarely questioned and tests about sampling strategies for bottom trawl surveys are seldom reported in the literature.

Portuguese bottom trawl surveys (ptBTS) have been carried out on the Portuguese continental waters since June 1979 on board the R/V Noruega, twice a year, during Summer and Autumn. The main objectives of these surveys are: (i) to estimate indices of abundance and biomass of the most important commercial species; (ii) to describe the spatial distribution of the most important commercial species, (iii) to collect individual biological parameters as maturity, sex-ratio, weight, food habits, etc. (SESITS, 1999). The target species are hake (*Merluccius merluccius*), horse mackerel (*Trachurus trachurus*), mackerel (*Scomber scombrus*), blue whiting (*Micromessistius poutassou*), megrims (*Lep-*

idorhombus boscii and *L. whiffiagonis*), monkfish (*Lophius budegassa* and *L. piscatorius*) and Norway lobster (*Nephrops norvegicus*). A Norwegian Campbell Trawl 1800/96 (NCT) with a codend of 20 mm mesh size, mean vertical opening of 4.8 m and mean horizontal opening between wings of 15.6 m has been used (ICES, 2002). Between 1979 and 1980, a stratified random sampling design with 15 strata was adopted grouping for similar depth and geographical areas. In 1981 the number of strata was revised to 36. In 1989 the sampling design was reviewed and a new stratification was defined using 12 sectors along the Portuguese continental coast subdivided into 4 depth ranges: 20-100m, 101-200m, 201-500m and 501-750 m, with a total of 48 strata. Accounting for constraints in vessel time, a sample size of 97 locations was adopted, with about 2 locations in each stratum. Within each stratum the coordinates of the sampling locations were selected nearly randomly, constrained by the historical records of clear tow positions and other information about the sea floor. This sampling plan was kept fixed over following the years.

Considering that fish populations have an explicit spatial behavior interacting with each other looking for food, reproductive conditions, protection, etc; it is natural to assume that the abundance of fish between spatial locations is correlated. Geostatistics explicitly take into account spatial patterns of the variable of interest, by adopting a model that contains a function to explain how the covariance between locations behaves with distance (see e.g. Cressie, 1993; Chiles and Delfiner, 1999; Rivoirard et al., 2000; ICES, 2004b). Besides, geostatistical principles are widely accepted for modeling fish abundance (Rivoirard et al., 2000; ICES, 2004b). Geostatistics are a model-based technique with two main advantages in what concerns inference about fish abundance: (i) robustness to odd observations, in particular with small data sets; and (ii) flexibility, allowing the estimation of variance for systematic sampling designs, or to compute statistics for which analytical expressions are not available using simulation. The major problems with model-based methods is model mis-specification and over parametrization. We relied on our experience with bottom trawls surveys

(ICES, 2002, 2003, 2004a, 2005a, 2006; Sousa et al., 2005; Mendes et al., in press) to provide contextual information to support adoption of a particular class of models, and used a two step approach to deal with over parametrization. To make inference about the model parameters we chose to use maximum likelihood (Diggle et al., 1998) instead of the traditional geostatistics approach(Isaaks and Srivastava, 1989; Cressie, 1993). The former provides unique estimates for the same data and model, while the last requires an analyst decision about the empirical semivariogram computation (lag interval, estimator, etc) and can provide different estimates depending on those decisions.

Under these considerations alternative sampling designs should be considered such as systematic or more complex sampling designs that combine systematic and random strategies. Muller (2001) and Zimmerman (2006) showed that to estimate a global mean of a spatial process a regular design is better then a random design, although the latter would be better for estimation of the correlation parameters. Jardim and Ribeiro Jr. (2006, submitted) showed that the use of sampling statistics in a situation of spatial correlation can underestimate the variance, which would be misleading for the assessment of a sampling design. Therefore, there is scope and need to test and validate such design proposals on the field, constraint by the usual operational conditions.

The main objective of the present work was to test based on field data and conditions four different sampling designs for the Autumn Portuguese bottom trawl survey, three proposed by Jardim and Ribeiro Jr. (2006, submitted) and the design in use at the moment. We aimed at exploring new spatial configurations and possible increases on sample size which could be achieved by e.g. reducing the hauling time from 1 hour to 1/2 hour. A secondary objective was to propose a new statistical approach to analyze and compare the results obtained, which combines a set of statistical methods available for the analysis of spatial data.

2 Material

Our work focused on hake (*Merluccius merluccius*) and horse mackerel (*Trachurus trachurus*) due to the relevance of these species for the commercial fisheries. The data used were collected during a BTS in July 2001 with the R/V Noruega on the southwest of Portugal (Figure **1**), in an area between 20m and 500m depth, limited on the south by the cape of S.Vicente and on the north by the Sines' Canyon, with 4300km^2 and a maximum distance within the area of approximately 150km. The information collected consisted of catch in weight (kg) by species, geographical location, date, time and haul duration. The protocols were the same used for other BTS (ICES, 2002).

The coordinates were transformed into UTM units and the area swept was computed using the haul start and ending positions, to correct for possible speed variations during the haul. The variable "yield" was computed in kg/hour and allocated to the haul starting coordinates.

Four sampling designs were tested (Figure 2): the design currently adopted for this survey, named "ACTUAL" with 19 locations, distributed following a stratified random strategy (ICES, 2002); a systematic design also with 19 locations distributed regularly over the sampling area, named "S19"; a design that overlapped both previous designs with 36 locations named "R36"; and a systematic design also with 36 locations based on S19 and adding a set of locations positioned regularly at smaller distances creating 4 denser sampling areas, named "S36". The proposed designs resulted from a pragmatic account of the operational constraints, which require clear grounds to perform the haul, and historical consistency with the sampling design currently used. A set of locations were common between designs due to the way these were constructed. The mentioned locations were sampled only once and the observation shared.

3 Methods

3.1 Geostatistical framework

The data consists of pairs (x, y) with elements $(x_i, y_i) : i = 1, \ldots, n$, where x_i denotes the coordinates of each of the n spatial locations within a study region $A \subset \mathbb{R}^2$ and y_i the measurement of the observable study variable at this location. We adopt the Box-Cox transformed Gaussian model as presented in Christensen et al. (2001) with transformation parameter λ. Denoting by z_i the transformed values, such that $g_\lambda(y_i) = z_i$, the Gaussian model for the vector of variables Z can be written as a linear model:

$$Z(x) = S(x) + \epsilon \tag{1}$$

where $S(x)$ is a stationary Gaussian process at locations x, with $E[S(x)] = \mu$, $Var[S(x)] = \sigma^2$ and an isotropic correlation function $\rho(h) = Corr[S(x), S(x')]$, where $h = \|x - x'\|$ is the Euclidean distance between the locations x and x'. The terms ϵ are assumed to be mutually independent and identically distributed $\epsilon \sim \text{Gau}(0, \tau^2)$. For the correlation function $\rho(h)$ we adopt the exponential function with algebraic form $\rho(h) = \exp\{-h/\phi\}$ where ϕ is the *range* parameter such that $\rho(h) \simeq 0.05$ when $h = 3\phi$. Following usual geostatistical *jargon* (Isaaks and Srivastava, 1989) we call $\sigma_T^2 = \tau^2 + \sigma^2$ the total sill, σ^2 the partial sill, τ^2 the nugget effect and 3ϕ the practical range. A possible expansion of this model is to allow for directional effects by assuming *geometric anisotropy* which implies different rates of decay of the correlation function in different directions following an elliptic behavior. This adds two parameters $\psi = (\psi_A, \psi_R)$ to the model, the anisotropic angle ψ_A and ratio ψ_R, which are used to obtain new coordinates in a transformed isotropic space given by:

$$x' = x \begin{bmatrix} \cos(\psi_A) & -\sin(\psi_A) \\ \sin(\psi_A) & \cos(\psi_A) \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \psi_R^{-1} \end{bmatrix}$$

where x are the original spatial coordinates space and $x^{'}$ are the corresponding coordinates on the transformed isotropic space. The analysis is carried out in the isotropic space and afterward the coordinates are back transformed to the original space.

Hereafter we use $[\cdot]$ to denote *the distribution of* the quantity indicated within the brackets. Following the adopted model, $[g_\lambda(Y)] \sim \mathrm{MVGau}(\mu\mathbf{1}, \Sigma)$, i.e. $[Y]$ is multivariate trans-Gaussian with expected value μ and covariance matrix Σ parametrized by (σ^2, ϕ, τ^2). Parameter estimates for such model can be obtained by maximizing the log-likelihood given by:

$$l(\mu, \sigma^2, \phi, \tau^2, \lambda) = (\lambda - 1) \sum_{i=1}^{n} \log(y_i) - 0.5\{n \ \log(2\pi) + \log|\Sigma| + (z_i - \mathbf{1})'\Sigma^{-1}(z_i - \mathbf{1})\} \tag{2}$$

and then used to obtain spatial prediction at any particular location within the study area. Likelihood based methods for inference on this class of geostatistical models are presented and discussed e.g. by Cressie (1993); Diggle et al. (1998) and Diggle and Ribeiro (2006).

Consider a prediction target $T(x_0) = g_\lambda^{-1}(S(x_0))$, the value of the process in the original measurement scale at spatial locations x_0. Typically x_0 defines a grid over the study area. Under the model assumptions, the predictive distribution $[T|Y]$ is multivariate trans-Gaussian and inferences about prediction means, variances and other statistics of interest can be derived. Simulations from $[T|Y]$ are obtained by simulating from the multivariate Gaussian $[S(x_0)|Y]$ and back transforming the simulated values to the original scale of measurement (Chiles and Delfiner, 1999; Diggle and Ribeiro, 2006). These simulations are usually called *conditional simulations* referring to the conditioning on the observed values Y. More generally any prediction target can be denoted by a functional $\mathcal{F}(S)$ for which inferences are obtained by computing the quantity of interest for each of the conditional simulations. For instance, the percentage of the area where the abundance is above a certain threshold, can be computed by defining a grid of points x_0 over the area, simulating the process $S(x_0)$ conditional on the observations Y, back transforming to the original scale and computing the proportion of values above the threshold. Repeating this procedure several times will produce an empirical distribution of this quantity, from which we can draw inferences.

3.2 Inference and prediction

Spatial correlation assumed in spatial models implies there is partial redundancy on the observed values and reliable parameter estimation usually demands reasonable amounts of data. Geostatistical methods can easily become over parametrized when the data sets are small, which is the case for most of the BTS, and it can be difficult to estimate all model parameters (Zhang, 2004). In general, parameters like ψ and τ^2 are difficult to identify unless a large number of observations is available. Therefore, in the analysis reported here we divided the parameter estimation in two steps. First the Box-Cox transformation parameter λ and the anisotropy parameter ψ are investigated using profile likelihoods (Diggle and Ribeiro, 2006) and afterward the estimated values are regarded as fixed values for subsequent parameter estimation. We started with the transformation parameter λ, which is approximately orthogonal to the correlation parameters (Christensen et al., 2001), and therefore can be estimated from a profile likelihood of a model without spatial terms. There is no need to fine tune the estimate of this parameter since it is often rounded to a value with some natural interpretation such as log, inverse, square-root, etc. For the anisotropy parameters we considered the north-south coastal orientation of the study region as the direction of greater spatial continuity and fixed the anisotropy angle ψ_A in 0 degrees, azimuthal angle; remaining the anisotropy ratio ψ_R to be estimated from the data. The profile likelihood for ψ_R is obtained by taking a sequence of values for this parameter and, for each one, computing the corresponding values of the likelihood, maximized with respect to the remaining model parameters. Inferences based on the profile likelihood relies on the asymptotic approximation that twice the differences between log-likelihood values are proportional to a $\chi^2_{(1)}$.

Having estimated and fixed these two parameters, we proceeded by computing the maximum likelihood estimates for the model parameters using equation 2. It is important to note that inference about the model parameters was not our aim and was considered an intermediate step to proceed with the abundance prediction and conditional simulations. Afterward we used the estimated model parameters to compute the kriging predictions on a grid x_0 with 1070 locations and performed 1000 simulations of the conditional distribution $[Y(x_0)|Y]$, for each design.

3.3 Performance statistics

The statistics selected to assess for the performance of each sampling design were organized in two groups, global and local statistics. The former are taken over all the study area to summarize the conditional distribution $[Y(x_0)|Y]$ and included the global mean μ, the k^{th} percentile p_k, and their variances, σ^2_μ and σ^2_p. The latter are related with measures at locations where data was observed summarizing the behavior in each of these locations and included the coverage of the prediction confidence interval ξ and a generalized cross validation index ε. The global mean and its variance were computed using analytical expressions while the other statistics were computed using conditional simulations.

To compute global statistics we consider the discretization of the study area by a grid x_0 with individual locations $x_i \in x_0$, $i = 1, \ldots, m$ and $m = 1070$. The conditional distribution $[Y(x_0)|Y]$ is obtained from the kriging predictor which are given as weighted averages of the observed values Y transformed to the the gaussian scale and need to be back transformed to the original scale. Consider $E[Z(x_i)]$ and $\sigma^2_z(x_i)$ the kriging predictor and its variance on a location x_i, the back transformation is given by $E[Y(x_i)] = \exp(E[Z(x_i)] + 0.5\sigma^2_z(x_i))$ if $\lambda = 0$ and $E[Y(x_i)] = (1 + 0.5E[Z(x_i)])^2 + 0.25\sigma^2_z(x_i)$ if $\lambda = 0.5$. The global mean is estimated as the average of the predicted values $\hat{\mu} = m^{-1} \sum_{i=0}^{m} \hat{E}[Y(x_i)]$. The variance of $\hat{\mu}$ is given by $\hat{\sigma}^2_\mu = m^{-2}\Sigma_0$ where Σ_0 is the covariance matrix of $[Y(x_0)|Y]$, once that kriging predictor at locations x_i are dependent random variables and being the variance of a sum of dependent random variables given by the sum of all terms of the covariance matrix. This parameter also need to be back transformed to the original scale by $\Sigma_y = Y^2(x)\exp(\Sigma_0) - 1)$ when $\lambda = 0$ or $\Sigma_y = \Sigma_0(8^{-1}\Sigma_0 + (1 + 0.5E[Z(x)])^2)$ when $\lambda = 0.5$. Further, consider $t_s(x_i)$ a realized value of the conditional simulation $s = 1, \ldots, S$ from $[T|Y]$ at the location x_i. The 95th percentile was estimated by $\hat{p} = S^{-1}\sum_s \hat{p}_s$ where $\hat{p}_s = p_{95}(t_s(x_i))$, the average of the empirical distribution $\hat{p}$ obtained from the conditional simulations, and the varianceσ^2_p of the empirical distribution of $\hat{p}$ estimated by $\hat{\sigma}^2_p = (S-1)^{-1}\sum_s(\hat{p}_s - \hat{p})^2$.

The local measures ε and ξ were computed using cross-validation statistics (Hastie et al., 2001) combined with conditional simulations. Briefly, we create a new data set by leaving one observation out at a location x_j, and simulating 1000 values from the $[Y(x_j)|Y]$. This procedure was repeated for all data locations with the empirical distributions being compared with the observed value to compute the cross-validation statistics. Consider $y(x_i)$ an observation of the process Y on location x_i, $i = 1, \ldots, n$ where $x_i \in \Delta = \{ACTUAL, S19, R36, S36\}$. Sample size n will be 19 or 36 depending on the design being $\{ACTUAL, S19\}$ or $\{R36, S36\}$, respectively. Consider $y(x_{(i)})$ the observed data set without the observation $y(x_i)$ and $t_s(x_i)$ a conditional simulation $s = 1, \ldots, S$ of $[T|Y = y(x_{(i)})]$ on location x_i. The prediction confidence interval is given by $CI(x_i) = [p_{2.5}(t_s(x_i)), p_{97.5}(t_s(x_i))]$ and the percentage of the number of observations lying inside the intervals $\xi = n^{-1}\sum_i(y(x_i) \in CI(x_i))$ is the coverage of the prediction confidence interval. The cross validation index we use is given by $\varepsilon = n^{-1}\sum_i(S^{-1}\sum_s(t_s(x_i) - y(x_i))^2)$, the average of the mean quadratic error on each location estimated using the full set of conditional simulations.

The statistics presented above entangle effects of parameter estimation and prediction of the unknown abundance at a location. We aim to isolate these effects by computing in two different ways the estimates of error measures σ_μ^2, σ_p^2 and ε: (i) using parameters estimates obtained from a pooled dataset combining all observations of the four designs, hereafter named "polled estimates"; and (ii) using parameters estimates from observations of each sampling design, hereafter named "design specific estimates". To evaluate the magnitude of parameter estimation effect we compute the ratios between both estimates of the error measures.

4 Results

In order to compare the designs we considered two groups according to their size: the *19-spots designs* $\{ACTUAL, S19\}$ and *36-spots designs* $\{R36, S36\}$ and restrict ourselves in comparing designs with equal number of points. The size of the designs would obviously have a strong effect on the precision of the predictions, specially considering these are small datasets.

Figure 3 shows the abundance of horse mackerel and hake observed during the survey for each sampling design. The circles are proportional to the logarithm of the yield (kg/hour) and the symbol "+" indicates observations equal to zero. The spatial distribution of horse mackerel was concentrated on the southeast of the study area showing higher variability than hake, with greater proportion of high values (> 4 log kg) and zeros. Hake was more evenly spread over the area, although also more concentrated towards the southern zones.

Table 1 shows sampling statistics for both species. The index of abundance obtained by the sampling mean was more homogeneous for hake than for horse mackerel across the four sampling designs. Horse mackerel presented larger variances than hake for the sampling mean, with wider confidence intervals, which in some cases presented a negative lower bound. For the 19-spots designs, the smaller variances of the abundance estimates were found for the S19 design for hake, and ACTUAL for horse mackerel. For the 36-spots designs, S36 presented lower variance in the case of horse mackerel, and both presented equal variances for hake. The small variance for horse mackerel with the ACTUAL design, is explained by the fact that one observation of 128kg/hour was not present in this design, but was present on the other designs.

The profile log-likelihood for the Box-Cox parameter λ obtained from the pooled data set is shown in Figure 4. Both species presented different behaviors with 95% confidence interval of $\approx [0.12, 0.55]$ and $\approx [-0.25, 0.05]$ for the abundance of hake and horse mackerel, respectively. For which specie we have chosen estimates of λ with natural interpretation within these confidence intervals resulting in $\hat{\lambda} = 0$ for horse mackerel, the logarithmic transformation, and $\hat{\lambda} = 0.5$ for hake, a square root transformation. For the anisotropy ratio parameter ψ_R the profile log-likelihood showed no evidence of anisotropy as the value one is within the 95% confidence interval (Figure 4). Nevertheless, we carried out analysis using different values of the anisotropy ratio to check the sensibility of the results to this parameter, which proved negligible. From this moment on the analysis assumed an isotropic spatial process.

Table 2 presents both, pooled and design specific maximum likelihood estimates for the model parameters, keeping fixed the parameter values $\psi_A = 0, \psi_R = 1$ and $\lambda = 0$ or $\lambda = 0.5$ for hake and horse mackerel, respectively. The total variance σ_T^2 was similar within species, with the random design ACTUAL estimating a maximum for hake (4.04); and the pooled estimates producing a maximum for horse mackerel (6.99). Estimates of τ^2 were quite small with a maximum relative value of 36% of the total variance in the case of hake with the S19 design. In some cases τ^2 estimates were zero, reflecting the difficulty in identifying this parameter with relatively small data sets. The variance of the correlated process σ^2 showed the same pattern as σ_T^2 with maximums of 4.00 for hake with ACTUAL and 5.76 for horse mackerel with pooled estimates. The range parameter ϕ showed higher values for the pooled estimates, with practical ranges (3ϕ) above $90km$ for hake and $190km$ for horse mackerel. For hake the design specific estimates of ϕ presented a maximum value of 17.52km for S19 and a minimum of 10.21km for S36; while for horse mackerel the estimates of ϕ presented a maximum of 33.77km for S36 and a minimum of 8.45 for S19.

The relation $\frac{\sigma^2}{\phi}$ was smaller for the pooled estimates, below 0.1; for hake, ACTUAL and S36 presented values of 0.25; and for horse mackerel, S19 showed an estimate of 0.5. The combined analysis of τ^2_{REL} and $\frac{\sigma^2}{\phi}$ give information about the variability of the spatial process. Higher τ^2_{REL} are characteristic of processes with an higher random variability, and higher $\frac{\sigma^2}{\phi}$ represent less spatial structure in relation with the variability of the dependent process. Both characteristics contribute to less structured spatial processes and higher variability of the observations.

4.1 Hake

Table 3 shows results of the geostatistical analysis applied to hake. The estimates of μ and p_{95} were similar for all designs and both, pooled and design specific estimates. For μ the minimum estimate was 3.98kg/hour (ACTUAL) and the maximum 4.29kg/hour (S19), whereas p_{95} presented a minimum of 10.66kg/hour (S36) and a maximum of 11.18kg/hour (ACTUAL). Within the 19-spots designs ACTUAL presented the lowest variance in both pooled and specific design estimates, and within the 36-spots designs R36 presented the lowest estimates for both estimation procedures. The variances of the 95th percentile show a lower value of ACTUAL and R36 for the pooled estimates and the opposite for the design specific estimates, where S19 and S36 performed better. The coverage of the prediction confidence intervals ξ for the abundance were above the nominal level of 0.95 for the 19-spots designs and 0.94 for the 36-spots designs. The generalized cross validation index ε showed contradictory results for the 19-spots designs, with a lower value for S19 with pooled estimates and the opposite in the case of design specific estimates. Among the 36-spots designs, R36 produced the lowest values of ε in both situations.

The variance ratios were close to one for all designs and statistics with the exception of the ACTUAL design, that presented a ratio of 0.87 for the variance of the global mean and 1.23 for the variance of the 95th percentile. These results reflect a low influence of the inference process on the abundance estimation.

4.2 Horse mackerel

Table 4 shows results of the geostatistical analysis for horse mackerel. The estimates of μ showed a minimum of 4.78kg/hour (ACTUAL) and a maximum of 8.35kg/hour (S36). The variance σ_μ^2 showed lower values for ACTUAL with both pooled and design specific estimates, 11.43 versus 40.60 and 8.32 versus 18.73, respectively. In the case of 36-spots designs R36 performed better for both pooled and designs specific estimates. The 95th percentile showed a minimum of 19.95kg/hour (ACTUAL) and a maximum of 32.39kg/hour (S36). Note that in some situations the 95th percentile is lower than the mean, which is mainly due to the lack of robustness of the mean to large observations, that can be generated by a lognormal distribution. The variance estimates of this parameter were lower for ACTUAL and R36 with both pooled and design specific estimates. Coverage of the prediction confidence interval ξ were above the nominal level of 0.95 for R19 but all the other designs showed coverages below the nominal level. S19 had coverages of 0.84 for pooled estimates and 0.89 for design specific estimates; R36 presented coverages of 0.92 for pooled estimates and 0.94 for design specific estimates; and S36 had coverages of 0.89 for pooled estimates and 0.92 for design specific estimates. The main problem of the low confidence interval coverage is that it may reflect a tendency to under estimate the variance and jeopardizes the comparison with other results. The generalized cross validation index ε was lower for ACTUAL and S36 for both pooled and design specific estimates.

Analyzing the variance ratios it is obvious that the inference procedure is more important for horse mackerel, with values around 0.7 for ACTUAL, R36 and S36. The systematic design S19 showed an awkward value of 6.70 for the ratio of ε, which can be explained by the combined influence of the 128kg/hour observation and the low number of locations on the variance estimates.

5 Discussion

Assessing sampling designs for BTS raises interesting questions about the methods to analyze data and derive statistics of interest, which are particularly relevant considering the multipurpose nature of the surveys. There are several information to be collected for a particular population, such as population structure in length or age, sex, maturity, stomach contents or several individual weights. All these can be aimed considering or not the spatial distribution of the target variables, including the relation between them. From an ecological perspective, BTS aims to collect information on several species and how they relate to each other, like trophic relations or species assemblages. This complexity makes it very difficult to set a suitable criteria and a loss function to be minimized with relation to the designs. Here we follow a pragmatic approach using different species and statistics. We choose for analysis the variable yield in kg/hour and two species with distinct statistical and spatial distributions, hake and horse mackerel, being the former a ubiquitous species and the latter a more scholastic species. The analysis was then carried out using linear and non-linear, global and local statistics. Thus our approach enabled us to capture as much as possible the large complexity of bottom trawl surveys.

An additional source of variability for BTS are the operational conditions under which the surveys are carried out. It is common to adjust the sampling design, changing haul coordinates to account for fishing activities in the area, or removing locations under bad sea conditions. These constraints must be taken into account and that was one of the motivations to proceed with field tests for the proposed designs. Figure 2 indicates the planned and executed initial positions of the hauls and the haul's tray of our survey showing some target coordinates were relocated.

Another important feature of BTS is its destructive sampling procedure due to the trawling operations. The replication of the observation is not possible and analysis rely on a single sample. This was the main justification for sharing observations between designs. The alternative of performing the haul several times on the same location, or on a neighborhood, would introduce a confounding effect as the probability of finding an individual on the following observations would be affected by the previous measurement. However, the sampling areas are the same used by commercial fishing and there is no control over the time interval between the observation and the last trawling operation, introducing an undesirable source of variability.

Comparing the results of the sampling designs described above with different sizes and spatial configurations raises problems of confounded effects. Jardim and Ribeiro Jr. (2006, submitted) proposed to use simulated random designs and the variance ratios of the target variable between the study designs and the simulated random designs, to identify in which design there would be a greater decrease in variance compared with the random designs. Our analysis here avoids the comparisons between designs with different sizes.

The estimates of the model parameters were consistent with our knowledge of these species. Hake presented lower variance and spatial correlation range than horse mackerel. In the case of the horse mackerel the pooled estimate of $\hat{\phi} \approx 64km$, corresponds to a practical range of approximately $190km$, that surpassed the maximum distance within the area of about $150km$. This may reflect a non-stationary stochastic process but, on the context of our work, it was not relevant and it was not further explored.

The performance statistics were selected to reflect relevant characteristics and different aspects of the spatial prediction. The global mean is the most used index of abundance, often estimated by the sample average. We favor the geostatistical estimator as presented here and its variance as a measure of uncertainty, since it takes into account the spatial dependency within the area and accounts for insights about the spatial process, through the adoption of an explicitly model specification motivated by the knowledge of the area. The percentile estimated by conditional simulations was used as a non linear measure of abundance, more robust to odd observations than the global mean, an important feature for species like horse mackerel. The coverage of the prediction confidence intervals was used as a diagnostic tool. A small coverage may reflect an underestimation of the variance, in which situation the conclusions should take it into account, or the innadequacy of the model to explain the available data, flagging odd situations. The cross validation index, combined with conditional simulations, incorporates the prediction precision to the index, which is not taken into account by the traditional cross validation index. For example, for two locations sharing the same predicted value by different designs but with different prediction variances, our approach would distinguish both situations, whereas the the traditional cross validation index would not.

Overall, the results obtained for the 19-spots designs were better for the design ACTUAL. S19 performed better only for the case of hake with σ_p^2 estimated from design specific estimates and ε with pooled estimates. One of the reasons for such results are the parameter estimates which implies in lower variability of the process for ACTUAL. The estimates from ACTUAL and S19 for hake were, respectivelly, $\hat{\tau}^2_{REL}$ equals 0.01 and 0.36, and $\sigma^2\phi^{-1}$ equals 0.25 and 0.12. For horse mackerel $\hat{\tau}^2_{REL}$ equals to 0 for both designs, and$\hat{\sigma}\hat{\phi}^{-1}$were 0.37 in the case of ACTUAL and 0.50 in the case of S19. The systematic design should balance the better model estimates with better prediction characteristics. However, ACTUAL stratification was built to cover as much as possible all the study area, approaching a regular design; and the adjustments made to S19 to provide clear tow positions, changed the regularity of the systematic design. This softening of the strategic principles of both designs together with the odd horse mackerel observation found in S19, blur the conclusion that ACTUAL is the best choice.

Insofar, concerning the 36-spot designs, our results showed that R36 performed better in all cases except in the case of hake's σ_p^2 estimates obtained with pooled estimates. An interesting result is obtained for ε estimates for horse mackerel, for which S36 showed lower values but the coverage of the prediction confidence interval, ξ, was below the nominal level of 0.95 and lower than the R36 coverage. In this situation results should be taken with care, once that the comparison is compromised by the underestimation of the variance. The locations in R36 are a mix between the random and systematic designs ACTUAL and S19, and resulted in a design that covers all the study area, improving prediction, and includes some positions at close distances, allowing for better estimation of the model parameters. A clear parallel can be established with the *lattice plus closed pairs* designs of Diggle and Lophaven (2006), the *EK-optimal* designs of Zimmerman (2006) or the D_{EA} designs of Zhu and Stein (2006). All of these cover the study area and include a set of positions at small distance, albeit following different constructions, these designs performed better than their random or systematic competitors. Common to all these studies and our work, is the fact that the analysis were carried out in situations where the model parameters were considered unknown and needed to be estimated from the data, which made it clear that both parameter estimation and prediction are important for the precision of the prediction target.

The main conclusions with regards to the designs is that the design that perform consistently better should mix a random component with a systematic basis, like R36. In the case of small designs the best approach is to use a random design that covers all the area, somehow mixing both characteristics. The methods proposed covered a large area of the BTS statistical characteristics and could easily be extended for other variables if necessary, defining a consistent set of tools to analyse BTS data.

6 Acknowledgements

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Table 1: Sampling statistics for the abundance of hake and horse mackerel for each design: mean ($\bar{x}$), variance ($s^2_{\bar{x}}$) and the 95% confidence interval ($[\mathrm{IC}_{low}, \mathrm{IC}_{up}]$).

	Hake				Horse Mackerel			
	ACTUAL	S19	R36	S36	ACTUAL	S19	R36	S36
$\bar{x}$	4.22	4.13	4.12	4.33	3.96	9.11	6.77	7.12
$s^2_{\bar{x}}$	0.87	0.59	0.35	0.35	3.51	44.73	13.25	12.66
IC_{low}	2.26	2.52	2.92	3.13	0.02	−4.94	−0.62	−0.11
IC_{up}	6.18	5.75	5.32	5.53	7.90	23.16	14.17	14.34

Table 2: Pooled and design specific parameter estimates for hake and horse mackerel. The Box-Cox transformation parameter λ and the anisotropy parameters $\{\psi_A, \psi_R\}$ were estimated in a previous analysis and kept fixed. β is the mean of the spatial process, τ^2 the short distance variance or nugget effect, σ^2 is the variance of the spatial process, σ^2_T is the total variance, ϕ is the correlation range parameter, τ^2_{REL} is the relative nugget and $\sigma^2\phi^{-1}$ is the relative sill to range.

	Hake				
	Pooled	ACTUAL	S19	R36	S36
β	1.17	1.23	1.71	1.39	1.59
τ^2	1.22	0.04	1.16	0.75	0.61
σ^2	2.41	4.00	2.03	3.00	2.59
σ^2_T	3.62	4.04	3.19	3.75	3.20
ϕ	30.02	16.13	17.52	16.64	10.21
τ^2_{REL}	0.34	0.01	0.36	0.20	0.19
$\sigma^2\phi^{-1}$	0.08	0.25	0.12	0.18	0.25
ψ_A	0.00	0.00	0.00	0.00	0.00
ψ_R	1.00	1.00	1.00	1.00	1.00
λ	0.50	0.50	0.50	0.50	0.50

	Horse Mackerel				
	Pooled	ACTUAL	S19	R36	S36
β	-0.55	-0.36	-0.39	-0.44	-0.26
τ^2	1.23	0.00	0.00	0.65	1.30
σ^2	5.76	3.73	4.24	3.56	3.98
σ^2_T	6.99	3.73	4.24	4.21	5.28
ϕ	64.36	10.09	8.45	13.76	33.77
τ^2_{REL}	0.18	0.00	0.00	0.15	0.25
$\sigma^2\phi^{-1}$	0.09	0.37	0.50	0.26	0.12
ψ_A	0.00	0.00	0.00	0.00	0.00
ψ_R	1.00	1.00	1.00	1.00	1.00
λ	0.00	0.00	0.00	0.00	0.00

Table 3: Hake local and global statistics obtained with pooled and design specific estimates and rations between some of them: $\bar{\mu}$ and $\sigma^2_{\bar{\mu}}$ are the mean and variance of the global abundance; $\hat{p}_{95}$ and $\hat{\sigma}^2_p$ are the mean and variance of the 95th percentile of the global abundance; ε is the generalized cross validation index and ξ is the coverage of the prediction confidence interval with nominal level of 95%.

	19 spots designs					
	pooled		design specific		ratio	
	ACTUAL	S19	ACTUAL	S19	ACTUAL	S19
$\hat{\mu}$	4.05	4.29	3.98	4.26		
$\hat{\sigma}^2_{\mu}$	0.34	0.38	0.30	0.41	0.87	1.07
$\hat{p}_{95}$	10.86	10.94	11.18	10.85		
$\hat{\sigma}^2_p$	1.84	2.13	2.26	1.95	1.23	0.92
ξ	1.00	1.00	1.00	1.00		
ε	19.49	19.01	19.04	20.08	0.98	1.06

	36 spots designs					
	pooled		design specific		ratio	
	R36	S36	R36	S36	R36	S36
$\hat{\mu}$	4.07	4.25	4.07	4.20		
$\hat{\sigma}^2_{\mu}$	0.22	0.29	0.23	0.31	1.07	1.06
$\hat{p}_{95}$	10.71	10.66	11.01	10.78		
$\hat{\sigma}^2_p$	1.32	1.53	1.55	1.43	1.17	0.93
ξ	0.94	0.94	0.94	0.94		
ε	16.24	18.44	16.32	18.82	1.00	1.02

Table 4: Horse mackerel local and global statistics obtained with pooled and design specific estimates and rations between some of them: $\bar{\mu}$ and $\sigma^2_{\bar{\mu}}$ are the mean and variance of the global abundance; $\hat{p}_{95}$ and $\hat{\sigma}^2_p$ are the mean and variance of the 95th percentile of the global abundance; ε is the generalized cross validation index and ξ is the coverage of the prediction confidence interval with nominal level of 95%.

19 spots designs						
		pooled	design specific		ratio	
	ACTUAL	S19	ACTUAL	S19	ACTUAL	S19
$\hat{\mu}$	5.25	6.42	4.78	6.47		
$\hat{\sigma}^2_{\mu}$	11.43	40.60	8.32	18.73	0.73	0.46
$\hat{p}_{95}$	20.56	25.38	19.95	23.45		
$\hat{\sigma}^2_p$	136.76	417.84	91.29	143.48	0.67	0.34
ξ	0.95	0.84	0.95	0.89		
ε	609.35	1618.47	379.43	10825.54	0.62	6.70

36 spots designs						
		pooled	design specific		ratio	
	R36	S36	R36	S36	R36	S36
$\hat{\mu}$	5.72	8.35	5.45	8.24		
$\hat{\sigma}^2_{\mu}$	11.36	54.99	8.14	42.58	0.72	0.77
$\hat{p}_{95}$	22.32	32.39	20.92	31.51		
$\hat{\sigma}^2_p$	118.00	486.09	87.97	404.00	0.75	0.83
ε	0.92	0.89	0.94	0.92		
ξ	1285.95	944.85	1859.01	1026.03	1.45	1.09

Figure 1: Portuguese cost with solid line showing the Portuguese mainland coastline and dashed line the 500m batimetry. Gray shaded area indicates the study area.

Figure 2: Sampling designs locations with planned and executed hauls ($\diamond$ = initial position planned; $\circ$ = initial position executed; $-$ = haul tray).

Figure 3: Sampling designs locations with abundance observations of horse mackerel and hake represented by circles proportional to the log scale of the weights (kg/hour) sampled.

Figure 4: Profile log likelihoods for the Box-Cox transformation parameters λ with horizontal lines indicating the approximated 95% confidence intervals and the anisotropic ratio ψ_R for both species. In the case of ψ_R the 95% confidence interval could not be estimated due to the flatness of the likelihood.

fig1

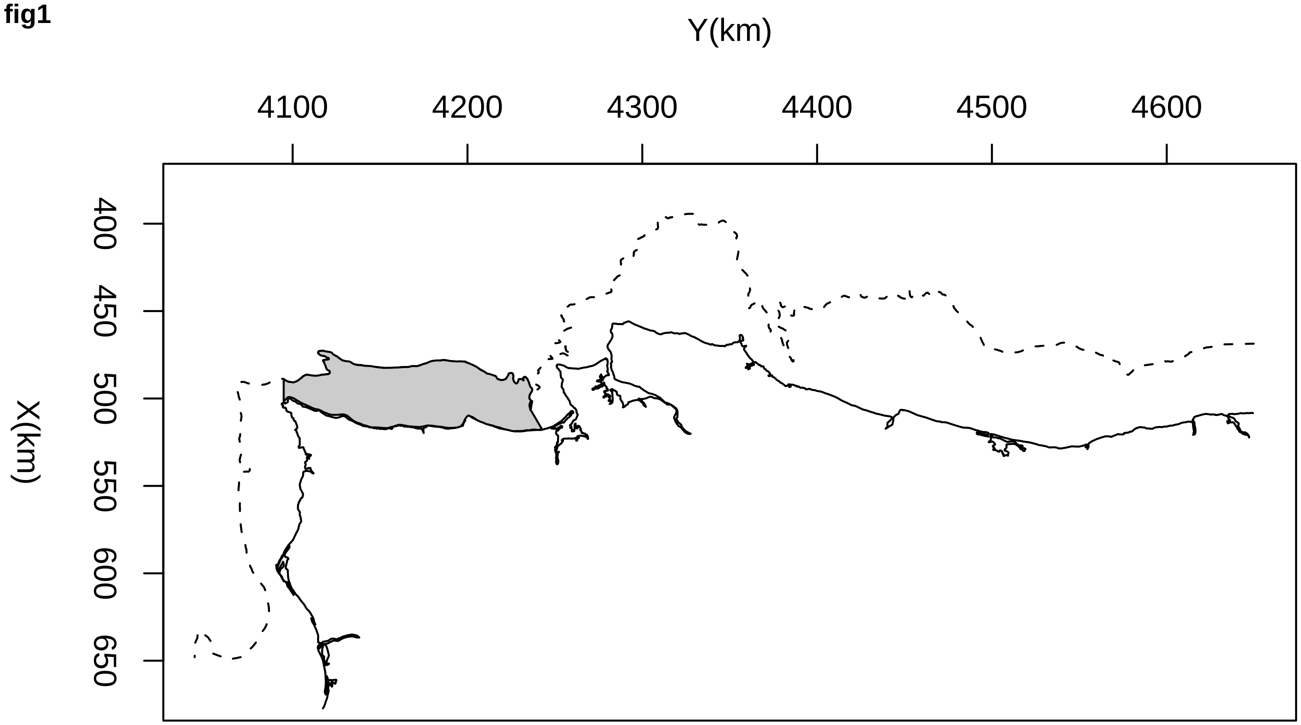


fig2

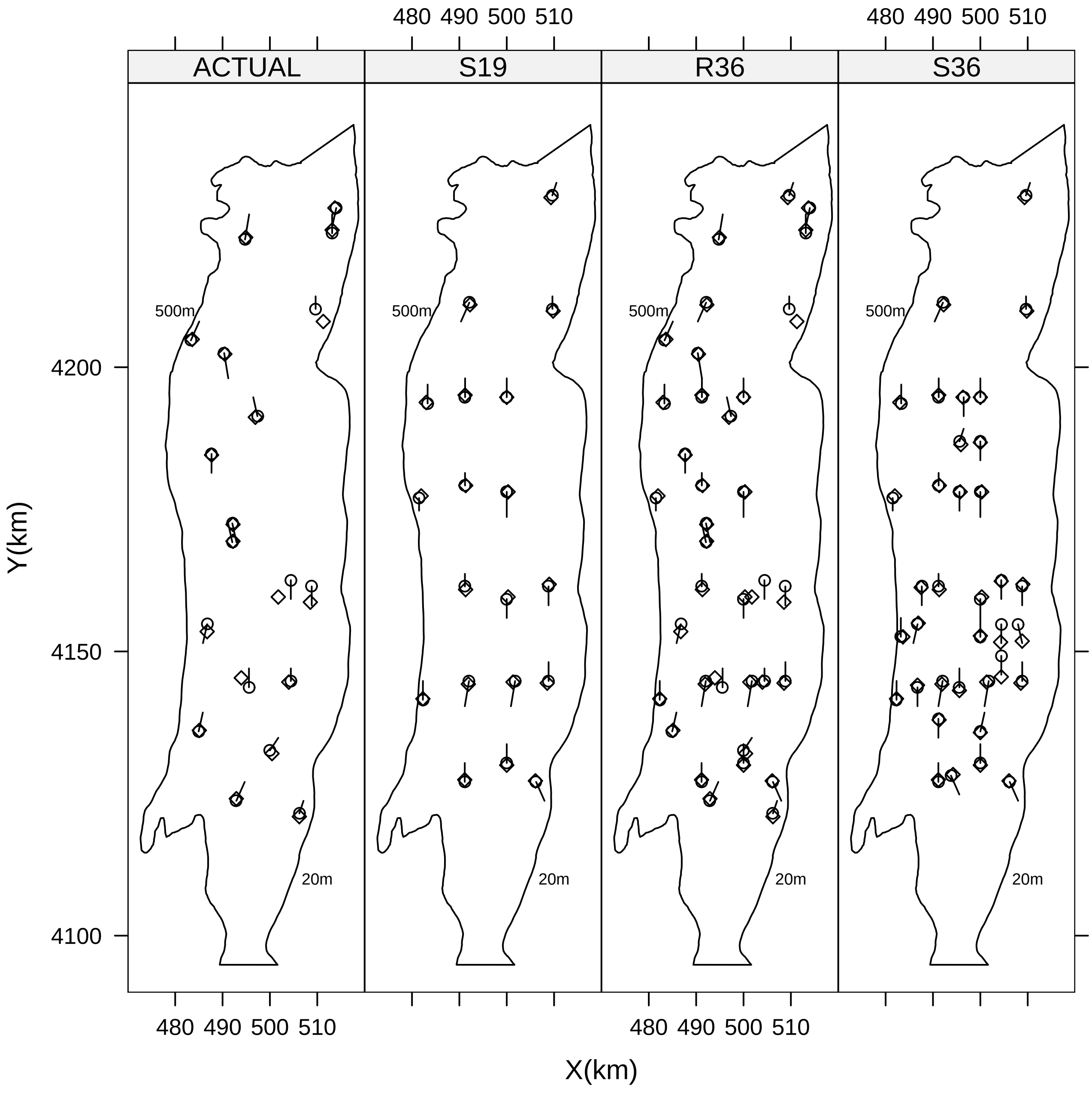
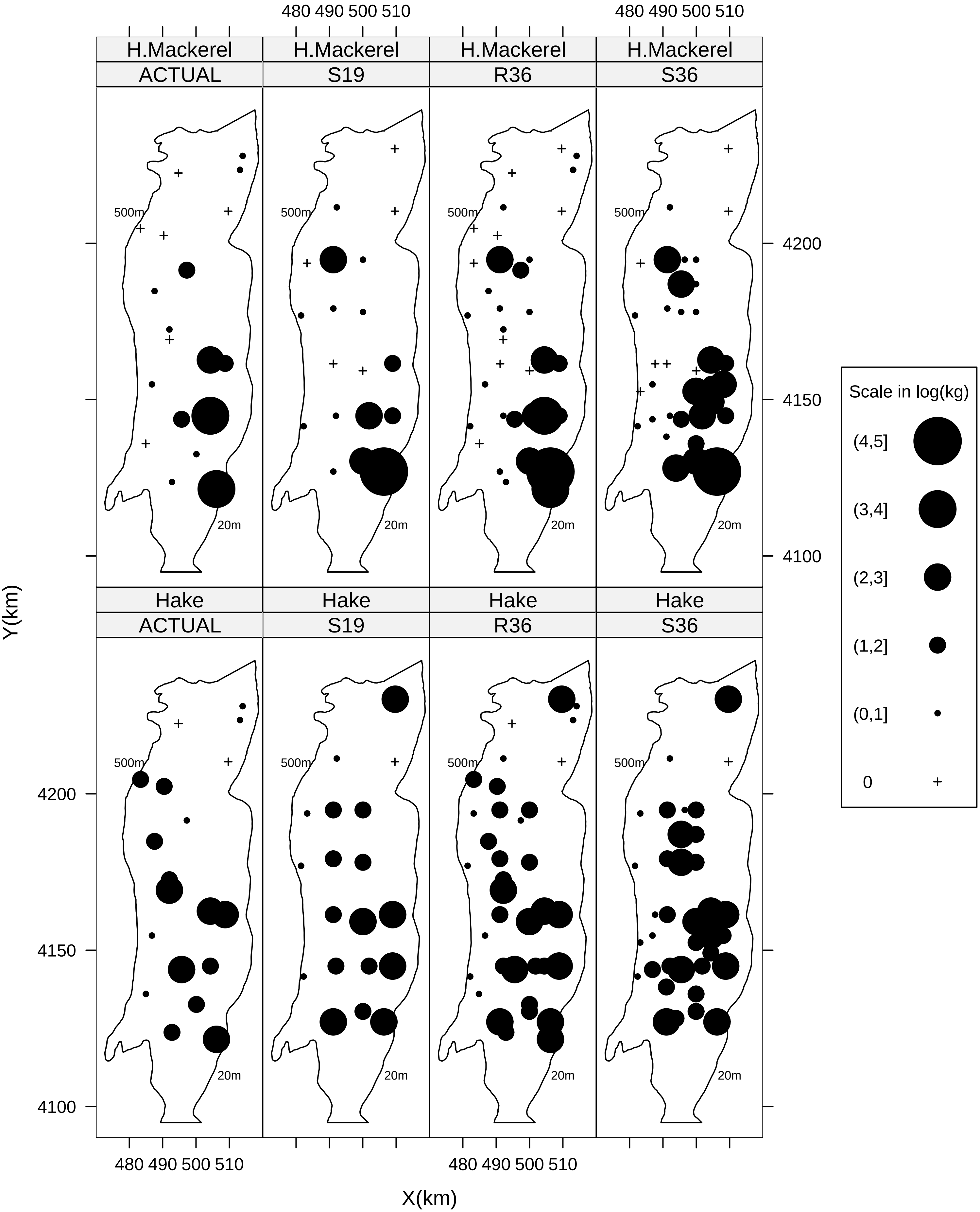
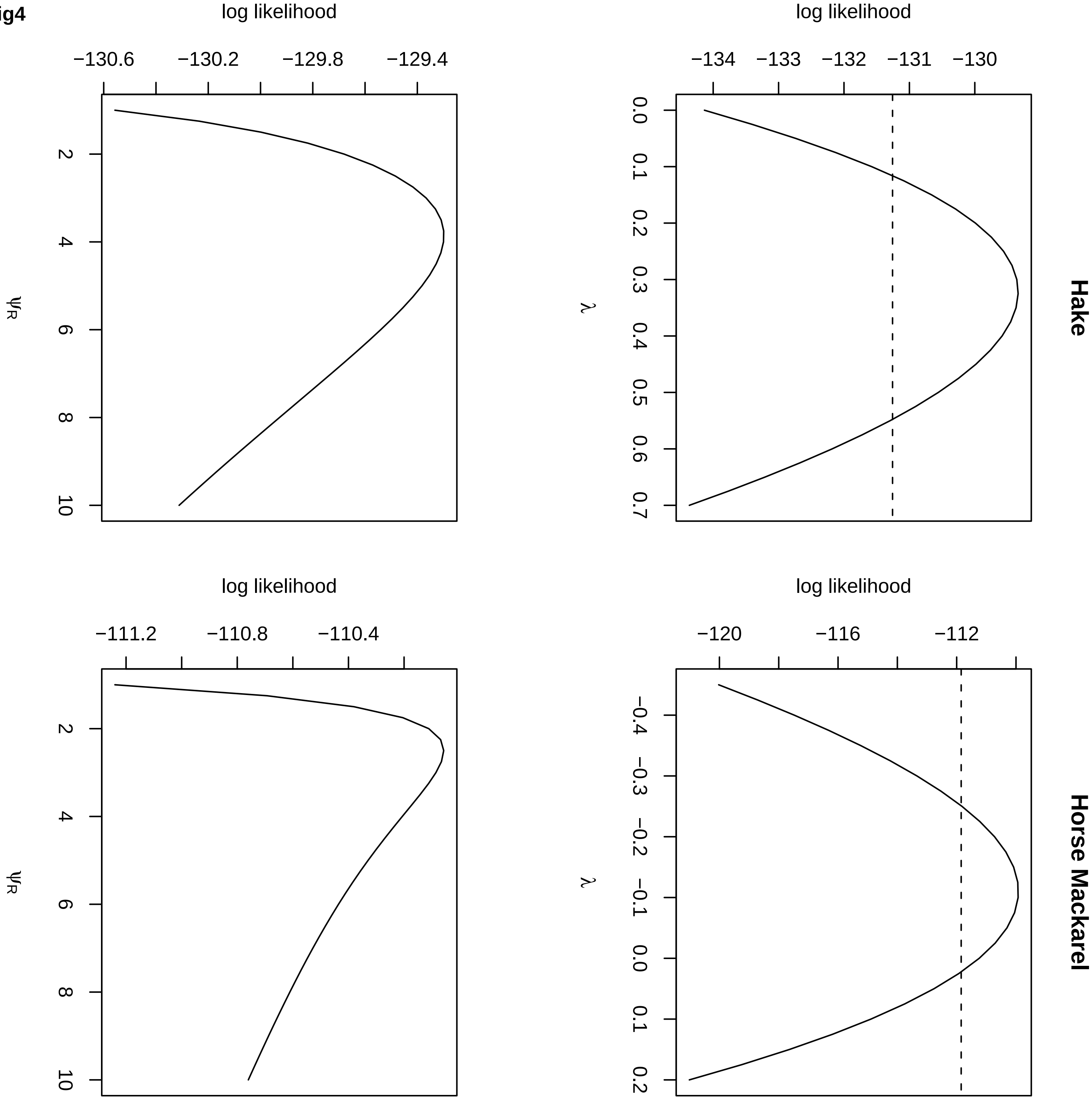

ACTUAL
S19
R36
S36
480 490 500 510
500m
20m
4200
4150
4100
Y(km)
X(km)

fig3



H.Mackerel
ACTUAL
S19
R36
S36
Hake
500m
20m
Scale in log(kg)
(4,5]
(3,4]
(2,3]
(1,2]
(0,1]
0
480 490 500 510
4100
4150
4200
Y(km)
X(km)

fig4



log likelihood
−130.6
−130.2
−129.8
−129.4
2
4
6
8
10
ψR
log likelihood
−134
−133
−132
−131
−130
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
λ
Hake
log likelihood
−111.2
−110.8
−110.4
ψR
log likelihood
−120
−116
−112
−0.4
−0.3
−0.2
−0.1
0.0
0.1
0.2
λ
Horse Mackarel

Cover Letter

Dear Sirs,

Please consider for publishing the research article "Sampling Designs for Bottom Trawl Surveys:The Portuguese Autumn Survey Field Experience".

This is the second paper of my PhD thesis which deals with independent indices of abundance, from design to estimation.

This is original research not submitted for publication elsewhere.

Thanks

EJ