Geostatistical Tools for Assessing Sampling Designs Applied to a Portuguese Bottom Trawl Survey Field Experience

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Abstract

This paper presents a bottom trawl survey (BTS) field experience carried out off the Portuguese Continental shelf to test two sampling designs proposals previously analysed by simulation (Jardim and Ribeiro Jr, 2007) which implement an hybrid random-systematic and a systematic sampling strategy. We used a common base regular grid covering the survey area and overlap it with the existent random design to build the hybrid design while the systematic design adds a set of regular locations at smaller distances creating four denser sampling areas. We use hake (*Merluccius merluccius*) yield and model-based geostatistics (Diggle and Ribeiro Jr, 2007) to compute tools like: mean abundance, μ, and the 95% percentile, p_{95}, that summarise the areal behaviour; coverage of the prediction confidence interval, ξ, to assess the adequacy of the model; and a modified generalised cross validation index, ε, to evaluate prediction precision. The hybrid design showed a lower coefficient of variation for μ (11.89% against 13.25%); a slightly higher coefficient of variation for p_{95} (11.31% against 11.09%); similar ξ (0.94); and lower ε (16.32 against 18.82). We conclude that: the hybrid design performs better and our procedure to build it can be used to adjust BTS designs to modern geostatistical techniques; and the statistics used constitute valuable tools to assess BTS performance.

Key-words: model-based; geostatistics; hake; sampling design; bottom trawl survey.

1 Introduction

Designs for Bottom trawl survey (BTS) rely on previous knowledge of the target species regarding spatial distribution and population structure combined with statistical analysis of preliminary data (e.g. Ault et al., 1999; Hata and Berkson, 2004) or simulation procedures (e.g. Schnute and Haigh, 2003; Anon., 2005b). These results are confronted with operational constraints such as trawlable grounds and vessel availability, among others, to define the definitive BTS sampling design. The survey design is typically reviewed from time to time to adjust the 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), technical issues such as gear changes (e.g. Zimmermann et al., 2003; Cooper et al., 2004) and other factors which may change over the years.

The Portuguese BTS started in June 1979, covering the continental shelf and following a stratified random design. In 1989 the stratification was defined by 12 sectors along the coast subdivided into 4 depth ranges: 20-100m, 101-200m, 201-500m and 501-750 m, with a total of 48 strata. Due to constraints in the vessel time available the sample size was set to 97 locations evenly allocated to each stratum. The coordinates of the sampling locations were selected randomly, albeit constrained by the historical records of clear tow positions and other information about the sea floor, thus avoiding places where trawling was not possible. During this period haul duration was set to one hour but recent experiments proved that half hour hauls provide the same information about length distributions (Cardador, pers.comm.). In light of this findings haul duration was reduced to half hour and an additional set of hauls were available which motivated a revision of the sampling design. The revision was splitted into a preliminary phase using simulations and geostatistical analysis (Jardim and Ribeiro Jr, 2007) and a second phase during which a field test was executed to provide real information about the proposed sampling designs. In a third moment the decision will have to be made based on the scientific data provided and the existing financial and administrative constraints.

The field experience was carried out during the summer of 2001, with R/V Noruega off the southwest of Portuguese Continental shelf (Fig. 1) using a Norwegian Campbel Trawl 1800/96 (NCT) with a codend of 20mm, mean vertical opening of 4.8m and mean horizontal opening between wings of 15.5m. The survey executed two sampling designs selected from the simulation study reported by Jardim and Ribeiro Jr (2007). The survey area was limited on the south by the cape of S.Vicente (37.00^o north), on the north by Setubal's Canyon (38.30^o north), on the east by the 20m depth isoline and on the west by the 500m isoline. The survey area had approximately 4300km^2 and the maximum distance within the area was approximately 150km. The data collected on both designs and considered here consists of date/time, geographical location and hake (*Merluccius merluccius*) catch in weight (kg). Geographical coordinates were transformed into UTM units and hake abundance was computed in kg/km and assigned to the haul starting coordinates. The area swept was computed using the haul start and ending positions to correct haul speed variations.

Our analysis adopts model-based geostatistical method (Diggle et al., 1998; Diggle and Ribeiro Jr, 2007) to explicitly take into account spatial patterns of abundance and provide a flexible modelling framework. The designs are accessed by a set of statistics to provide information about different aspects of the data, relevant for modelling fish abundance. In a global perspective, referring to the entire study region, we use mean abundance and the 95% percentile to summarise the areal behaviour of abundance, commonly used for studying time trends and building abundance indices for stock assessment. In a local perspective, referring to particular locations within the study area, we use the observed values to assess the adequacy of the model, computing the coverage of the prediction confidence interval, and the prediction precision, computing a modified generalised cross validation index. Note that the assessment of the model adequacy and the prediction precision are extremely valuable statistics, once that kriging is in fact a linear predictor and the maps produced with it will be used to estimate the spatial distribution of abundance and the abundance index mentioned before. With relation to the analysis reported here we rely on our experience with bottom trawls surveys (Anon., 2002, 2003, 2004, 2005a, 2006; Sousa et al., 2005; Mendes et al., 2007; Sousa et al., 2007) to provide contextual information which supports the adoption of a particular class of models, and avoid as much as possible model mis-specification.

The work described on this paper aims at: (i) reporting a BTS field experience to test sampling designs, and (ii) describe geostatistical tools to assess the performance of sampling designs. Although the results obtained are constraint by the characteristics of the area and the species analysed, we believe the methodology defined by our approach can be applied to other areas and species, providing an important source of information when revising sampling design.

2 Methods

This section describes the sampling designs to be tested and how they were built. It also describes the geostatistical modelling framework and the adjustments considered to cope with the small dataset available, a common characteristics of BTS due to its high price. At last we describe the technical details of the performance statistics chosen.

2.1 Sampling designs

Several authors discussed the advantages of systematic designs over random designs to sample spatial correlated variables like fish abundance (Cochran, 1960; Ripley, 1981; Thompson, 1992; Cressie, 1993; Chiles and Delfiner, 1999; Kimura and Somerton, 2006; Diggle and Ribeiro Jr, 2007). Nevertheless, in the case of spatial correlated variables there are two conflicting objectives that can not be combined in a single criteria, estimation of the covariance function parameters and prediction (Muller, 2001). In the first situation it is important to have locations at short distances to inspect the behaviour of the correlation function close to the origin, and locations at distances close to the limit of spatial correlation to estimate the correlation range (Muller, 2001). In the second situation the best predictions will result from the design with higher covariance with the locations to be predicted (Thompson, 1992). In the case of predicting fish abundance it is common to require a complete map of the study area and the best choice will be a design that covers the area evenly. However, when the covariance function is unknown, a common characteristic of fish abundance analysis, it must be estimated from the data before predicting and both objectives must be combined. Several authors propose designs that mix a set of locations covering the area with additional locations at short distances (Muller, 2001; Diggle and Lophaven, 2006; Zhu and Stein, 2006) to balance between both objectives. Such designs were not considered for bottom trawl surveys until now, although fish abundance characteristics fit well in the assumptions of these proposals. Our sampling designs were built mixing a set of operational constraints with the geostatistical principles elaborated above and the need to keep the continuity of the survey history. In particular, the two designs tested were built to distinguish between an hybrid random-systematic sampling strategy and a systematic strategy. Both designs were built from a common basis, a regular grid covering the survey area. The *hybrid design* overlaps this regular grid with the existent random design keeping some continuity with the survey historical records (top-left plot in Fig. 2). The *systematic design* includes a set of locations positioned regularly at smaller distances creating 4 denser sampling areas (bottom-left plot in Fig. 2).

2.2 Geostatistical model

Geostatistical observations consist 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 corresponding observable study variable. We adopted the Box-Cox transformed Gaussian model with transformation parameter λ as presented in Christensen et al. (2001). Denoting by z_i the transformed values, such that $g_\lambda(y_i) = z_i$, the model for the vector of variables Z observed at locations x can be written as a linear model $Z(x) = S(x) + \epsilon$, where S is a stationary Gaussian stochastic process, 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 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 terminology (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. Geometric anisotropy (Isaaks and Srivastava, 1989; Cressie, 1993) is considered an extension of this model with extra parameter $\psi = \{\psi_A, \psi_R\}$ where ψ_A is the anisotropic angle and ψ_R is the anisotropic ratio.

Hereafter we use $[\cdot]$ to denote *the distribution of* the quantity indicated within brackets. Following the adopted model, $[g_\lambda(Y)] \sim \text{MVGau}(\mu\mathbf{1}, \Sigma)$, i.e. $[Y]$ is multivariate trans-Gaussian with expected value μ and covariance matrix Σ parametrised by $\{\sigma^2, \phi, \tau^2\}$. Parameter estimates can be obtained by maximum likelihood (Cressie, 1993; Diggle et al., 1998; Diggle and Ribeiro Jr, 2007) and used for spatial prediction. In its simplest format, spatial prediction given by the *kriging predictor* consists of obtaining expected values and associated variances at unsampled locations. More generally, the *predictive distribution* of quantities of interest can be obtained analytically, if possible, or by sampling from this distribution. Consider a prediction target $T(x_0) = g_\lambda^{-1}(S(x_0))$, the realised value of the process in the original measurement scale at spatial locations x_0. Simulations from the conditional distribution $[T(x_0)|Y(x)]$ are obtained by simulating from the multivariate Gaussian $[S(x_0)|Y(x)]$ and back transforming the simulated values to the original scale of measurement (Chiles and Delfiner, 1999; Diggle and Ribeiro Jr, 2007). These simulations are called *conditional simulations* referring to the fact they are obtained from the distribution of the quantity of interest conditioned to the observed values $Y(x)$.

We split inference in two steps. First the Box-Cox transformation parameter λ and the anisotropy parameter ψ_R are investigated by pooling all the observations in a single dataset and computing profile likelihoods (Diggle and Ribeiro Jr, 2007). We consider the north-south coastal orientation of the study region as the direction of greater spatial continuity and fix ψ_A in 0 degrees azimuthal angle. Afterward, having estimated these two parameters we regard their point estimates as constants in the model and proceed by computing, for each design, the maximum likelihood estimates of the remaining model parameters. The reasoning for the two steps procedures is twofold. Pragmatically, this overcome the difficulty to identify all parameters with a small dataset, whereas in terms of modelling assumptions we regard the transformation and anisotropy parameters as part of the model specification, reflecting the nature of the data and contextual information and therefore not to be identified by the designs. Thereafter, we compute kriging predictions on a 2×2km grid within the study area, x_0, with a total of 1070 locations, and obtain 1,000 conditional simulations from $[Y(x_0)|Y]$ for each design.

2.3 Performance statistics

Consider $E[Z(x_i)]$ and $\sigma_z^2(x_i)$ the kriging predictor and its variance on the Gaussian scale at location $x_i \in x_0$ and the transformation parameter $\lambda = 0.5$. Back transformation to the original scale gives $E[Y(x_i)] = (1 + 0.5E[Z(x_i)])^2 + 0.25\sigma_z^2(x_i)$ and the global mean is estimated by averaging the predicted values $\hat{\mu} = m^{-1}\sum_{i=0}^{m} \hat{E}[Y(x_i)]$. The variance of $\hat{\mu}$, denoted by $\hat{\sigma}_\mu^2$, is computed by the sum of all terms in the covariance matrix $\Sigma_Y(x_0) = Var[Y(x_0)|Y(x)]$, back transformed by $\Sigma_Y(x_0) = \Sigma_Z(x_0)[8^{-1}\Sigma_Z(x_0) + (1 + 0.5E[Z(x)])^2]$, where $\Sigma_Z(x_0)$ is the covariance matrix of $[S(x_0)|Z(x)]$. More generally, inferences on other quantities of interest $T(x_0)$ are obtained from the conditional simulations. Denote by $t_s(x_0)$, $s = 1, \ldots, S = 1,000$ conditional simulations from $[T(x_0)|Y(x)]$. For example, an α-th percentile is estimated by $\hat{p} = S^{-1}\sum_s \hat{p}_s$ where $\hat{p}_s = p_\alpha(t_s(x_0))$, the average of the empirical distribution $\hat{p}$ obtained from the conditional simulations. The variance of $\hat{p}$ is given by $\hat{\sigma}_p^2 = (S-1)^{-1}\sum_s(\hat{p}_s - \hat{p})^2$.

The coverage of the prediction confidence interval, ε, and the generalised cross validation index, ξ, were computed using cross-validation statistics (Hastie et al., 2001) combined with conditional simulations as follows. First, create a new data set by leaving one observation out at a location x_i, simulate 1,000 values of the variable at that location, and repeated this procedure visiting all data locations. Subsequently, consider $y(x_i)$ an observation of the process Y on location x_i, $i = 1, \ldots, n$; $y(x_{(i)})$ the observed data set without the observation $y(x_i)$ and $t_s(x_i)$ a conditional simulation $s = 1, \ldots, S$ of $[T(x_i)|Y = y(x_{(i)})]$ on location x_i. The predictive confidence interval is given by $CI(x_i) = [p_{2.5}(t_s(x_i)), p_{97.5}(t_s(x_i))]$ and the proportion of observations lying inside the intervals $\xi = n^{-1}\sum_i(y(x_i) \in CI(x_i))$ provides the *coverage* of the prediction confidence interval. The cross validation index 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.

3 Results

The two sampling designs and the observations of hake yield are presented in the leftmost panels of Figure 2 where the base regular design is represented by the black triangles. The abundance of hake observed showed that the distribution of yield was spread over the area, presenting lower values in the north and a small number of zeros.

The 95% confidence interval obtained for the Box-Cox transformation parameter was $[0.12, 0.55]$ and we set $\hat{\lambda} = 0.5$, corresponding to a square root transformation. The profiled log-likelihood of the anisotropy ratio showed no evidence of anisotropy. Nevertheless, we carried out analysis using different values of ψ_R to check the sensibility of the results, which proved negligible.

Covariance parameters estimates presented higher values for the hybrid design than the corresponding ones given by the systematic design (Table 1). The total variance $\hat{\sigma}^2_T$ was 3.75, with $\hat{\tau}^2 = 0.75$ and $\hat{\sigma}^2 = 3.00$; and $\hat{\phi} = 16.64$. While the systematic design estimates were $\hat{\sigma}^2_T = 3.20$, with $\hat{\tau}^2 = 0.61$ and $\hat{\sigma}^2 = 2.59$; and $\hat{\phi} = 10.21$. Looking at τ^2_{REL} and $\sigma^2\phi^{-1}$, that give information about the variability of the spatial process, both designs showed similar relative nuggets but the hybrid design showed a lower ratio between sill and range, reflecting a higher spatial structure of the stochastic process. Notice that the practical range, 3ϕ, was $\approx 50km$ for hybrid and $\approx 30km$ for the systematic design.

The rightmost panels of Figure 2 show the abundance maps predicted and their variance, for each design. Both predictions are similar and the spatial pattern of variance reflects the influence of the observations, showing lower variability near the observed locations and higher variability in areas where extrapolation was further extended. The hybrid design had higher variance in the centre-east of the study area and lower variance on the north due to a better coverage in this area.

The estimates of μ and p_{95} were similar although the hybrid design presented slightly lower values. The hybrid design showed a lower coefficient of variation for μ, $\mathrm{CV}_\mu = 11.89\%$ than the systematic design, $\mathrm{CV}_\mu = 13.25\%$. The p_{95} variance was slightly lower for the systematic design, $\mathrm{CV}_{p95} = 11.09\%$, while the hybrid design presented $\mathrm{CV}_{p95} = 11.31\%$. The coverage of the prediction confidence intervals was 0.94 for both designs. These results reinforce our modelling choices given that if the model was wrong we'd expect ξ to be different from the nominal value of the confidence interval. The generalised cross validation index presented a lower estimate with the hybrid design, 16.32, than with the systematic design, 18.82, showing an higher prediction precision of the hybrid design. The above mentioned results reflect that the higher spatial structure of the stochastic process estimated for the hybrid design surpassed its higher total variability with relation to the estimation of these performance statistics.

4 Discussion

Assessing sampling designs for BTS raises interesting questions about appropriated methodologies to analyse data and derive statistics of interest, which are particularly relevant considering the multipurpose/multispecies nature of BTS and the small sample sizes.

The adoption of a formal criteria and loss function to find an optimum design seems unrealistic in practice due to the multidimensionality of the data and the conflicting objectives of inference and prediction. Here we follow a pragmatic approach to sampling design and started by choosing a design that joins a regular grid with the old random design, followed by a second design that uses the same regular grid but reallocates the random locations in a regular shape. This way we build designs that implement the two most promising strategies, considering the wide literature that support the use of systematic designs for spatial correlated variables, and test the possibility of keeping the continuity with the historical time series. To compare these proposals we rely on spatial modelling to compute statistics of primary interest and look for consistency among them, exploring several aspects of the same dataset. We advocate that the approach described above will provide valuable information to support the decision process.

The performance statistics were selected to reflect relevant characteristics and different aspects of spatial prediction. The global mean is the most used index of abundance, often estimated by the sample average. We favour the geostatistical estimator presented and its variance as a measure of uncertainty, considering it takes into account the spatial dependency within the area and insights about the spatial process. The 95th percentile estimated by conditional simulations can be used to identify areas of high abundance, giving information about candidate areas to protect. The coverage of the prediction confidence intervals is a diagnostic tool. A small coverage reflects an underestimation of the variance or the inadequacy of the model to explain the available data. The cross validation index combined with conditional simulations, incorporates the prediction precision in the index, which is not taken into account by the traditional cross validation. For example, if a location has the same predicted value by different designs but with different prediction variances, our approach would distinguish both situations, differently from the usual cross validation index.

Our results showed that the hybrid design performed better in all cases except for σ_p^2. 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.

Concluding, we consider that our results give indications that keeping the old random design and add a regular grid to build a new design can be a good and pragmatic solution to adjust BTS designs to modern model-based geostatistics techniques. Secondly, the performance statistics described above seem to capture the most important features of the data with relation to abundance estimation, constituting good measures to assess BTS performance.

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Table 1: Estimates of model parameters and performance statistics by design. Model parameters are: τ^2, the short distance variance or nugget effect; σ^2 the variance of the spatial process; σ_T^2 the total variance; ϕ the correlation range parameter; and the transformation parameters λ, the Box-Cox parameter and the anisotropy parameters $\{\psi_A, \psi_R\}$. The relative nugget, τ_{REL}^2, and the ratio between relative sill and range $\sigma^2\phi^{-1}$, were computed to give more insights about the spatial process. Performance statistics are: $\bar{\mu}$ and $\sigma_{\bar{\mu}}^2$, the mean and variance of the global abundance; $\hat{p}_{95}$ and $\hat{\sigma}_p^2$, the mean and variance of the 95th percentile of the global abundance; ε, the generalised cross validation index and ξ, the coverage of the prediction confidence interval with nominal level of 0.95.

	hybrid	**systematic**
	model parameters	
τ^2	0.75	0.61
σ^2	3.00	2.59
σ_T^2	3.75	3.20
ϕ	16.64	10.21
τ_{REL}^2	0.20	0.19
$\sigma^2\phi^{-1}$	0.18	0.25
ψ_A	0.00	0.00
ψ_R	1.00	1.00
λ	0.50	0.50
	performance statistics	
$\hat{\mu}$	4.07	4.20
$\hat{\sigma}_\mu^2$	0.23	0.31
cv	11.89	13.25
$\hat{p}_{95}$	11.01	10.78
$\hat{\sigma}_p^2$	1.55	1.43
cv	11.31	11.09
ξ	0.94	0.94
ε	16.32	18.82

Figure 1: Survey area on the southwest of the Portuguese Continental shelf between 20m and 500m.

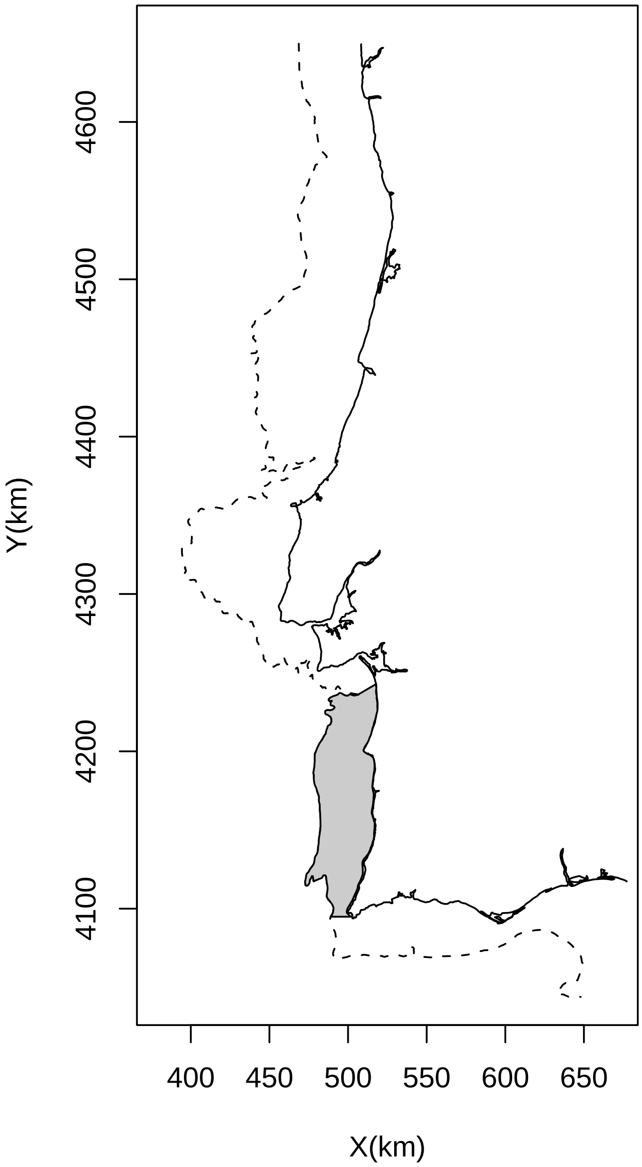

Figure 2: Study area on the Portuguese southwest coast. The top panels show information about the hybrid random-systematic design and the bottom panels about the systematic design. The leftmost plots show the sampling designs locations, the black triangles represent the regular grid common to both designs, and the open circles the additional locations. Follows the observations of hake yield (kg/km) and the predictions obtained by kriging, both on the square root scale. The rightmost plots present the kriging variance