Estimating Abundance at Age with Bayesian Geostatistics and Compositional Data Analysis

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Abstract

This work presents a new methodology to estimate abundance indices by age and year that combines the spatial distribution of the stock and the relation between age groups in a single model. By separating the age compositions from the age-aggregated catch per unit effort, suitable models can be applied to each variable, greatly improving the analysis of the importance of each factor. Age structures were studied by compositional data analysis allowing the full covariance structure of age compositions to be considered. Age-aggregated catch data was modelled with geostatistical methods explicitly modelling the correlation between abundance at different locations. The methodology produces several abundance indicators that provide an overview of abundance along different perspectives. The analysis of age compositions provides an insight on how the population structure evolves over time. The geostatistical submodel returns abundance indicators in both space and time perspectives. An important outcome of this methodology is a framework to obtain simulations of abundance at age that can be used as input to large simulation frameworks like Management Strategy Evaluation. An application to Hake (*Merluccius meluccius*) caught by the Autumn Series of Portuguese Bottom Trawl Surveys (BTS) is presented, and methods are proposed to handle specific characteristics of the problem at hand, namely, asymmetry and over-dispersion. The application presented assumed that age compositions were independent from age aggregated catches, an assumption supported by the exploratory data analysis.

Key-words: model-based geostatistics; compositional data analysis, bottom trawl surveys; hake; abundance indices.

1 Introduction

Estimates of abundance are important indicators of stock size and space-time distribution of marine populations. Such indicators contain valuable information for stock assessment, where they are used as fisheries-independent inputs, and, more generally, for fisheries advice and ecological management. Several methods have been proposed to study abundance using design-based techniques (Cochran 1960; Thompson 1992; Smith and Gavaris 1993); specific statistical distributions like log-normal (McConnaughey and Conquest 1993; Brynjarsdottir and Stefansson 2004; Dingsor 2005; Smith 1990), delta (Pennington 1983; Stefansson 1996; Smith 1988), Poisson and negative binomial (O'Neill and Faddy 2003; Pradhan and Leung 2006) or zero inflated distributions (Martin et al. 2005; Mendes 2007); and different modelling procedures like generalised linear models (Smith 1990; Stefansson 1996; Brynjarsdottir and Stefansson 2004; Chen et al. 2004; Sousa et al. 2007), generalised additive models (Piet 2002), geostatistics (Rivoirard et al. 2000; Roa-Ureta and Niklitschek in press) or hierarchical models (Mendes 2007).

Considering that individuals of the same age or length, group together looking for food, protection, reproductive conditions, etc; sampling these populations will naturally originate datasets with high correlation, both in population structure and spatial distribution. Recently, Hrafnkelsson and Stefansson (2004) and Babak et al. (2007), following the work of Aitchison (1982, 2003) on statistical analysis for compositional data, describe methods to model the correlation between length groups using Bayesian methods and maximum likelihood estimators, respectively. It must be noticed that compositional data is defined by the vector of proportions of some whole, subject to the constraint of the sum of all proportions being one, which is exactly what the population age structure represents. On the other hand, the spatial patterns encountered on abundance data are expressed by the correlation between observations related to the distance between the geographical locations where the observations were collected, which can be modelled with geostatistical methods (Cressie 1993; Diggle et al. 1998; Chiles and Delfiner 1999; Diggle and Ribeiro 2007).

Our aim with this work is to propose a new methodology that combines the spatial distribution of the stock and the relation between age groups in a single model. The methodology provides a framework to obtain simulations of abundance at age that can be used as input to large simulation frameworks like Management Strategy Evaluation (MSE) (Hammond and Donovan in press; Johnston and Butterworth 2005; Punt et al. 2005; Kell et al. 2007), a major subject for modern scientific advice on fisheries and ecological management. An application to Hake (*Merluccius meluccius*) caught by the Autumn Series of Portuguese Bottom Trawl Surveys (BTS) is presented, and methods are proposed to handle specific characteristics of the problem at hand.

The next section describes the Portuguese BTS, the data collected and the dataset used for analysis. On the Methods section we will start by presenting the model and its most important characteristics followed by a detailed description of parameter estimation for abundance at age. The Results section describes the adjustments required to apply the proposed model to estimate the Hake abundance at age off the Portuguese mainland and presents abundance estimates by year, at age by year, and spatial distribution by year. Finally, we discuss the model and its limitations, and compare the results obtained with the abundance at age estimates obtained using design-based statistics.

2 Material

The Portuguese BTS have been carried out in Portuguese continental waters since 1979 on board the R/V Noruega and R/V Capricórnio. 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, and (iii) to collect individual biological parameters such as maturity, sex-ratio, weight, food habits, etc. The target species are hake (*Merluccius merluccius*), horse mackerel (*Trachurus trachurus*), mackerel (*Scomber scombrus*), blue whiting (*Micromessistius poutassou*), megrims (*Lepidorhombus 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 (Anonymous 2002).

The sampling design between 1989 and 2004 followed a stratified random strategy. The stratification was defined by 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. Due to constraints in vessel time the sample size was limited to a total of 97 locations, which were allocated evenly to obtain 2 locations in 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. In 2005 a new sampling design, composed by a regular grid with a set of additional random locations, was introduced following Jardim and Ribeiro (2007). The tow duration was 60 minutes until 2001 and then reduced to 30 minutes for the subsequent years, based on an experiment that showed no significant differences in the mean abundance and length distribution between the two tow durations (Cardador, pers.comm.). Historically the Portuguese Autumn bottom trawl survey has been carried out between September and December and hauls occurred during daylight. The number of hauls per year, the estimates of abundance by year together with its standard deviation and coefficient of variation are presented in the first five columns of Table 1. Sampling statistics of abundance at age per year and coefficient of variation are showed on the top panel of Table 2.

The dataset included all valid hauls executed during the Autumn surveys between 1989 and 2006. Each record corresponds to hake catches in number of individuals by age, haul duration (minutes), haul time, haul date, coordinates (UTM, Zone 29), bottom salinity and bottom temperature. Catches obtained with R/V Capricórnio (1996, 1999, 2003 and 2004) were calibrated to R/V Noruega's catches using factors by age estimated in a calibration exercise in 2006 (Cardador, pers.comm). Figure 1 shows the map of observed age aggregated catches of hake during the study period.

3 Methods

The model we propose for the abundance at age variable I consists of a product of two random variables $I_{ij} = Y_i P_{ij}$ where $i = 1, \ldots, n$ indexes years and $j = 1, \ldots, m$ indexes ages. In this notation Y_i represents the age aggregated abundance for the i^{th} year and P_{ij} refers to the proportion of individuals at the i^{th}year and j^{th}age and the vector $\mathbf{P}_i$ denotes the age composition for each year. Our aim is to disentangle population abundance from its composition by age, so that appropriate statistical modelling methods can be used independently, taking into account the nature of these variables. Inferences on I_{ij} are based on Monte Carlo methods to derive the distribution of I by the product of simulated values from the distributions of Y and P.

$\mathbf{P}_i$ was modelled using compositional data analysis (Aitchison 1982, 2003), with additive log-ratios transforming compositions to the multivariate Gaussian (MVG), a convenient scale for parameter estimation and simulation. The main advantage of these methods is that the covariance structure of the age compositions can be estimated from the data and subsequently used in the simulation procedure. Consider the common univariate observation of catch per unit effort in year i, age j and haul $h = 1, \ldots, H$ represented by C_{ijh}, then proportion at age is $P_{ijh} = C_{ijh}(\sum_{j=1}^{m} C_{ijh})^{-1}$ and the transformed values are $D_{ijh} = \log(P_{ijh} P_{ij=a,h}^{-1})$ with $j \neq a$. $\mathbf{D}_i \sim MVG(\Lambda_i, \Sigma_i)$ and the multivariate expected value $\Lambda_i \sim \mathrm{MGV}(\mu_i, \varsigma_i)$ with maximum likelihood estimators $\hat{\mu}_i = \bar{\mu}_i$, the vector of marginal arithmetic means, and $\hat{\varsigma}_i = \hat{\rho}(\mathbf{D}_i)\hat{\boldsymbol{\sigma}}_i^2 H_i^{-1}$, where $\hat{\rho}(\mathbf{D}_i)$ is the sample correlation matrix and $\hat{\boldsymbol{\sigma}}_i^2$ is the vector of marginal sample variances (Murteira 1990). Using parametric bootstrap (Efron and Tibshirani 1993) we sample from $\mathrm{MGV}(\hat{\mu}_i, \hat{\varsigma}_i)$ to simulate the empirical distribution of the transformed age composition by year and then back-transform to get the empirical distribution of age compositions.

Abundance Y_i was modelled as a spatial stochastic process (Diggle et al. 1998; Diggle and Ribeiro 2007) explicitly taking into account the spatial correlation between locations. However, there are factors affecting abundance observations unrelated to population size such as lighting and sea conditions (Petrakis et al. 2001; Chen et al. 2004; Hjellvik et al. 2004; Johnsen and Lilende 2007), that might blur the spatial patterns. In those situations where information about those factors exist, a GLM (McCullagh and Nelder 1991) can be used to estimate their effect and calibrate the observations to equal hauling conditions. The *calibrated* *abundance* represents the predicted observations if the hauling conditions were the same. To compute it a GLM is used to predict yearly abundance in specific conditions, the reference conditions, and the deviance residuals are then added. A second advantage that may be encountered if GLMs are applied at this stage, is to be able to deal with asymmetry and over-dispersion caused by the large number of null catches (Martin et al. 2005; Maunder and Punt 2004) or the occurrence of very large catches (Smith 1997; Kappenman 1999).

Consider now a new variable $Z_i(x_k)$ that represents the calibrated abundance in year i at location x_k where $k = 1, \ldots, K$ indexes sampled locations in the study region $A \subset \mathbb{R}^2$. Following the formulation proposed by Diggle and Ribeiro (2007) the Gaussian model for the vector of variables $Z(x)$ can be written as $Z(x) = S(x) + \epsilon$ where $S(x)$ is a stationary Gaussian process at locations x, with $E[S(x)] = \beta$, $Var[S(x)] = \sigma^2$ 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 $\mathrm{Gau}(0, \tau^2)$. Under these settings $Z(x) \sim \mathrm{MVG}(\beta, \Theta)$ with Θ parametrised by (σ^2, ϕ, τ^2), where ϕ is the correlation range. Several geostatistical methods are available to make inference about Θ (Isaaks and Srivastava 1989; Cressie 1993; Diggle et al. 1998; Chiles and Delfiner 1999; Rivoirard et al. 2000; Diggle and Ribeiro 2007). We adopt Bayesian methods to compute the posterior distributions of the correlation parameters and predictive distributions for the values of $Z(x_0)$, where x_0 is a grid of unsampled locations over the study area (Diggle and Ribeiro 2007). Our main goal with this approach is to take into account explicitly parameter uncertainty. Notice that β reflects mean abundance over the study area and the posterior distribution is used to obtain the empirical distribution of Y. On the other hand, the predicted $Z(x_0)$ over the study area reflects the spatial distributions of abundance allowing the study of spatial patterns and their evolution by year.

The analysis of both, Y_i and $\mathbf{P}_i$ are performed in parallel and the Monte Carlo simulations are combined to produce the distribution of abundance at age by $I_{ijs} = Y_{is} P_{ijs}$ where $s = 1, \ldots, S$ indexes simulations. Statistics of interest are computed based on I_{ijs} and the abundance at age simulations can be used as input to large simulation frameworks, like those requested by MSE.

All analysis were carried out using the R software (R Development Core Team 2007) and the add-on package geoR (Ribeiro Jr and Diggle 2001).

4 Results

We have started the analysis searching for diagnostics for the model assumptions and suitable transformations. The assumption of independence between compositions and total catch was supported by fitting a multinomial model with proportions explained by the total catch and comparing it to a model without covariates. For all the years the non significance of the coefficient provides enough evidence that the proportions are not associated with the total catch. For the additive log-ratio transformation it is necessary to choose the reference class and, given the occurrence of zero values, a constant needs to be added to the data. Choices for age class two as reference class and a value 0.1 for the constant ensure, for most of the datasets, better properties in terms of skewness and normality at transformed scale, all together inducing only a small average change rate for all ages, except for age 5 which showed some rates of around 3, mainly due to the small values observed.

Figure 2 shows the results of 1000 bootstrap simulations of the age compositions per year. In most years age 1 has the highest relative catch and ages 4 and 5 the lowest with age zero behaving more erratically. In 1989, 1991, 1995, 1997, 1999, 2000, 2002 and 2006 age 2 had the highest relative catches. Such shift between ages 1 and 2 can be caused by ageing errors known to exist in Hake (de Pontual et al. 2006; Pineiro et al. 2007). Notice that, despite of the survey occurring on the recruitment season, age 0 is not the most caught, although in recent years an increase in the proportion of individuals of age 0 has been observed. There is a higher variability in the proportions at age, presenting higher values than expected by the log transform.

To model Y_i we calibrated the observations to remove effects not related with population abundance however influencing abundance observations. The data showed greater variability than predicted by a Poisson model and a negative binomial GLM with log link function provided the best fit. The available covariates were *dayperiod*, *fortnight*, *bottom salinity* and *bottom temperature*. Dayperiod aimed to capture the effect of daylight with tree levels: until one hour after sunrise, after one hour before sunset and between both limits. Fortnight captured seasonal effects with seven levels, starting from the second half of September until the end of December. Bottom temperature and salinity were included as continuous variables to capture geophysical effects. The GLM was fitted by firstly including and fixing the *year* effect and then testing for all the other covariates including second degree interactions. The analysis showed significant effects only for year, fortnight and their interaction. The non-significance of the other covariates can be explained by the fact that all hauls are executed with some daylight and the bottom temperature and salinity are roughly constant at the depths where most sampling took place. The adjusted model explained only 13% of the data variability, a situation not unusual for this kind of analysis (Maunder and Punt 2004).

The calibrated dataset $Z_i(x_k)$ used in the geostatistical analysis was obtained by predicting abundance per year for the second fortnight of October and adding these values to the corresponding deviance residuals. To verify the univariate normality of $Z_i(x_k)$ the Shapiro-Wilks normality test was computed and 16 out of 18 datasets did not reject the null hypothesis of normality at an $\alpha = 0.01$, whereas for the log-transformed original dataset, the null hypothesis was not rejected only for one out of 18.

To carry out the geostatistical analysis we adopted the exponential function with algebraic form $\rho(h) = \exp\{-h/\phi\}$ where $\rho(h) \simeq 0.05$ when $h = 3\phi$, a common choice for spatial correlation modelling. Taking into account the small dataset available and the lack of observations at short distances, we decided to avoiding estimating one more correlation parameter from the data. Before proceeding with inference and prediction we checked for anisotropy effects using profiled likelihoods (Diggle and Ribeiro 2007). The profiles obtained were too flat to identify anisotropy parameters and the analysis proceeded assuming an isotropic spatial process. In practice, anisotropy effects are extremely difficult to identify and usually require subjective information and/or a fairly large amount of samples which is uncommon on bottom trawl surveys datasets. Taking into account isotropy and the small number of samples available per year we rotated the southern continental shelf 90^{o} clockwise so that it became aligned with the western coast in order to use as much information as possible for inference on model parameters.

The priors for the correlation parameters were set based on our knowledge of the stochastic process correlation structure. For the range parameter ϕ we used an exponential prior distribution with an expected value of 20km, reflecting higher beliefs on short correlations. The nugget variance parameter τ^2 was reparameterized into a relative nugget $\tau^2_{REL} = \tau^2\sigma^{-2}$ and the prior set as a zero inflated Poisson (ZIP) distribution with mean of the positive values of 1.25 and a probability of zero values of 0.25. These probabilities were computed for values 0 to 8 but attributed to 9 even intervals between 0 and 2 of the relative nugget. Our choice is based on the prior belief that the GLM analysis should have removed most of the random noise from the data and τ^2 should be small. On the other hand, to estimate τ^2 it is necessary to have observations at the same location or at very close distances which is operationally not feasible for BTS. For the mean parameter β we used a flat prior. Common priors were adopted for all years. The prior and posterior distributions of ϕ and τ^2_{REL} are shown in Figure 3. The posterior distributions of ϕ showed modes approximately between 10 and 20 km, reflecting a correlation range between 30 and 60 km, perfectly acceptable considering the length of the Portuguese coast, whereas for τ^2_{REL} it is clear that the data does not contain much information about the parameter and the posterior distributions are very similar to the priors, in particular in 1990 and between 1992 and 1997. This has a large impact in the results, in particular on the prediction variances as τ^2 reflects the random variability of the process.

Yearly abundance simulations were computed by $Y_{is} = \exp(\beta_{is})$ where β_{is} are the yearly simulations of the posterior distribution of β. The abundance index and the 95% credibility intervals were obtained computing the median and the 0.025 and 0.975 percentiles of Y_i (Figure 4). Abundances showed a cyclic pattern with high values in 1991, 1997, 2001 and 2005; and low values in 1993, 1996, 1999, 2003 and 2006. There is a persistent increase from 1993 although still within the historical limits. The credibility intervals are asymmetric and showed larger intervals in the highest estimates as expected by the GLM log transformation. Table 1 presents several metrics computed using design statistics and geostatistics. Considering the asymmetry of Y_{is} we computed the relative median absolute deviation, the ratio between the median absolute deviation and the median, that can be seem as a robust adimensional indicator of precision, comparable to the coefficient of variation. The values obtained by geostatistics are smaller than those obtained by design statistics, although the time trend is similar. This result can be explained by a screening effect (Isaaks and Srivastava 1989) that downweights groups of observations nearby as the information contained in each observation becomes redundant. Aggregations of high observations in space (Figure 1) have a lower impact on the results of the geostatistical analysis than on design-based methods given the sensibility of the sample mean to high values. The higher precision obtained with design estimators is apparently over-optimistic for BTS, where sample sizes are always small due to the operational costs. Ignoring the correlation between samples overestimates the quantity of information contained in each sample leading to an underestimated variance. Geostatistical results present a relative median absolute deviation between 14 and 25, more in agreement with other studies (*e.g.* see Smith and Gavaris 1993; Dingsor 2005; Sousa et al. 2007; Roa-Ureta and Niklitschek in press).

Spatial predictions were carried out on a grid over the study area with locations at 5 km of each other resulting in 1255 locations within the study area. Figure 5 presents the spatial distribution of Hake over the study area standardised by the maximum in each year so that the year effect was removed and only the spatial effect is present on the maps. It is possible to identify persistent areas of high abundance on the west coast at latitudes approximately of 4150km (UTM), 4280km (UTM) and 4400km (UTM). The first and second areas are known recruitment spots and the last one is less persistent, but also known to be an area of high recruitment.

Abundance at age and year are presented in the bottom panel of Table 2 with the relative median absolute deviation between brackets. As with Y_i the estimates of abundance at age are smaller and less precise than the design-based ones, resulting from the fact that I_{ij} accounts for the variability of Y_i and $\mathbf{P}_i$. The same reasoning presented above regarding the screening effect and variance underestimation also applies here. In Figure 6 a comparison between design-based statistics and our estimates is presented with both time series standardised to mean 0 and variance 1. In general both series are similar and identify the same maxima and minima.

5 Discussion

Modelling abundance at age requires that two main characteristics, the aggregation of individuals of similar length and the spatial patterns of abundance, are taken into account, so that the major sources of variability are considered. The model proposed here tackles both issues and suggests solutions to common practical problems when modelling fish abundance using data from an area with specific characteristics. By separating the age compositions from the age-aggregated catch per unit effort, suitable models can be applied to each variable, greatly improving the analysis of the importance of each factor. Age structures were studied by compositional data analysis (Aitchison 1982, 2003) allowing the full covariance structure of age compositions to be considered. Age-aggregated catch data was modelled with geostatistical methods (Diggle and Ribeiro 2007) explicitly modelling the correlation between abundance at different locations. Geostatistical models for compositional data (Walvoort and de Gruijter 2001; Pawlowsky-Glahn and Olea 2004) are still incipient and our view is that the scarcity of data provided by BTS tend to impair the use of data demanding approaches.

Modelling abundance data requires several adjustments depending on the species, area and study objectives. Our case study has allowed us to point out possible solutions but it will always be necessary to allocate some research effort at understanding the individual characteristics of the problem at hand and find appropriate solutions before simulating and computing yearly distributions of abundance at age. The application presented assumed that age compositions were independent from age aggregated catches, an assumption supported by the exploratory data analysis. However, more generally, this issue can be solved by post-stratification of the study area into strata where this assumption stands, either by discretizing the age aggregated catches and modelling each dataset independently or by explicitly modelling this relation.

The problem of asymmetry and over-dispersion surfaced during the analysis of our dataset, caused by a large number of null or small observations and occasional very large catches. The GLM with negative binomial errors used to calibrate the observations provide a way to sort out such problems, and explained a considerable part of the spatially unstructured variability, as indicated by the low values of τ^2. On the other hand, the issue of null observations is restricted to the modelling of $\mathbf{P}_i$ and had a negligible impact on the geostatistical analysis which uses the age-aggregated catches, less likely to have null observations. This is another major advantage of the proposed approach, as modelling abundance at age using geostatistics can be severely limited by null observations, commonly present on ages poorly represented in the sample. Attempts to apply geostatistical models separately to different ages will most likely result in different and eventually conflicting inferences on the correlation parameters, and inconsistent spatial predictions.

Another major advantage of the proposed model is the full parametric specification allowing for Monte Carlo simulation methods. Simulation provides the means to overcome difficulties in obtaining an analytical expression for the full distribution of abundance at age, while still allowing for the computation of several statistics of interest. Outputs can also be used as inputs for larger simulation frameworks like MSE. MSE constitutes a modern and sophisticated approach to management of fisheries and ecosystems but, despite its formal complexity, the output and advice obtained it is equally reliant on the quality of its inputs. The approach presented in this work is one step forward in that direction.

The methods advocated in this paper produce several abundance indicators that provide an overview of abundance along different perspectives. The analysis of age compositions provides an insight on how the population structure evolves over time. The geostatistical submodel returns abundance indicators in both space and time perspectives, whereas the possibilities of explicitly modelling space-time interactions can be investigated (Silva et al., 2007).

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References

Aitchison, J., 1982. The statistical analysis of compositional data. Journal of the Royal Statistical Society. Series B 44 (2), 139–177.

Aitchison, J., 2003. The Statistical Analysis of Compositional Data. The Blackburn Press.

Anonymous, 2002. Report of the International Bottom Trawl Survey Working Group. CM D:03, ICES.

Babak, O., Hrafnkelsson, B., Palsson, O., 2007. Estimation of the length distribution of marine populations in the gaussian-multinomial settings using the methods of moments. Journal of Applied Statistics 34 (8), 985–995.

Brynjarsdottir, J., Stefansson, G., 2004. Analysis of cod catch data from icelandic groundfish surveys using generalized linear models. Fisheries Research 70, 195–208.

Chen, J., Thompson, M., Wu, C., 2004. Estimation of fish abundance indices based on scientific research trawl surveys. Biometrics 60, 116–123.

Chiles, J.-P., Delfiner, P., 1999. Geostatistics: Modeling Spatial Uncertainty. Wiley, New York.

Cochran, W., 1960. Sampling Techniques. Statistics. John Wiley and Sons, INC, New York.

Cressie, N., 1993. Statistics for spatial data - Revised Edition. John Wiley and Sons, New York.

de Pontual, H., Groison, A. L., Pineiro, C., Bertignac, M., 2006. Evidence of underestimation of european hake growth in the bay of biscay, and its relationship with bias in the agreed method of age estimation. ICES J. Mar. Sci. 63 (9), 1674–1681.

Diggle, P., Ribeiro, P., 2007. Model-based Geostatistics. Springer, New York.

Diggle, P. J., Tawn, J. A., Moyeed, R. A., 1998. Model-based geostatistics (with discussion). Appl. Statist. 47, 299–350.

Dingsor, G. E., 2005. Estimating abundance indices from the internationsl 0-group fish survey in the Barents Sea. Fisheries Research (72), 205–218.

Efron, B., Tibshirani, R., 1993. An Introduction to the Bootstrap. Chapman & Hall, New York.

Hammond, P. S., Donovan, G. P., in press. Development of the iwc revised management procedure. Journal of Cetacean Research and Management, Special Edition 4.

Hjellvik, V., Godo, O., Tjostheim, D., 2004. Decomposing and explaining the variability of bottom trawl survey data from the barents sea. Sarsia: North Atlantic Marine Science 89 (15), 196–210.

Hrafnkelsson, B., Stefansson, G., 2004. A model for categorical length data from groundfish surveys. Canadian Journal of Fisheries and Aquatic Science 61, 1135–1142.

Isaaks, E., Srivastava, M., 1989. An Introduction to Applied Geostatistics. Oxford University Press, New York.

Jardim, E., Ribeiro, P. J., 2007. Geostatistical assessment of sampling designs for portuguese bottom trawl surveys. Fisheries Research 85, 239–247.

Johnsen, E., Lilende, T., 2007. Factors affecting the diel variation in commercial cpue of namibian hake - can new information improve standard survey estimates ? Fisheries Research 88, 70–79.

Johnston, S. J., Butterworth, D. S., 2005. The evolution of operational management procedures for the south african west coast rock lobster fishery. New Zealand Journal of Marine and Freshwater Research 39, 687–702.

Kappenman, R. F., 1999. Trawl survey based abundance estimation using data sets with unusually large catches. ICES Journal of Marine Science 56, 28–35.

Kell, L. T., Mosqueira, I., Grosjean, P., Fromentin, J.-M., Garcia, D., Hillary, R., Jardim, E., Mardle, S., Pastoors, M. A., Poos, J. J., Scott, F., Scott, R. D., 2007. Flr: an open-source framework for the evaluation and development of management strategies. ICES Journal of Marine Science 64 (4), 640–646.
URL http://icesjms.oxfordjournals.org/cgi/content/abstract/64/4/640

Martin, T. G., Wintle, B. A., Rhodes, J. R., Kuhnert, P. M., Field, S. A., Low-Choy, S. J., Tyre, A. J., Possingham, H. P., 2005. Zero tolerance ecology: improving ecological inference by modelling the source of zero observations. Ecology Letters 8 (11), 1235–1246.

Maunder, M., Punt, A., 2004. Standardizing catch and effort data: a review of recent approaches. Fisheries Research 70, 141–159.

McConnaughey, R. A., Conquest, L. L., 1993. Trawl survey estimation using a comparative approach based on lognormal theory. Fishery Bulletin 91 (1), 107–118.

McCullagh, P., Nelder, J., 1991. Generalized Linear Models, 2nd Edition. No. 37 in Monographs on Statistics and Applied Probability. Chapman and Hall.

Mendes, K. F. T. J. M., 2007. A bayesian hierarchical model for over-dispersed count data: a case study for abundance of hake recruits. Environmetrics 18, 27–53.
URL http://dx.doi.org/10.1002/env.800

Murteira, B. J., 1990. Probabilidades e Estatistica, 2nd Edition. Vol. 2. McGraw-Hill.

O'Neill, M. F., Faddy, M. J., 2003. Use of binary and truncated negative binomial modelling in the analysis of recreational catch data. Fisheries Research 60, 471–477.

Pawlowsky-Glahn, V., Olea, R. A., 2004. Geostatistical Analysis of Compositional Data. Oxford University Press, USA.

Pennington, M., 1983. Efficient estimators of abundance, for fish and plankton surveys. Biometrics 39 (1), 281–286.

Petrakis, G., MacLennan, D., Newton, A., 2001. Day-night and depth effects on catch rates during trawl surveys in the North Sea. ICES Journal of Marine Science (58), 50–60.

Piet, G., 2002. Using external information and gams to improve catch-at-age indices for north sea plaice and sole. ICES Journal of Marine Science 59, 624–632.

Pineiro, C., Rey, J., de Pontual, H., Goni, R., 2007. Tag and recapture of european hake (merluccius merluccius l.) off the northwest iberian peninsula: First results support fast growth hypothesis. Fisheries Research 88, 150–154.
URL http://www.sciencedirect.com/science/article/B6T6N-4PK7P0J-1/2/ff9effeb42b316b491cbb28f83d68fd2

Pradhan, N. C., Leung, P., 2006. A poisson and negative binomial regression model of sea turtle interactions in hawaii's longline fishery. Fisheries Research 78, 309–322.

Punt, A. E., Pribac, F., Taylor, B., Walker, T., 2005. Harvest strategy evaluation for school and gummy shark. Journal of Northwest Atlantic Fisheries Science (Online) 35.

R Development Core Team, 2007. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0.
URL http://www.R-project.org

Ribeiro Jr, P. J., Diggle, P. J., June 2001. geoR: a package for geostatistical analysis. R-NEWS 1 (2), 14–18, iSSN 1609-3631.
URL http://CRAN.R-project.org/doc/Rnews/

Rivoirard, J., Simmonds, J., Foote, K., Fernandes, P., Bez, N., 2000. Geostatistics for Estimating Fish Abundance. Blackwell Science, London, England.

Roa-Ureta, R., Niklitschek, E., in press. Biomass estimation from surveys with likelihood-based geostatistics. ICES Journal of Marine Science, 12.

Silva, A. S., Ribeiro Jr, P. J., Elmatzoglou, I., 2007. Modelagem geoestatï¿œstica utilizando a famï¿œlia de gneiting de funï¿œï¿œes de covariï¿œncia espaï¿œo-temporais. Revista de Matemï¿œtica e Estatï¿œstica, v. 25, p. 65-83, 2007. 25 (2), 65–83.

Smith, S., Gavaris, S., 1993. Improving the Precision of Abundance Estimates of Eastern Scotian Shelf Atlantic Cod from Bottom Trawl Surveys. North American Journal of Fisheries Mangement (13), 35–47.

Smith, S. J., 1988. Evaluating the efficiency of the delta-distribution mean estimator. Biometrics 44 (2), 485–493.

Smith, S. J., 1990. Use of statistical models for the estimation of abundance from groundfish trawl survey data. Canadian Journal of Fisheries and Aquatic Science 47, 894–903.

Smith, S. J., 1997. Bootstrap confidence limits for groundfish trawl survey estimates of mean abundance. Canadian Journal of Fisheries and Aquatic Science 54, 616–630.

Sousa, P., Lemos, R., Gomes, M., Azevedo, M., 2007. Analysis of horse mackerel, blue whiting, and hake catch data from portuguese surveys (1989-1999) using an integrated glm approach. Aquatic Living Resources 20, 105–116.

Stefansson, G., 1996. Analysis of groundfish survey abundance data: combining the glm and delta approaches. ICES Journal of Marine Science 53, 577–588.

Thompson, S., 1992. Sampling. Statistics. John Wiley & Sons, INC, New York.

Walvoort, de Gruijter, 2001. Compositional kriging: A spatial interpolation method for compositional data. Mathematical Geology 33, 951–966.
URL http://dx.doi.org/10.1023/A:1012250107121

Table 1: Age aggregated abundance estimates by design statistics and geostatistics. The design statistics were the stratified mean, $\hat{Y}$, its standard deviation, $\sigma_{\hat{Y}}$, and coefficient of variation, $\mathrm{CV}_{\hat{Y}}$. The geostatistics were the median, $\tilde{Y}$, the median absolute deviation, $\mathrm{MAD}_{\tilde{Y}}$, the relative median absolute deviation, $\mathrm{RMAD}_{\tilde{Y}}$, the 0.025, $\mathrm{Q}(\tilde{Y}, 0.025)$, the 0.975 percentiles, $\mathrm{Q}(\tilde{Y}, 0.975)$, and the interquartile range, $\mathrm{IQR}_{\tilde{Y}}$.

		design statistics			geostatistics					
Year	hauls	$\hat{Y}$	$\sigma_{\hat{Y}}$	$\mathrm{CV}_{\hat{Y}}$	$\tilde{Y}$	$\mathrm{MAD}_{\tilde{Y}}$	$\mathrm{RMAD}_{\tilde{Y}}$	$\mathrm{Q}(\tilde{Y}, 0.025)$	$\mathrm{Q}(\tilde{Y}, 0.975)$	$\mathrm{IQR}_{\tilde{Y}}$
1989	130	59.2	1.7	0.03	33.6	6.6	0.2	21.2	49.7	28.4
1990	108	157	9.7	0.06	38.9	6.4	0.16	25.9	52.8	26.9
1991	80	194.1	12.2	0.06	154.8	27.4	0.18	101.3	250.4	149.1
1992	44	65.3	3.2	0.05	46.1	10.4	0.22	26.4	79.5	53
1993	58	54.1	4.5	0.08	8.1	1.5	0.18	5.5	11.9	6.5
1994	76	95.9	4.7	0.05	61.8	8.5	0.14	46.6	82.3	35.7
1995	80	85.2	4.1	0.05	59.4	8.5	0.14	42.1	80.7	38.5
1996	63	44.6	2.3	0.05	25.1	6.4	0.25	15.7	44.1	28.4
1997	51	207.2	21.5	0.1	123.9	20.1	0.16	86.9	188.4	101.4
1998	64	139.8	7.8	0.06	109.4	21.3	0.19	65.5	164.5	99
1999	71	71.2	2.5	0.04	27.3	5.8	0.21	16.1	42.2	26.1
2000	65	102.2	5.8	0.06	89.2	14.3	0.16	63	134.3	71.4
2001	58	164	15.3	0.09	140.3	23.2	0.17	91	199	107.9
2002	66	117.5	7.9	0.07	75	18.7	0.25	41.8	120.4	78.6
2003	72	55.3	2	0.04	41.5	8.4	0.2	25.6	65.2	39.6
2004	79	124.4	6.3	0.05	77.8	19.4	0.25	42.6	134.7	92.1
2005	87	214	9.4	0.04	153	29.7	0.19	93.6	235.2	141.7
2006	88	125.9	4.4	0.03	42.6	8.8	0.21	26.4	66.3	39.9

Table 2: Abundance at age estimates by design statistics on the top panel and this study on the bottom panel. The design statistics are the stratified mean and between brackets its coefficient of variation. The estimates provided by this study are the median and between brackets the relative median absolute deviation.

Estimator	Year	0	1	2	3	4	5
Design based	1989	12.9 (0.08)	20.1 (0.05)	16.9 (0.04)	7.4 (0.06)	1.5 (0.09)	0.4 (0.14)
	1990	82.1 (0.11)	45.4 (0.05)	19.3 (0.05)	7.4 (0.05)	2.4 (0.07)	0.4 (0.12)
	1991	56.6 (0.14)	82.4 (0.10)	36.7 (0.11)	14.6 (0.08)	3.1 (0.09)	0.6 (0.12)
	1992	12.1 (0.16)	20.4 (0.09)	19.3 (0.08)	10.2 (0.07)	2.7 (0.10)	0.6 (0.17)
	1993	23.2 (0.18)	17.1 (0.09)	8.6 (0.11)	3.6 (0.10)	1.3 (0.14)	0.3 (0.32)
	1994	18.5 (0.14)	51.4 (0.07)	18.2 (0.08)	5.9 (0.10)	1.5 (0.15)	0.3 (0.21)
	1995	2.1 (0.16)	34.6 (0.09)	37.2 (0.07)	8.1 (0.13)	2.9 (0.17)	0.4 (0.23)
	1996	9.0 (0.10)	15.1 (0.09)	10.8 (0.12)	6.9 (0.12)	1.9 (0.16)	0.9 (0.17)
	1997	40.4 (0.22)	70.4 (0.18)	83.7 (0.18)	8.7 (0.17)	2.3 (0.29)	1.6 (0.32)
	1998	54.0 (0.11)	46.5 (0.10)	22.8 (0.08)	12.3 (0.09)	3.0 (0.13)	1.1 (0.17)
	1999	9.1 (0.12)	26.9 (0.05)	25.0 (0.07)	7.8 (0.09)	2.0 (0.13)	0.4 (0.22)
	2000	29.9 (0.14)	39.3 (0.09)	21.4 (0.08)	8.9 (0.10)	1.7 (0.12)	1.0 (0.16)
	2001	50.9 (0.23)	73.9 (0.13)	22.2 (0.10)	14.3 (0.09)	2.1 (0.15)	0.6 (0.20)
	2002	43.5 (0.16)	37.1 (0.09)	26.8 (0.08)	7.5 (0.11)	2.1 (0.15)	0.4 (0.26)
	2003	5.9 (0.08)	28.6 (0.05)	13.2 (0.08)	6.1 (0.09)	1.3 (0.15)	0.2 (0.27)
	2004	42.5 (0.10)	48.6 (0.08)	22.8 (0.08)	7.9 (0.11)	1.7 (0.16)	0.8 (0.18)
	2005	105.8 (0.08)	67.5 (0.05)	30.2 (0.06)	7.8 (0.10)	2.0 (0.13)	0.7 (0.20)
	2006	44.7 (0.07)	35.4 (0.06)	32.6 (0.06)	10.0 (0.09)	2.5 (0.13)	0.6 (0.21)
This study	1989	2.9 (0.25)	9.8 (0.21)	12.2 (0.20)	6.4 (0.22)	1.6 (0.24)	0.7 (0.25)
	1990	3.9 (0.26)	13.6 (0.20)	11.9 (0.19)	6.0 (0.23)	2.4 (0.24)	0.7 (0.25)
	1991	14.8 (0.32)	51.3 (0.25)	52.0 (0.23)	25.5 (0.26)	7.0 (0.30)	2.0 (0.30)
	1992	2.7 (0.40)	9.1 (0.31)	13.5 (0.27)	13.8 (0.26)	4.7 (0.34)	1.5 (0.38)
	1993	1.2 (0.30)	2.6 (0.24)	2.2 (0.23)	1.2 (0.29)	0.5 (0.29)	0.2 (0.33)
	1994	5.2 (0.24)	26.3 (0.21)	15.3 (0.20)	10.5 (0.23)	3.3 (0.26)	0.9 (0.27)
	1995	1.0 (0.30)	19.0 (0.19)	27.5 (0.16)	8.2 (0.19)	2.8 (0.23)	0.6 (0.26)
	1996	2.6 (0.34)	8.7 (0.30)	6.4 (0.28)	4.6 (0.28)	1.7 (0.33)	1.1 (0.32)
	1997	2.9 (0.38)	25.9 (0.29)	78.4 (0.18)	11.7 (0.25)	2.5 (0.29)	1.8 (0.31)
	1998	16.2 (0.36)	29.0 (0.26)	27.5 (0.23)	24.5 (0.26)	6.8 (0.31)	2.7 (0.31)
	1999	1.7 (0.31)	8.4 (0.26)	12.3 (0.21)	3.7 (0.26)	0.7 (0.28)	0.2 (0.30)
	2000	7.8 (0.32)	25.6 (0.23)	32.8 (0.19)	16.6 (0.22)	3.7 (0.24)	2.5 (0.25)
	2001	11.7 (0.31)	49.1 (0.25)	42.7 (0.22)	29.5 (0.24)	3.8 (0.28)	1.8 (0.29)
	2002	12.1 (0.32)	23.7 (0.3)	26.8 (0.27)	7.8 (0.29)	2.5 (0.32)	0.9 (0.35)
	2003	3.6 (0.27)	17.9 (0.24)	12.7 (0.22)	5.1 (0.26)	1.4 (0.29)	0.5 (0.28)
	2004	15.7 (0.29)	37.5 (0.25)	17.1 (0.3)	4.5 (0.33)	1.5 (0.32)	1.0 (0.33)
	2005	37.2 (0.26)	68.0 (0.21)	33.8 (0.24)	9.5 (0.26)	2.5 (0.28)	1.3 (0.29)
	2006	5.3 (0.29)	13.0 (0.23)	15.9 (0.23)	6.3 (0.24)	1.5 (0.27)	0.5 (0.28)

Figure 1: Yearly maps with locations of hauls (+) and observed catches of Hake (*Merluccius merluccius*) during the Autumn series of the Portuguese bottom trawl survey. The gray circles are proportional to the logarithm of the numbers of individuals caught per hour. The full line represents the Portuguese continental coast.

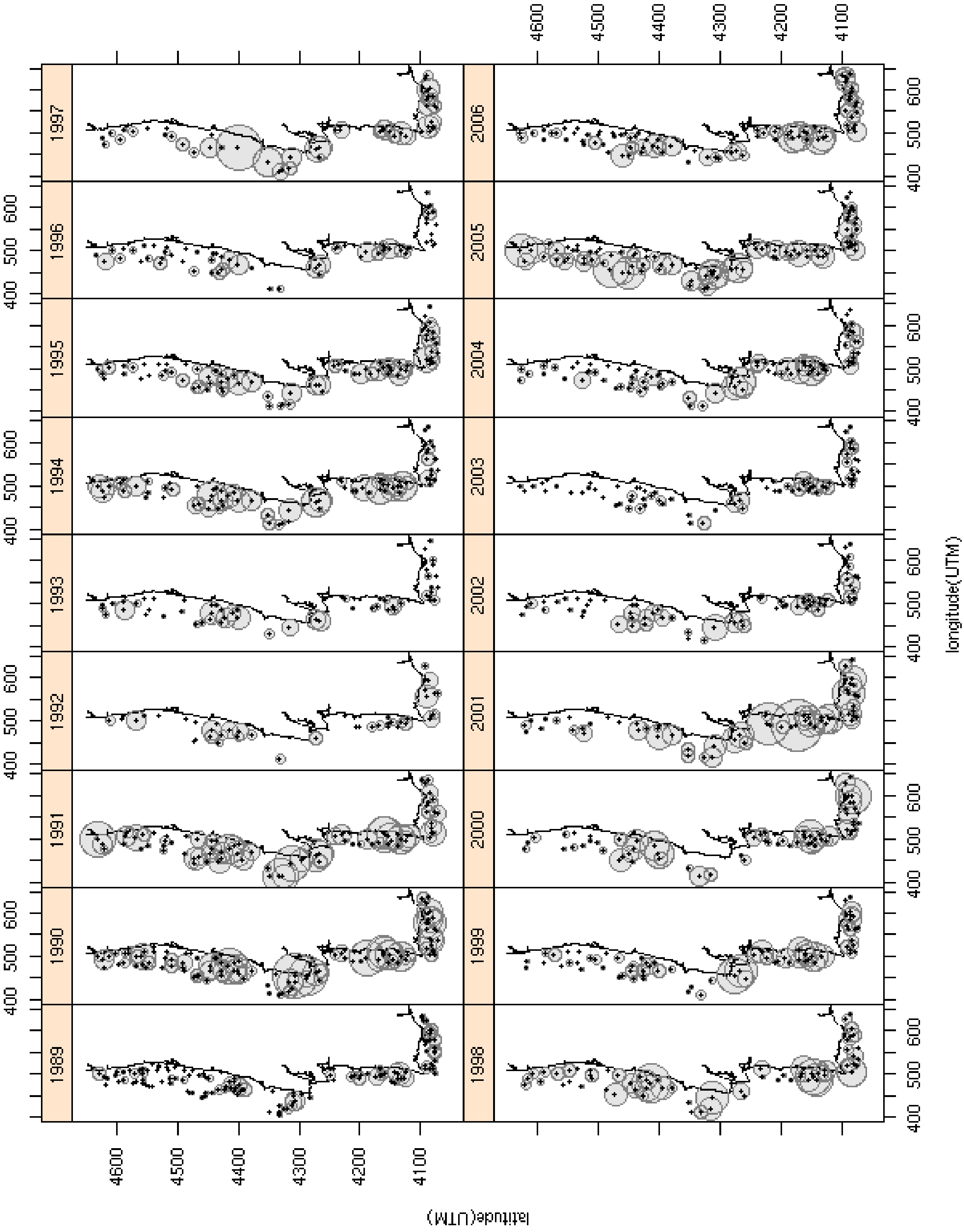

Figure 2: Age compositions empirical distribution obtained by parametric bootstrap. The full circle represents the median proportion and the gray lines represent the confidence interval computed by the 0.025 and 0.975 percentiles.

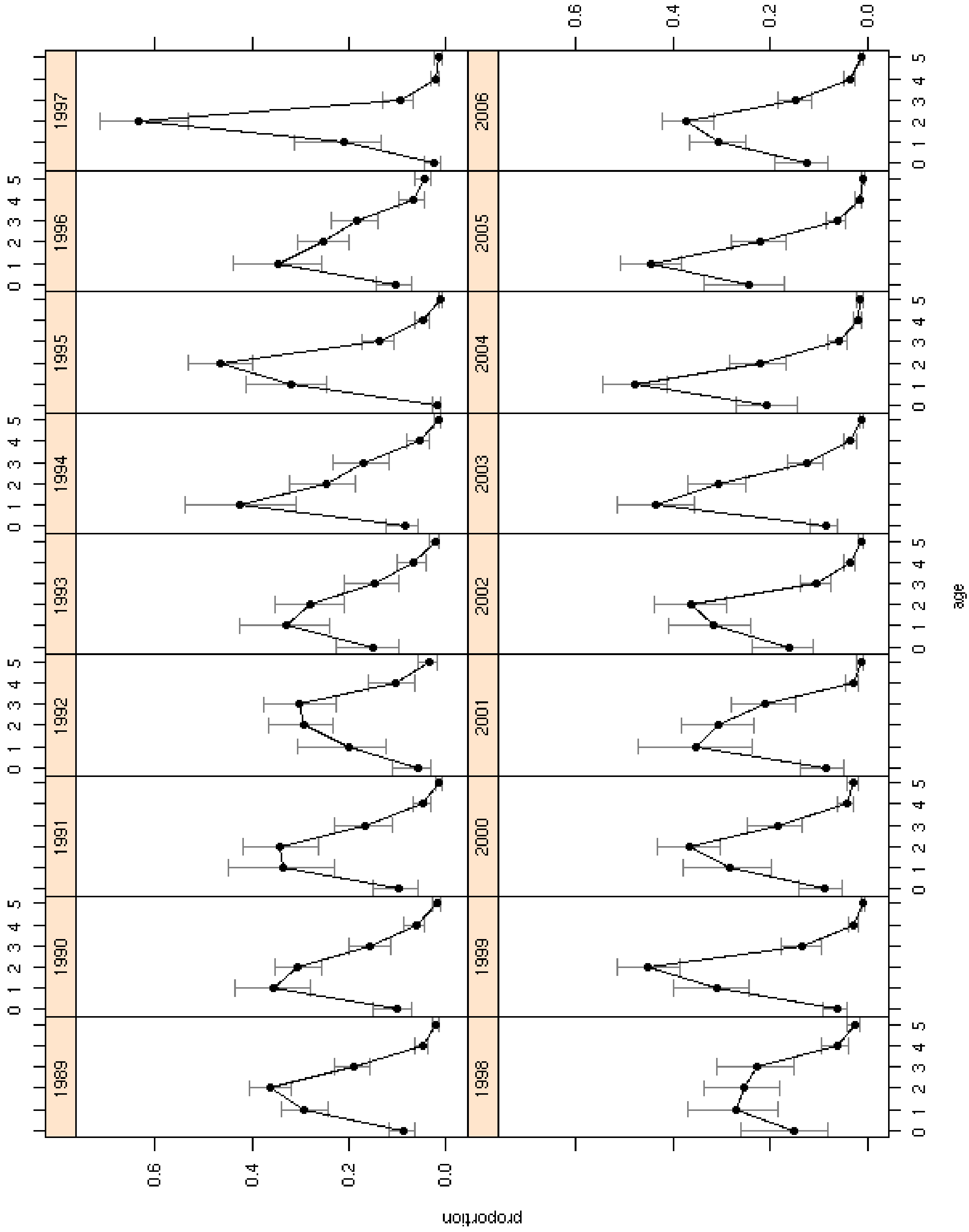

Figure 3: Yearly priors and posteriors for the correlation range ϕ and the relative nugget τ^2_{REL} used for the geostatistical analysis of the calibrated dataset. The dashed line represents the priors for each parameter, kept constant for all datasets. The full line represents the posteriors obtained per year for each dataset.

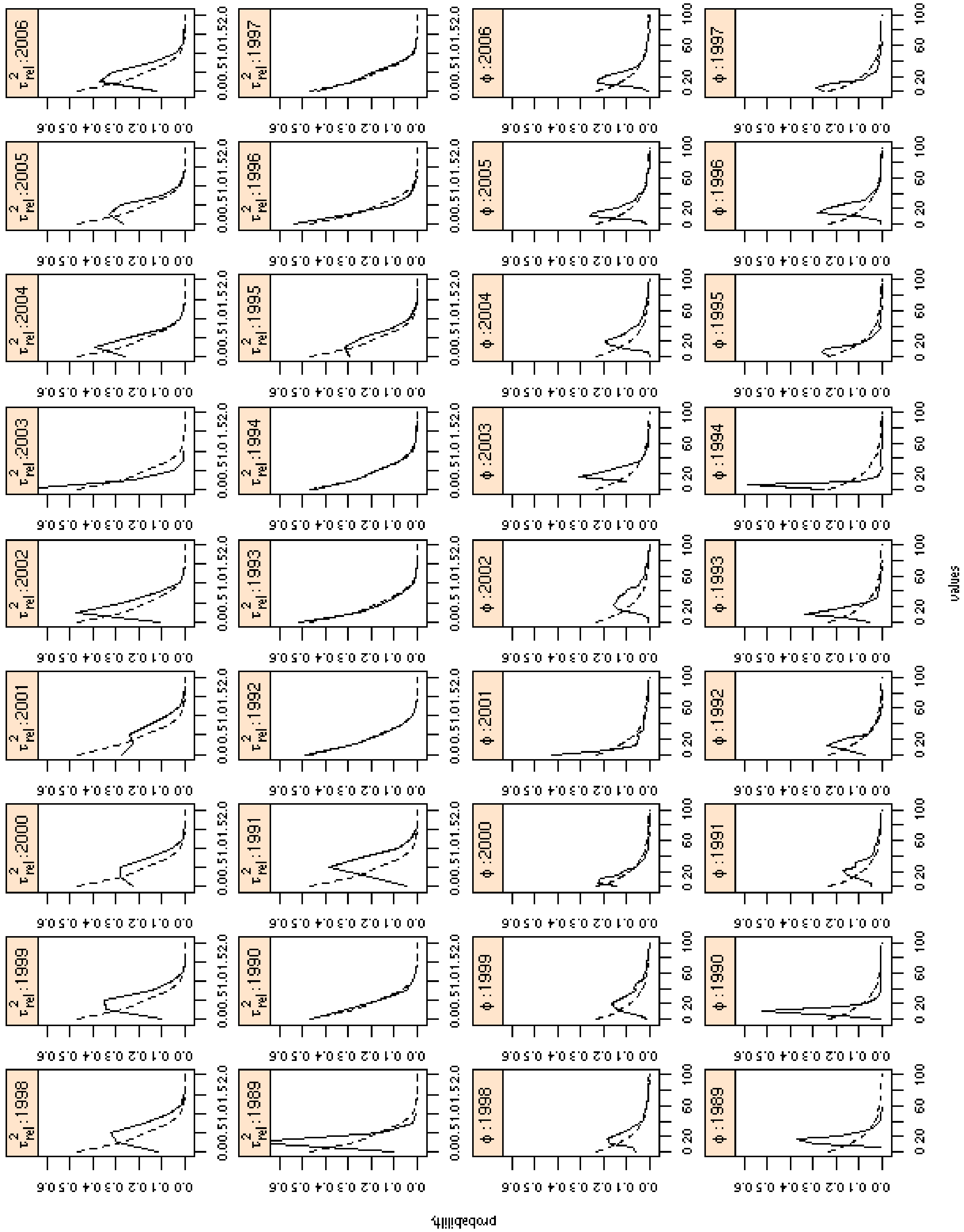

Figure 4: Yearly abundance estimates by design statistics (dashed line) and geostatistics (full line). The black circle represents the median abundance and the gray lines represent the confidence interval computed by the 0.025 and 0.975 percentiles.

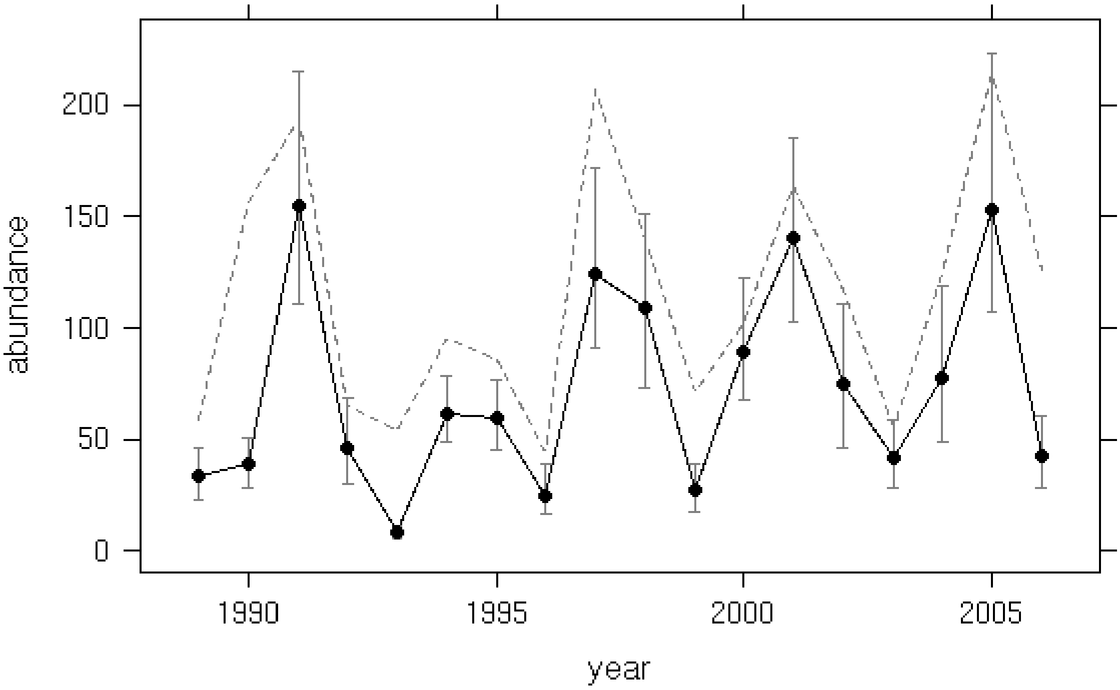

Figure 5: Spatial distribution of age aggregated abundance by year, standardised to the second fortnight of October. The gray degrees are proportional to the number of individuals caught by unit effort, rescaled to the maximum estimate within each year. The black color represent 1 and the white colour represents 0.

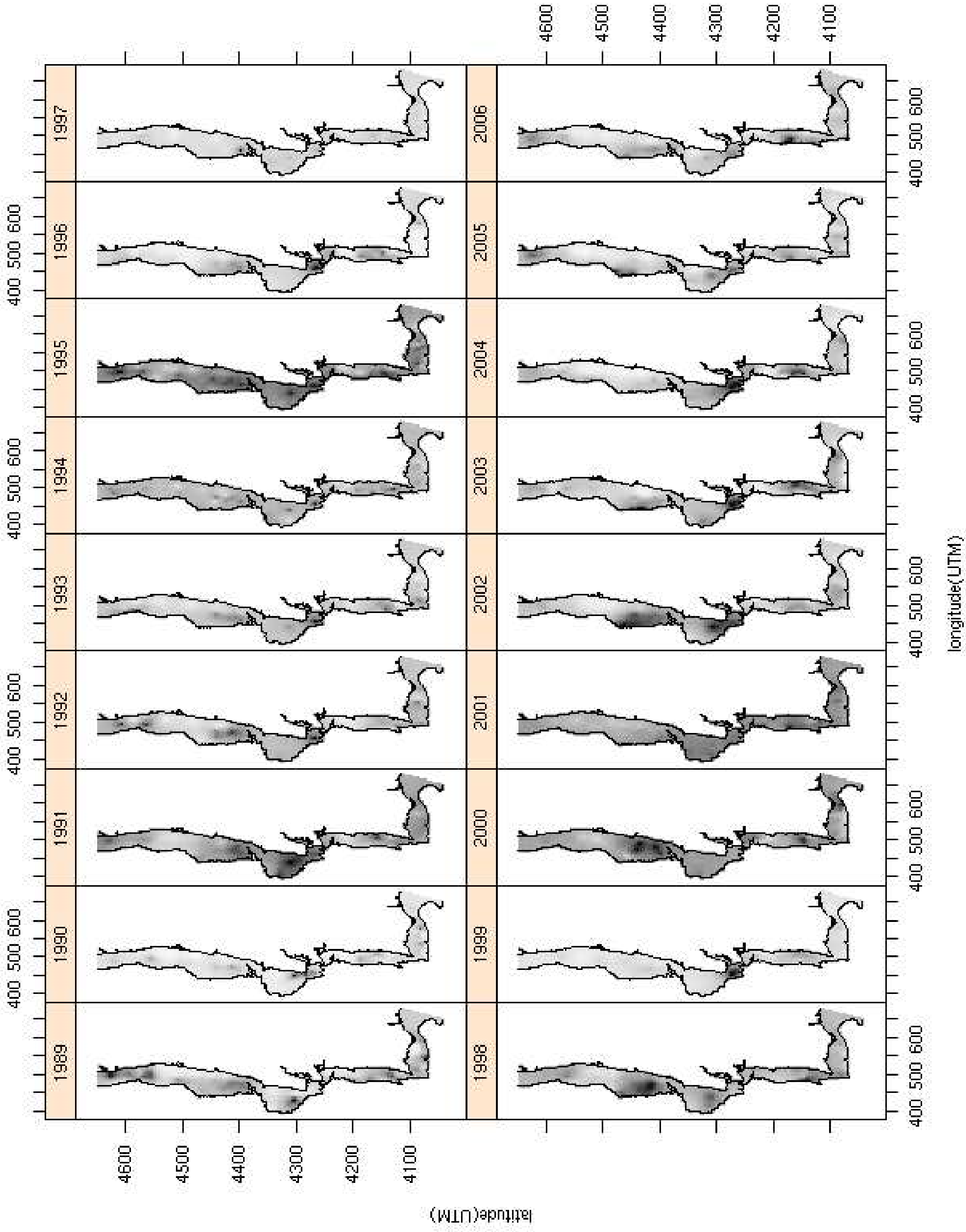

Figure 6: Abundance at age and year standardised to have mean 0 and variance 1. Design estimates in dashed line and geostatistical estimates in full line.