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Applications of spatial statistics to fish abundance.
Improving the abundance indices of hake, *Merluccius merluccius* (Linnaeus, 1758), off the Portuguese continental coast.

(Tese para a obtenção do grau de doutor no ramo de ciências e tecnologias das pescas, especialidade de pescas)

José Ernesto Jardim

Orientador: Manuel Seixas Afonso Dias

Co-orientador: Paulo Justiniano Ribeiro Jr.

Co-orientador: Maria Manuela Alves Azevedo Guedes Lebre

Constituição do Júri:

Presidente: Rui Santos

Vogais: Karim Erzini, Michael Pennington, Leonel Gordo

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To Cristina, Manuel, Clara and Teresa.

Nome: José Ernesto Jardim

Faculdade: Faculdade de Ciências do Mar e Ambiente

Orientador: Manuel Seixas Afonso Dias

Co-orientador: Paulo Justiniano Ribeiro Jr.

Co-orientador: Maria Manuela Alves Azevedo Guedes Lebre

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Título da tese: Applications of spatial statistics to fish abundance. Improving the abundance indices of hake, *Merluccius merluccius* (Linnaeus, 1758), off the Portuguese continental coast.

Resumo

Este trabalho contribui para a melhoria do conhecimento sobre abundância de populações de peixe e o seu uso para gestão pesqueira. Geoestatística *model-based* e simulações estocásticas são utilizadas de forma generalizada e aplicadas à pescada (*Merluccius merluccius* Linnaeus, 1758) e às campanhas demersais na costa continental Portuguesa. O Capítulo 2 apresenta um estudo de simulação que explora planos de amostragem alternativos para campanhas demersais. O Capítulo 3 apresenta uma experiência realizada numa campanha demersal onde uma parte dos planos amostrais anteriores foi testada. Ambas análises concluiram que um plano amostral híbrido aleatório-sistemático apresenta melhor performance na estimação da abundância de pescada. O Capítulo 4 apresenta um modelo espaço-tempo-idade para estimar abundância, com uma distribuição conjunta dada pelo producto da distribuição da abundância agregada e a distribuição condicional de proporções por idade, modeladas com geoestatística e análise de dados composicionais, respectivamente. No Capítulo 5, estratégias de gestão passíveis de recuperar o manancial de pescada Ibérica para níveis de biomass sustentáveis são avaliados e a sua robustez relativamente a incerteza na informação de capturas e dinâmica do manacial testada. Os resultados mostram que reduzir a a mortalidade por pesca é absolutamente essencial para recuperar o manancial. Complementarmente, reduzir as rejeições ao mar conduzirá a pescaria a desembarques de maior valor, associados a custos de exploração mais baixos. No Capítulo 6 são apresentadas as conclusões gerais.

Keywords: abundância, geoestatística, pescas, pescada, campanha de investigação, desenho amostral

Applications of spatial statistics to fish abundance. Improving the abundance indices of hake, *Merluccius merluccius* (Linnaeus, 1758), off the Portuguese continental coast.

Abstract

This work contributes to improve the knowledge about abundance of fish populations and its usage for fisheries management. Model-based geostatistics and stochastic simulation are widely used and applied to hake (*Merluccius merluccius* Linnaeus, 1758) and bottom trawl surveys off the Portuguese continental coast. Chapter 2 presents a simulation study exploring alternative sampling designs for bottom trawl surveys. Chapter 3 presents a bottom trawl survey field experience where a set of the previous designs were tested. Both analysis conclude that a hybrid random-systematic design shows better performance regarding hake abundance estimation. Chapter 4 presents a space-time-age model to estimate abundance-at-age, whose join distribution is the product of the distribution of age aggregated abundance and the conditional distribution of age proportions, modelled with model-based geostatistics and compositional data analysis, respectively. In Chapter 5 management strategies likely to recover the Iberian hake stock to safe biomass levels are evaluated and their robustness to uncertainty on catch information and stock dynamics is tested. Results show that reducing fishing mortality is an absolute requirement to recover the stock. Complementary, reducing discards will lead the fishery to more valuable landings associated with lower exploitation costs. Chapter 6 presents generic conclusions.

Keywords: abundance, geostatistics, fisheries, hake, survey, sampling design

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To my wife, Cristina, and my children, Manuel, Clara and Teresa, my endless gratitude for your patience and support during this six long years. From now on I will have more time for the things in life that really matter, you !

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Contents

Chapter 1

Introduction

1.1 Animal abundance

The abundance of animals is of obvious interest for humans and is likely to has been a factor with large impact in evolution. Since 2 million years ago, when *Homo erectus* started hunting, acquisition and ability to process information on the abundance of target animals and identification of the best hunting grounds and periods, would constitute an important survival and evolutionary advantage.

Later, $\approx$ 10000 BC during the Neolithic, the first *Homo sapiens* started domesticating animals, replacing the previous hunter-gathering society by sedentary societies (Gupta, 2004). Animals became an important resource supplying food, clothes, protection and working power. Under these circumstances more and better information about abundance was required so that new exploitation objectives could be tackled and incorporated into people's lives. In face of these challenges, it is reasonable to speculate that Man understood the limits of animal exploitation. It was obvious that killing all individuals would terminate the food supply. Some may even knew that some individuals were better breeders than others, producing more and better fitted descendants. It is likely that farmers which understood the dynamics of the populations they were farming, were able to assure stable supplies of food, clothes, protection and working power for longer periods, once more, obtaining an important survival and evolutionary advantage.

However it took several thousands of years until modern societies acknowledged that wild biological renewable resources have similar characteristics to farmed populations and irresponsible exploitations practices will drive the target populations to unsustainable levels, eventually discontinuing the supply. It is still doubtful, in the beginning of the XXI century, that all stakeholders accept and based their practices on these principles. Simply looking at the usage is being done of the renewable natural resources available speaks for itself. Most large mammals are facing extinction, large part of world fisheries resources are overfished, forests are devastated, etc.

In such harsh conditions improvement of scientific knowledge and making it available for the benefit of our societies should be the best answer to our problems. This thesis contribution focus on the improvement of methodologies to learn about fish abundance and their usage for advising on management of fish populations exploited by fishing.

1.2 Animal abundance estimation

Estimation of animal abundance as well as understanding the factors that influence its fluctuation are key elements for the management of exploited renewable natural resources. The subject attracts the attention of scientists for a long time and is not simple. In the scientific literature there are references dating back to the end of the nineteen century (e.g. Sturtevant, 1881; Pound and Clements, 1898) and in 1937 a report of the American Statistical Association (Bell, 1937) reflects the scientists' struggle to estimate animal abundance stating that:

> "Most forms of wildlife are so elusive, so really wild, and have so many hiding places, that the obtaining of anywhere near an accurate estimate of their numbers on any extensive area has proven exceedingly difficult."

Seber's work (Seber, 1982, 1986, 1992; Schwarz and Seber, 1999) constituted a major step forward on animal abundance estimation, describing sampling schemes and methods to collect and estimate abundance indicators. From these essays it is possible to split abundance estimation methods in the following main categories:

- Counting methods - Based on counting individuals or their signs on a random sample of plots.
  - In the case of individuals, the resulting sample estimate of the number per unit area can then be converted into a population total by multiplying by the population area.
  - In the case of signs a relative measure or "index" of population density is obtained. This is a number bearing a constant ratio to the size of the population. If the index doubles it is assumed that the population has doubled, even if the actual size of the population is not known.

- Distance methods - Based on measuring the distance between the observer and the animal. By modeling the probability of detection as a function of distance, these distances can then be converted to an estimate of population density.
  - In line transect sampling, the observer walks, flies by plane or helicopter or travels by boat down a random line (path). The observer measures or, more usually, estimates the perpendicular distances of all animals seen from the line out to a certain predetermined distance (or out to any distance).
  - In point sampling, one first chooses a sample of points. The observer then spends some time at each point and estimates the distances of all animals seen in any direction out to a given distance (or out to any distance).
- Capture-recapture methods - Based on the time gap between capture and recapture of individuals it is possible to estimate the survival rate and abundance.
  - In capture-recapture, a series of samples are collected. Animals in the first sample are tagged and are then released back into the population. The second sample then has tagged (i.e., recaptured) and untagged animals. This process is repeated using unique tags for each individual. At the end of the experiment, each animal that was caught during the experiment will have a capture history.
  - In radio tagging, miniaturized radio transmitters are used as tags so that individuals can be tracked. The extra information provide more data about movements and survival.
- Removal methods - Based on the idea of knowing how much effort is put into catching and removing animals from the population. Using the removals per unit effort is possible to estimate the density of the population. These methods are particularly useful in fisheries, where they are usually described as catch-effort models.

All the above methods can be used to estimated several parameters about fish populations. However, the characteristics of the target population severely constraints the application of each of them. Counting and distance methods can be applied to small scale populations of species with restricted movement, distributed inshore or on small lakes and rivers, e.g. shellfish, but can not be used for large and widely distributed stocks. Change-in-ratio methods may be used in laboratory experiments, although the results would be of very limited interest. Capture-recapture methods are primarily used to learn about fish growth and migrations, while the usage for abundance estimation must be considered with care due to the large variability about the ratio between the tagged and untagged individuals on the population (Hilborn and Walters, 1992) and the very small recapture rate.

By far the most suitable methods for fisheries science are removal methods. These methods allow the computation of absolute and relative abundance indicators. This work focus on relative abundance indices, a measure of abundance proportional to stock size which reflects the population's fluctuation patterns.

There are two main sources of information that can be used for estimating relative abundance indices, the commercial fleet catch and effort statistics, also known as *fishery-dependent* information, and abundance observations from scientific surveys, also known as *fishery-independent* information.

Using fishery-dependent data like catch and effort to estimate abundance, rely on the distribution of fishing effort allocated by the fishermen on their day-by-day activity to compute a catch per unit effort (CPUE) index. Even though CPUE seems an attractive measure it has several drawbacks. Fishermen follow large schools of fish or go to areas with high concentrations of individuals to get the highest economical yield and end up being able to keep a stable CPUE in spite of the stock decline. Such practice shifts the proportionality between CPUE and fish abundance, the catchability coefficient, and bias the abundance estimates. Hilborn and Walters (1992) discuss the relation between CPUE and abundance in detail and argue that CPUE can hardly be useful as a measure of relative abundance.

Surveys aiming for the direct estimation of relative abundance indices are the best process for collecting information about abundance patterns. Having the possibility to plan the survey's sampling design allows the distribution of effort to follow the space-time distribution of the population, instead of allocating more effort to areas with higher aggregations of fish. On the other hand, it is possible to control catchability by controlling several variables that affect abundance observations like sample size, haul duration, characteristics of the gear, etc.

One of the major objectives of the work presented here is the development of statistical methods to estimate abundance of fish populations exploited by fisheries, based on information obtained by bottom trawl surveys off the Portuguese continental shelf, described in detail on Section 1.4.

Animal abundance continues to be a major subject for scientists involved in ecology and ecology related subjects like fisheries. Recent developments can be found in, *e.g.* Philippi (2005); Royle and Dorazio (2006); Farnsworth *et al.* (2007); Adams *et al.* (2008); Clavel *et al.* (2008); Conroy *et al.* (2008); Friday *et al.* (2008); McClintock *et al.* (2008); Thompson and La Sorte (2008); Rowat *et al.* (2009).

1.3 Hake (*Merluccius merluccius*)

European hake (*Merluccius merluccius* Linnaeus, 1758) showed in Figure 1.1 (Cohen *et al.*, 1990) belongs to the family Merlucciidae, subfamily Merlucciinae, order Gadiformes and class Actinopterygii.

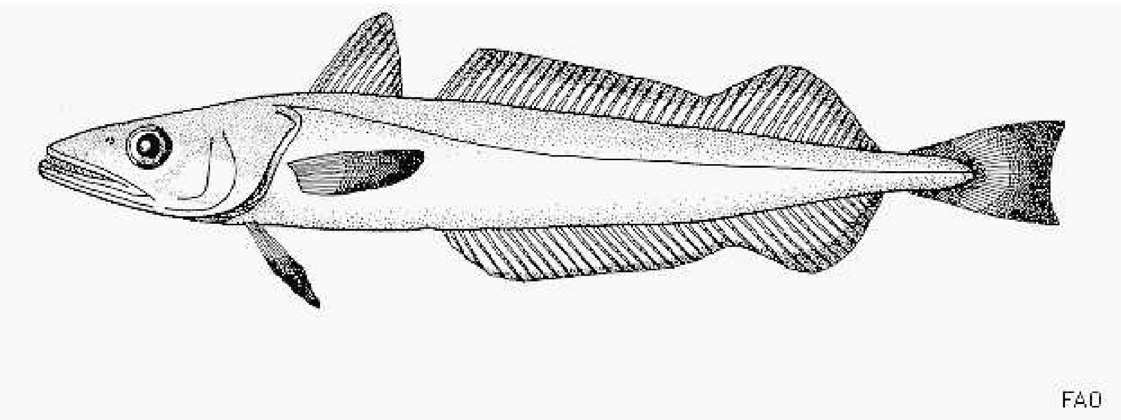


Figure 1.1: European hake (*Merluccius merluccius* Linnaeus, 1758). Maximum length recorded is 140 cm (Cohen *et al.*, 1990).

It is a widely distributed species in the northeast Atlantic (Figure 1.2), from Norway to Iceland (62^{o}N) to Mauritania (21^{o}N), expanding through the Mediterranean (Alheit and Pitcher, 1995). It is mainly found between 50m and 500m over mud, sand and rocky substrates (Casey and Pereiro, 1995). In the Mediterranean the highest abundance is found between 100 and 200m (Relini *et al.*, 2002).

Recent studies on genetic variation (Castillo *et al.*, 2004, 2005) support the existence of differences between Mediterranean and Atlantic populations owing to the barrier created by the Strait of Gibraltar. In the Mediterranean the high genetic variability found may indicate two distinct sub-populations.

Hake eggs are pelagic and are more common near the continental shelf edge close to the spawning grounds at depths between 100m and 250m (Casey and Pereiro, 1995). Larvae are transported to the continental shelf by wind-induced currents (Alvarez *et al.*, 2001) during a larval period of $\approx$ 5 weeks (Kacher and Amara, 2005), where they reach fully developed with $\approx$ 5cm. At this size individuals start migrating in the water column to depths between 50m and 100m for feeding, mainly on small crustaceans (Casey and Pereiro, 1995; Mahe *et al.*, 2007). This pelagic period is $\approx$ 5 weeks long also (Kacher and Amara, 2005). Morales-Nin and Morant (2004) reports the pre-settlement period to take $\approx$ 2 month.

Juveniles migrate to the bottom grounds near the coast where they stay until the first maturity (Casey and Pereiro, 1995). During this period the diet is constituted of small crustacean and small pelagic fish which are caught during night migrations on the water column (Papaconstantinou and Stergiou, 1995; Bozzano *et al.*, 2005).

As individuals grow larger they migrate to deeper grounds near the edge of the continental platform. In the Atlantic the diet becomes less generalized to be mostly composed of small pelagic fish and hake juveniles (Mahe *et al.*, 2007).

Cannibalism may play an important role on adult hake diet depending on the abundance of juveniles and the spatial overlap between different age groups. Cardador (1988) reported $\approx$ 7% cannibalism off the Portuguese Continental coast, while Casey and Pereiro (1995) and Mahe *et al.*

(2007) reported $\approx 20\%$ on the Bay of Biscay. Velasco and Olaso (1998) reports a small cannibalism rate $< 3\%$ off the Cantabrian coast.

Regarding the reproductive strategy Murua and Saborido-Rey (2003) classified European hake: (i) to be iteroparous, because females spawn more than once during their lives; (ii) to have asynchronous ovarian organization, because during each spawning season eggs are recruited and ovulated from the population of yolked oocytes in several batches over a protracted period; (iii) to be batch spawners, once that only a portion of the yolked oocytes is spawned in each batch; and (iv) to have indeterminate fecundity, once that potential annual fecundity is not fixed before the onset of spawning and unyolked oocytes continue to be matured and spawned during the spawning season.

As with other species the spawning period of hake is influenced by water temperature, with an optimum range between 10^{o}C and 12.5^{o}C (Alvarez *et al.*, 2001). Such driver may explain the latening of the spawning period along the south-north direction off the Atlantic European coast. Off the Iberian coast the spawning period start in December and extends through May (Casey and Pereiro, 1995; Piñeiro and Sainza, 2003), in the Bay of Biscay it starts in February and extends trough July (Casey and Pereiro, 1995), off the southwest of Ireland spawning starts on March through July and off the northwest coast of Scotland it starts in May through August (Lloris *et al.*, 2005). In the Mediterranean spawning extends for a longer period between December and June (Lloris *et al.*, 2005).

Recruitment on the Atlantic European waters occurs mainly during the Autumn (Figure 1.2). There are six main recruitment areas, on the southeast of the Gulf of Cadiz, southwest of the Portuguese coast, northwest of the Spanish coast, northwest of the French coast, west of Ireland and on the northwest of Scotland (Anon., 2006a, 2007c). On the Mediterranean recruitment is reported to occur all year round in western areas (Morales-Nin and Morant, 2004) with a peak in spring and summer on the Catalan coast (Maynou *et al.*, 2003). The main nurseries are the Gulf of Lions and Ligurian-Tyrrhenian Seas (Relini *et al.*, 2002).

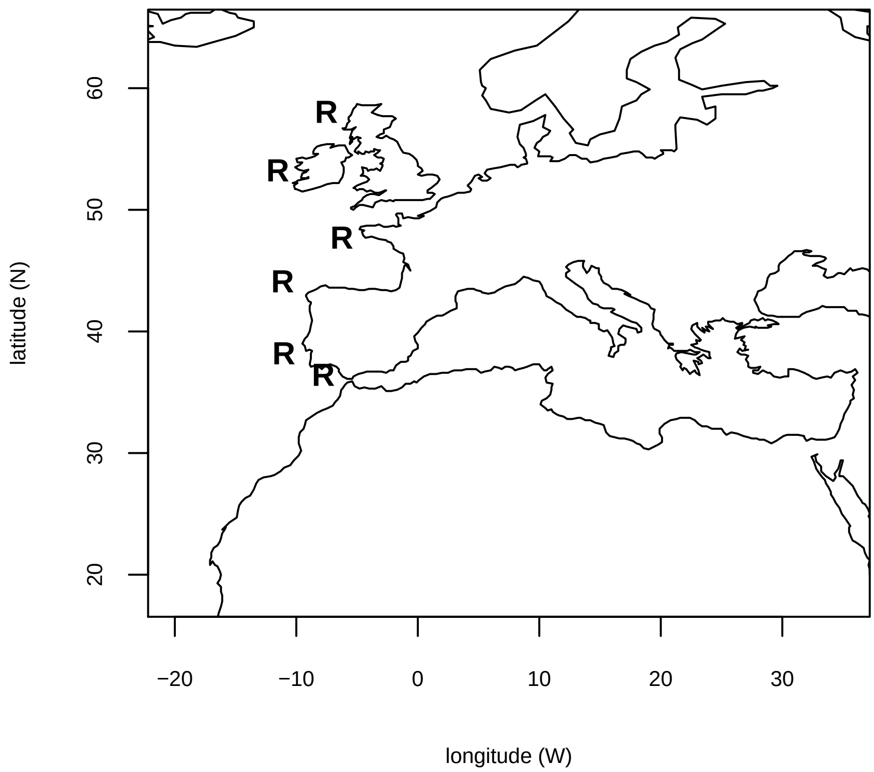


Figure 1.2: Hake distribution region and recruitment zones marked with “R”.

The growth of European hake is not clearly known. Piñeiro *et al.* (2009) makes a revision of methods and literature about age estimation and points out some solutions. The complexity of otolith interpretation due to the presence of many macrostuctures arising from the long spawning periods and almost continuous recruitment are the main sources of uncertainty. The authors refer to two distinct perspectives about the growth rate, fast growth supported by recent studies that claims hake would reach 25cm, 45cm and 60cm total length at the end of the first, second and third years of life; and slow growth envisaged by the internationally agreed ageing method (Piñeiro and Sainza, 2003) that estimates 20cm, 29cm and 37cm total length for the same ages.

1.4 Portuguese Bottom Trawl Surveys

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 in Summer and Autumn (Anon., 2007d). A Winter survey took place in 1992 and 1993 but was interrupted until 2005. The Summer survey was terminated in 2002.

The main objectives of the Autumn 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 information on 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 (Anon., 2002a).

Between 1979 and 1980, a stratified random sampling design with 15 strata was adopted. Those strata were set based on 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. Due to constraints in the vessel time available for this survey, the sample size was established to a total of 97 locations, which were allocated equally split to obtain 2 locations in each stratum. The locations' coordinates 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. This sampling plan has been kept fixed between 1989 and 2005 (Anon., 2007d). The survey started with 60 minutes tows, in 1979 and 1980. Between 1981 and 1988 the tow duration was reduced to 30 minutes, but in 1989 it was set to 60 minutes again, until 2001. Since 2002 tows were reduced to 30 minutes, based on an experiment that showed no significant differences in the mean abundance and length distribution of hake, horse mackerel and blue whiting between the two tow durations. Table 1.1 presents historical information about the Autumn ptBTS.

Table 1.1: Historical information about the Autumn Bottom Trawl Survey off the Portuguese Continental shelf. Sample size in number of hauls and haul duration. Sampling scheme in sampling strategy (SRS = stratified random sampling; HS = hybrid sampling) and number of strata.

Year	Sampling scheme		Sample size	
	strategy	number of strata	number of hauls	haul duration (minutes)
1979	SRS	15	55	60
1980	SRS	15	62	60
1981	SRS	36	112	30
1982	SRS	36	190	30
1983	SRS	36	117	30
1985	SRS	36	150	30
1986	SRS	36	117	30
1987	SRS	36	81	30
1988	SRS	36	98	30
1989	SRS	48	130	60
1990	SRS	48	108	60
1991	SRS	48	80	60
1992	SRS	48	44	60
1993	SRS	48	58	60
1994	SRS	48	76	60
1995	SRS	48	80	60
1996	SRS	48	63	60
1997	SRS	48	51	60
1998	SRS	48	64	60
1999	SRS	48	71	60
2000	SRS	48	65	60
2001	SRS	48	58	60
2002	SRS	48	66	30
2003	SRS	48	72	30
2004	SRS	48	79	30
2005	HS	-	87	30
2006	HS	-	88	30
2007	HS	-	96	30
2008	HS	-	87	30

The survey is coordinated internationally by the ICES International Bottom Trawl Survey Working Group (IBTS) and related workshops (Anon., 2002a, 2003b, 2004a,c, 2005a,c, 2006a). A large amount of work was carried out with the data collected by ptBTS. The indices of abundance estimates were extensively used for stock assessment of Iberian hake, anglerfish and megrims by the ICES Working Group on the Assessment of Southern Shelf Stocks of Hake, Monk and Megrim (Anon., 2000, 2001, 2002b, 2003c, 2004b, 2005b, 2006b, 2007e, 2008b) and recently, a set of papers dealing with abundance estimation were published (Sousa *et al.*, 2005; Mendes *et al.*, 2007; Silva *et al.*, 2007; Sousa *et al.*, 2007).

One of the major results of this thesis is the revision of the Autumn ptBTS sampling design, presented in Chapters 2 and 3.

1.5 Demersal fisheries off Portuguese continental coast

The fleet fishing off the Portuguese Continental shelf is distributed into three segments for administrative purposes (Anon., 2007a), seiners (PS), fixed gears (FIX) and trawlers (TR). The FIX segment is further split into vessels with less than 12m length-over-all (FIX<12m) and vessels with equal or more than 12m length-over-all (FIX>=12m), with the aim of splitting the small scale fleet working near the coast from the large vessels working in deeper areas.

The characteristics of the fleet, excluding the PS segment due to its irrelevance for demersal stocks, are shown in Figure 1.3. The contrast between the number of vessels (N) and their size (GT) shows that the small scale fleet is constituted by several thousands of small vessels. This fleet decreased in numbers for the last ten years but increased sharply in engine power (POT). The segment FIX>=12m shows a decrease trend in all indicators, while TR increased in size and engine power until early 2000's but decreased since then.

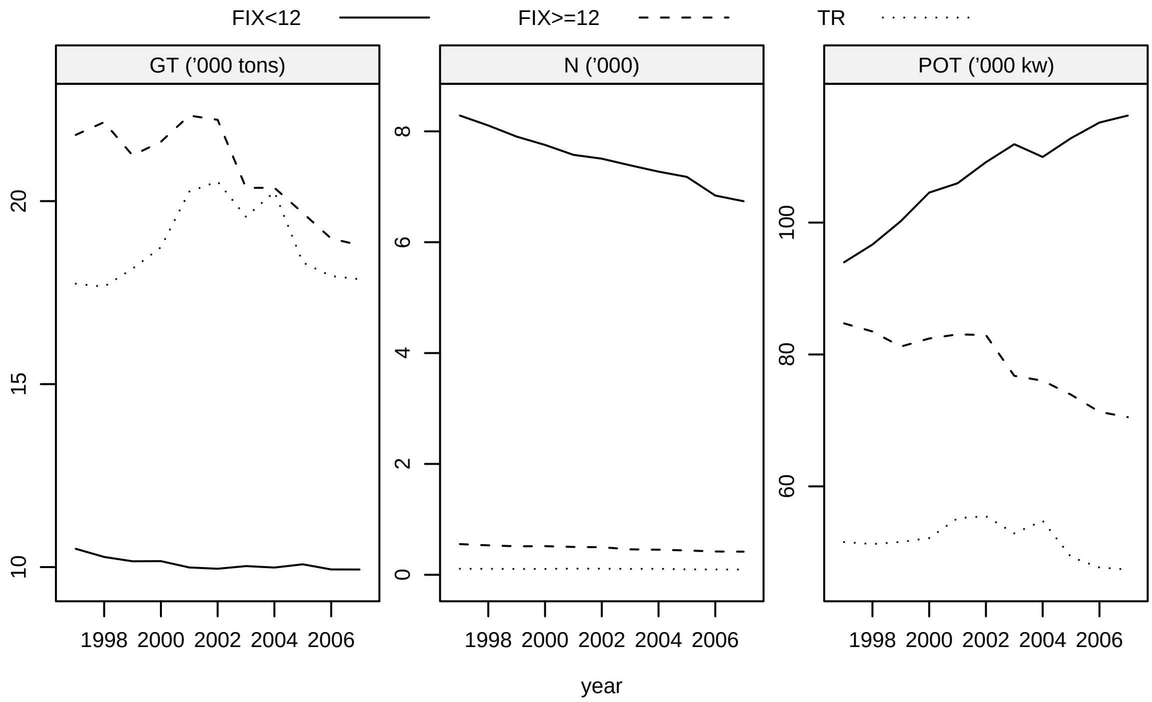


Figure 1.3: Characteristics of the fleet working off the Portuguese Continental shelf between 1997 and 2007, excluding purse seiners. The fleet is split into three segments: less than 12m length-over-all vessels using fixed gears (FIX<12m), equal or more than 12m length-over-all vessels using fixed gears (FIX>=12m) and trawlers (TR). The characteristics are gross tonnage (GT), number of vessels (N) and main engine power (POT).

Considering the latest data available (Anon., 2007a) the estimated landings of these fleets in 2007 were 69.2 thousand tons. There were 6739 vessels with less than 12m fishing with fixed gears, 417 vessels equal or larger than 12m fishing with fixed gears and 95 vessels fishing with trawl gears. The top five species in weight caught by FIX were octopus (≈ 7890ton), mackerel (≈ 7880ton), sardine (≈ 7070ton), black scabbard (≈ 3450ton) and Norway pout (≈ 2040ton); while in value were octopus (≈ 33.3M euros), black scabbard (≈ 10.1M euros), sea bass (≈ 5.9M euros), cuttle fish (≈ 5.5M euros) and sardine (≈ 5.4M euros). Regarding the TR fleet catches, the top five species in weight were horse mackerel (≈ 5700ton), blue whiting (≈ 3190ton), jack mackerel (≈ 1200ton), mackerel (≈ 950ton) and hake (≈ 660ton); while in value were horse mackerel (≈ 7.5M euros), rose shrimp (≈ 6.1M euros), Norway lobster (≈ 4.1M euros), hake (≈ 2.1M euros) and blue whithing (≈ 2.0M euros). Landings of these fleets occur along the Portuguese Continental coast harbours (Figure 1.4). Figure 1.5 shows landings in weight aggregated into three areas, north (N), centre (C) and south (S). The vessels using fixed nets landed mostly in the central area of the Portuguese Continental coast, but the last decade shows a sharp increase on landings in the other areas. The trawl fleet shows a decreasing trend in the landings on the North and, to a less extent, in the south, while in the centre the landings increased during the last decade.

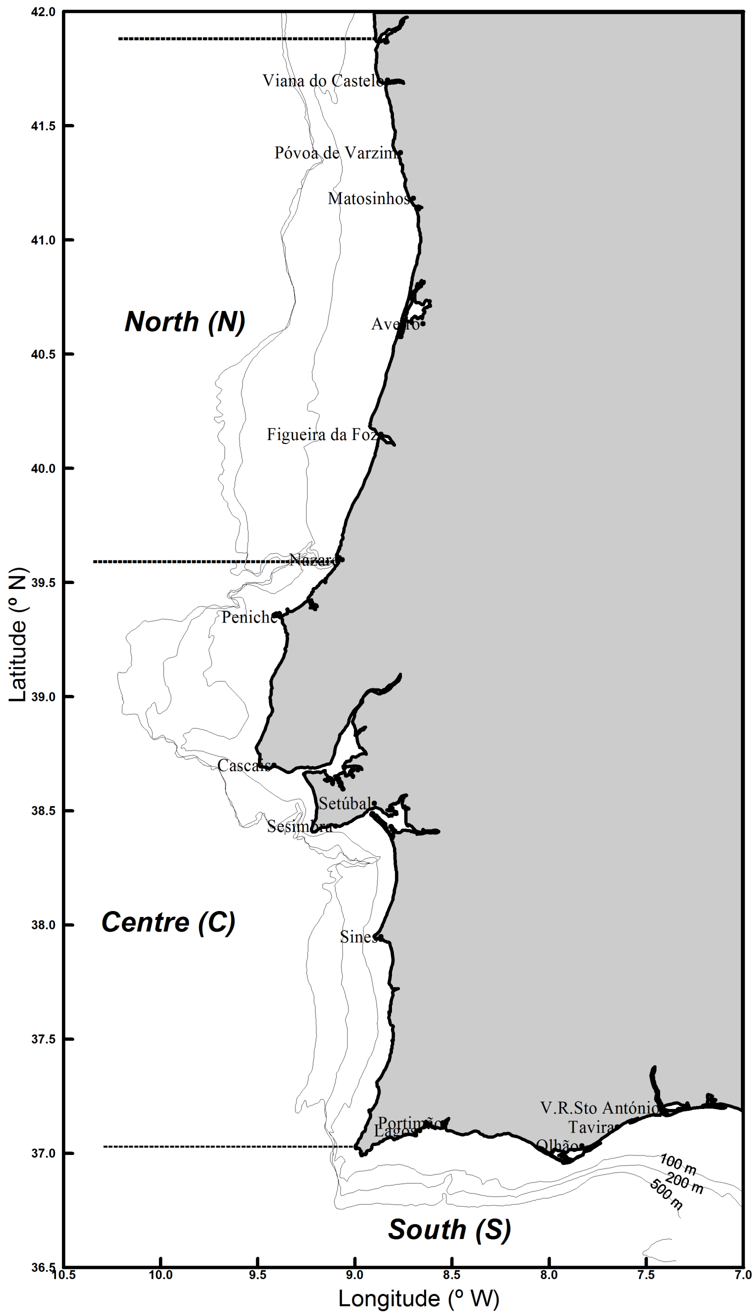


Figure 1.4: Portuguese Continental shelf harbours and regions.

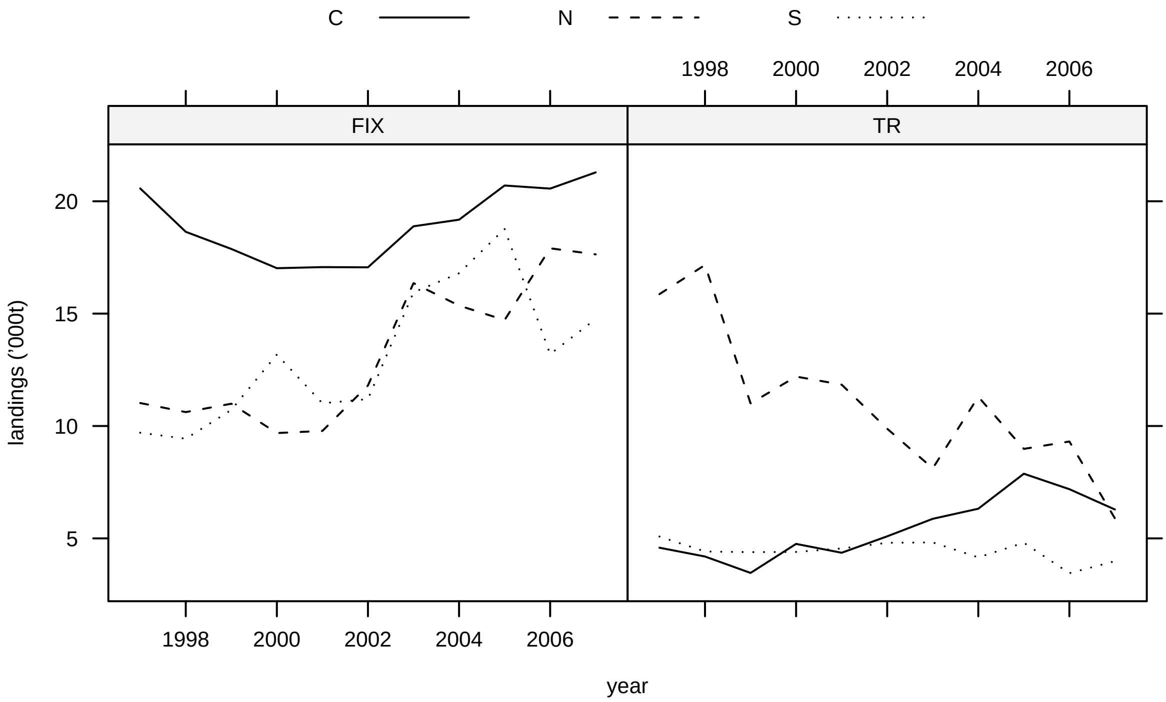


Figure 1.5: Landings in weight by region off the Portuguese Continental shelf harbours by the fleets using fixed nets (FIX) and trawlers (TR) between 1997 and 2007. Regions are coded as C=centre, N=north and S=south.

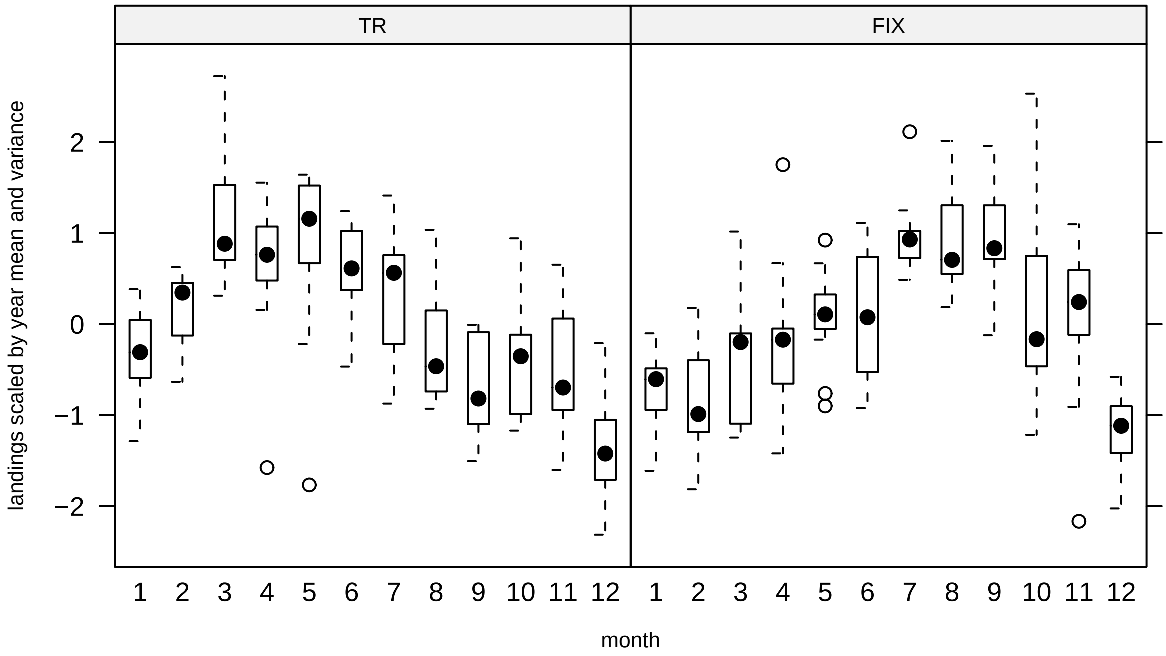


Figure 1.6: Seasonality of landings off the Portuguese Continental shelf harbours by the fleets using fixed nets (FIX) and trawlers (TR) between 1997 and 2007. Landings were normalized to have zero mean and unit variance to show the periodicity pattern.

Landings from trawlers occur mainly during Spring and Summer while the fix gears fleet show higher landings late Summer and Autumn (Figure 1.6). Both fleets show lower periods of activity on the Winter, likely to result from periods of poor sea conditions and quota closures.

Silva *et al.* (2009) analysed daily trips between 2003 and 2005 of vessels with more than 12m using trawl gears with the aim of classifying activity patterns. The trawl fleet vessels are licensed to use three different mesh sizes, >= 65mm for fish, 55mm for targeting shrimps and >=70mm for Norway lobster. In conformity with the licensing a clear split between trips targeting fish and crustacean was found. Within the first three distinct activities were found, targeting horse mackerel (35%), cephalopods (18%) and a mixture of species (47%), being the last the most present during the period analysed. During the year there is not a constant activity pattern and the study showed that vessels switch their activity between these groups. Regarding vessels with licenses for crustacean fisheries, two activity patterns were identified, one targeting rose shrimp (44%) and another Norway lobster (56%).

Duarte *et al.* (2009) analyses daily landings off the Portuguese continental coast of the FIX segment also to define activity patterns. This segment is constituted by a multi-gear fleet with each vessel having in average 4 distinct licenses. The authors identified fourteen different activity patterns reflecting the large heterogeneity of this fleet segment.

From the species caught by FIX and TR only a small group is subject to scientific advice by ICES: hake, horse mackerel, mackerel, blue whiting, megrims, monks and Norway lobster. These species are managed through a mixture of constraints set by the European Commission like total allowable catch, mesh size constraints, marine protected areas, fishing effort restrictions, etc. Figure 1.7 shows the landings reported to ICES of these species in Portuguese Continental harbours between 1989 and 2007.

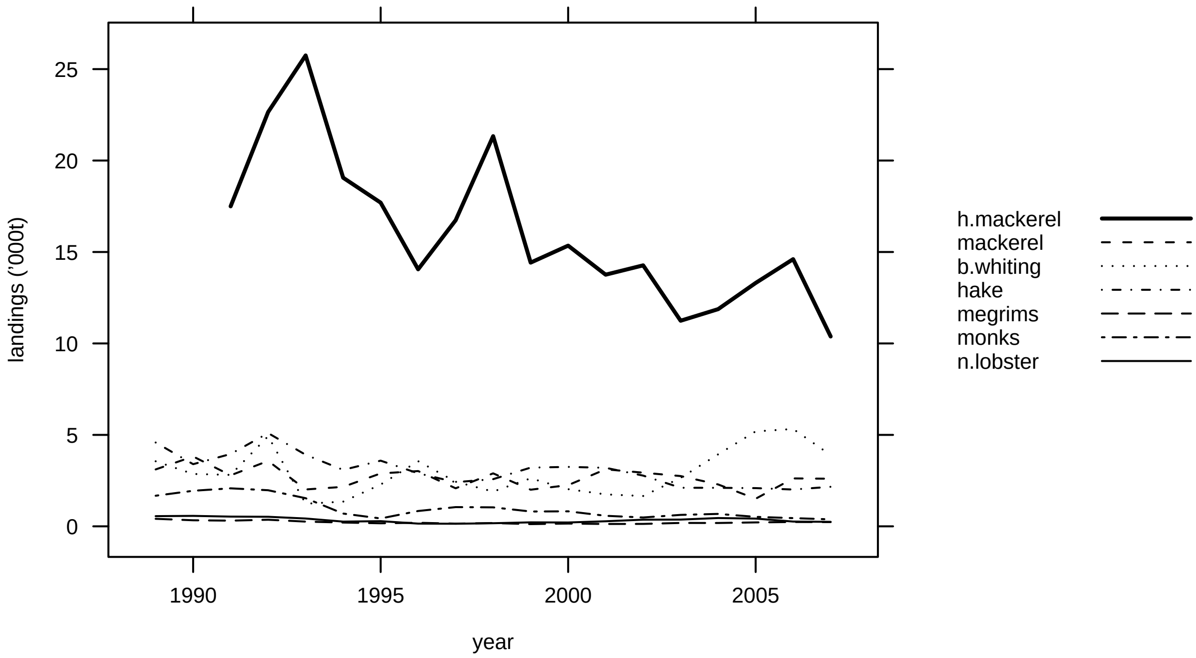


Figure 1.7: Total landings off the Portuguese Continental harbours of horse mackerel, mackerel, blue whiting, hake, megrims, monks and Norway lobster between 1989 and 2007.

The scientific advice in 2008 provided by ICES (Anon., 2008a) is presented in Table 1.2. All of the above mentioned species, except horse mackerel, are overfished, which means the exploitation is being carried out at a level above the maximum sustainable fishing mortality.

In the case of hake and Norway lobster there is a recovery plan introduced by the European Commission in 2006 (Reg. EC No 2166/2005) with the aim of rebuilding in a period of ten years, the spawning stock biomass of hake to 35 000t, the precautionary spawning stock biomass estimated by ICES (Anon., 2003a). The recovery plan foresees reductions of fishing mortality (F) of 10% per year until reaching 0.27, the F giving the maximum yield on a yield per recruit curve (F_{max}). Additionally, it enforces a constraint on the maximum change of the TAC between years of 15% in order to assure catch stability. The period of ten years chosen is in agreement with the compromises assumed in the Johannesburg World Summit on Sustainable Development in 2002 of exploring fish stocks at the maximum sustainable yield (MSY) in 2015. More information about the hake and Norway lobster recovery plan is presented in Chapter 5.

1.6 Modelling methods

The work presented in this thesis makes extensive use of modelling methods. The most important are:

- Model-based geostatistics (Diggle *et al.*, 1998; Diggle and Ribeiro Jr., 2007) - extensively used in Chapters 2, 3 and 4 to model the spatial patterns of fish populations and carry out simulation studies;
- Compositional data analysis (Aitchison, 1982) - used in Chapter 4 to model the age structure of fish populations;
- Management strategies evaluation (Butterworth *et al.*, 1997; Cooke, 1999; Butterworth and Punt, 1999; Punt *et al.*, 2005) - used in Chapter 5 to study the dynamics of the Iberian hake fishery and its recovery.

The following sections introduce these methodologies. Detailed descriptions are embedded on the relevant chapters.

Table 1.2: Status of the exploitation of the demersal stocks off the Iberian peninsula (ICES divisions VIIIc and IXa) where the Portuguese Continental coast is included, according to ICES based on the 2008 stock assessments(Anon., 2008a). SSB = spawning stock biomass, F = fishing mortality.

Stock	State of the stock			ICES considerations regarding single-stock based exploitation limits
	Spawning biomass in relation to precautionary limits	Fishing mortality in relation to precautionary limits	Fishing mortality in relation to high long-term yield	In relation to precautionary limits
Southern stock of hake	Reduced reproductive capacity (SSB < limit biomass)	Harvested unsustainably (F > limit fishing mortality)	Overfished (F > maximum sustainable fishing mortality)	Even with zero landings it is not possible to bring SSB above Bpa at the beginning of 2010
Megrim (*L. boscii and L. whiffiagonis*)	Not defined	Not defined	Overexploited (F > maximum sustainable fishing mortality)	F should not be allowed to increase.
Anglerfish (*L. piscatorius and L. budegassa*)	Not defined	Not defined	Overexploited (F > maximum sustainable fishing mortality)	Fishing mortality equal to zero or a recovery plan.
Southern horse mackerel (*Trachurus trachurus*)	Undefined	Undefined	Undefined	Recent level of catches do not seem to be detrimental to stock and can be maintained.
Nephrops	Undefined	Undefined	Undefined	Zero catches for FUs 26–27, 200 tonnes in FUs 28–29, 200 tonnes for FU 30

1.6.1 Model-based geostatistics

The spatial behaviour of fish is influenced by the local behaviour of the population up to a distance above which the individuals no longer influence each other. In other words, fish populations can show spatial patterns regarding some of its characteristics. Under this assumption, a model that takes into account the correlation of observed variables in different geographic locations can be adopted, in order to learn about the spatial dynamics of such variables. As such the geostatistical model can be regarded as a natural choice for modelling fish abundance.

In fisheries science geostatistics are mostly used for: (i) predicting the distribution of the marine resource, aiming, for instance, to define areas of high abundance of a given age, sex or maturity status, for the purpose of protection; or (ii) to compute abundance indices for stock assessment models (Anon., 2004c).

Geostatistics were developed to address problems of spatial prediction by Whittle (1954, 1962), Matérn (1960) and Matheron (1963, 1971), later included on the more general subject of spatial statistics by Ripley (1981) and Cressie (1993), who formalized the link between kriging, the spatial predictor, and linear modeling. However, model parameters are unknown and have to be estimated before proceeding with prediction. The traditional practice regarding estimation is based on *ad hoc* procedures (Isaaks and Srivastava, 1989; Cressie, 1993; Goovaerts, 1997; Rivoirard *et al.*, 2000) with two major characteristics: (i) the stochastic model is not explicitly declared, and (ii) the estimates are not unique, because they depend on the subjective intervention of the analyst to define the empirical variogram estimator and some of its parameters.

Diggle *et al.* (1998) suggested a formal approach to deal with geostatistical modeling based on explicit stochastic models, named *Model-based geostatistics*, later extended in (Diggle and Ribeiro Jr., 2007). Diggle declares the geostatistical model with observable variables on the class of the exponential family of distributions assuming conditional independence of the observables given an underlying Gaussian stochastic process. This defines an hierarchical extension of generalised linear models (McCullagh and Nelder, 1991) completed with specification of prior distributions for models parameters within the Bayesian paradigm. This model is referred as a *generalised linear* *geostatistical model* (Diggle and Ribeiro Jr., 2007). For the particular case of Gaussian observable variables the model is linear and can be declared as follows. Denoting by Z the vector of variables observed at locations x within a study region $A \subset \mathbb{R}^2$, the model is written as

$$Z(x) = S(x) + \varepsilon$$

where S is a stationary Gaussian stochastic process, with $E[S(x)] = \beta$, $Var[S(x)] = \sigma^2$ and an isotropic correlation function $\rho(u) = Corr[S(x), S(x')]$, where $u = \|x - x'\|$ is the Euclidean distance between locations x and x'. The terms ε are assumed to be mutually independent and identically distributed, $\varepsilon \sim \text{Gau}(0, \tau^2)$. Following usual geostatistical terminology (Isaaks and Srivastava, 1989), $\sigma_T^2 = \tau^2 + \sigma^2$ is the total sill, σ^2 the partial sill, τ^2 the nugget effect and ϕ is a function of the practical range, defined as the distance u for which $\rho(u) \simeq 0.05$.

The full parametric specification of the spatial model allows and promotes inference based on the likelihood function indiced by the assumed model and establishes a formal framework that does not require subjective decisions to estimate the model parameters. It allowed further methods of inference to be implemented such as Bayesian and Monte Carlo methods based on stochastic simulations, largely used in the analysis carried out on this thesis.

1.6.2 Compositional data analysis

Proportions represent an important indicator of the characteristics of many types of data, being geochemical composition of rocks, household income expenditures, population age distributions and similar data structures defined by fractions or proportions. Any variable partitionable into non-overlapping classes can be represented by a vector of proportions of the observations in each class. Compositional data consists of the vectors of proportions, constraint by the components of each vector summing one to represent all parts of the whole.

Aitchison (1982) formalized the statistical analysis of compositional data, describing methods to model the large variability found in vectors of proportions. In his work, Aitchison (1982, 2003) showed that the additive log-ratio transforms compositions with m components into $m-1$ vectors of multivariate Gaussian approximately distributed variables. Working on the multivariate Gaussian (MVG) scale opens the possibility of modeling the rich covariance structure of proportions, which is ignored by methods based on multinomial probabilities. However, it must be born in mind that the interpretation of the results in the transformed scale may not be used in the original scale, due to the difficulty of interpreting the covariance structure of proportion vectors. Nevertheless, Monte Carlo methods for stochastic simulations can be used to generate empirical distributions of the proportions.

The work presented in Chapter 4 is based on Bootstrap methods (Efron and Tibshirani, 1993) to generate simulations of the age structure of fish populations, using compositional data analysis, and integrate it in multivariate spatial models.

1.6.3 Management Strategies Evaluation

Management Strategy Evaluations (MSE) are a simulation framework that aims to test distinct management strategies regarding their success on achieving a management objective, and investigate the robustness of such strategies to departures from present knowledge. MSE have their genesis in the International Whaling Commission in the 90's and are being developed by *e.g.* Butterworth *et al.* (1997); Cooke (1999); Butterworth and Punt (1999); Kell *et al.* (2005). For an overview see Punt and Donovan, 2007.

MSE allows a wide view on fisheries management integrating different objectives and sources of uncertainty. The dialog with stakeholders is promoted by their engagement on the definition of management alternatives and performance metrics. While scientists define metrics regarding conservation, fishermen are encouraged to define metrics about exploitation. This approach gives managers a wider picture of the risks associated with each strategy and their previewed impacts on the different sectors, providing scientific support to the decision-making process based on the nation's political, social and development objectives.

MSE (Figure 1.8) consists of a generic framework with two modules, the operating model (OM) and the management procedure (MP). The OM is a theoretical framework that represents the "true" population and fishery dynamics and must be conditioned on available information about the stock and fishery in study. The MP contains a decision algorithm that implements a management strategy which triggers specific management actions based on the perception of the stock condition. The MP will constraint the fishery driving the population towards predefined goals. The linkages between both models are (i) the observation error model that adds error to the OM generating a distinct view of *reality* used for management; and (ii) the implementation error model that generates the differences between the management actions foreseen by the MP and the actions implemented in *reality*.

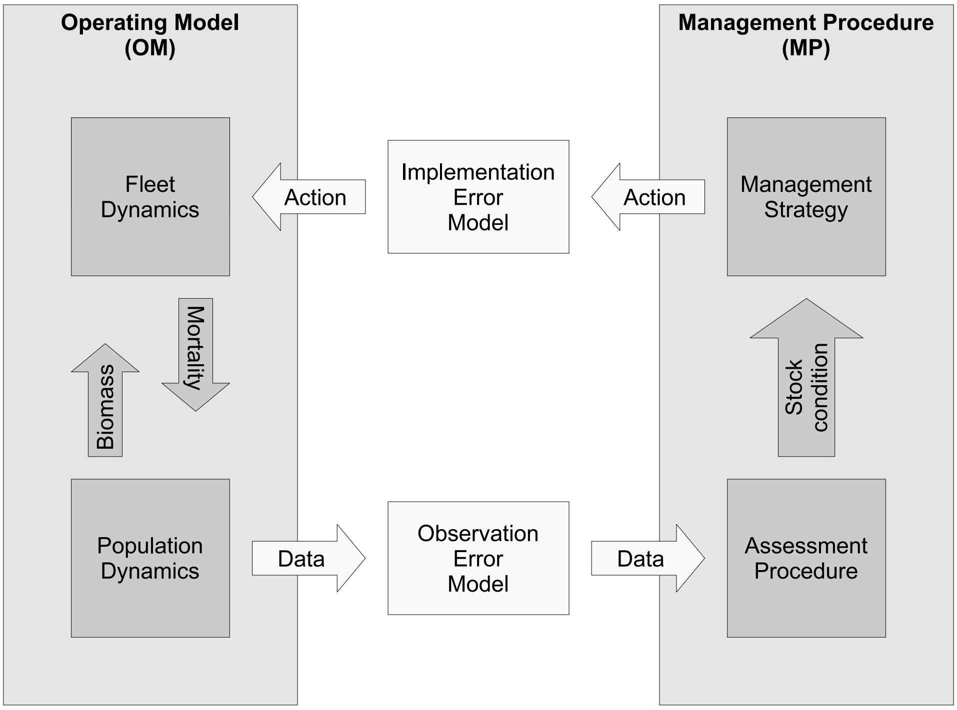


Figure 1.8: Framework of Management Strategies Evaluation

The MSE analysis considers a set of sources of uncertainty in fish stock assessment and management described by Kell *et al.* (2007) as:

- process error – caused by disregarding variability, temporal and spatial, in dynamic population and fisheries processes;

- observation error – sampling error and measurement error;
- estimation error – which arises when estimating parameters of the various models used in the assessment procedure;
- model error – related to the ability of the model structure to capture the core of the system dynamics;
- implementation error – where the effects of management actions may differ from those intended.

In fact, MSE is a super-model that includes several models to describe the distinct dynamic processes and their interactions. The MSE complexity depends on how many processes are included, how much knowledge exists about each and how complex are the interactions among them. This characteristic makes MSE a very flexible tool, which was the reason why it was considered to study the Iberian hake fishery in Chapter 5.

1.7 Data

The spatial analysis performed on chapters 2 to 4 were based on the observations of hake and horse mackerel abundance collected by Portuguese bottom trawl surveys. The analysis about the Iberian hake stock recovery presented in Chapter 5 were based on the data available to the International Council for the Exploitation of the Sea (ICES) for assessing the stock. Detailed descriptions of the datasets can be found in the relevant chapters.

Chapter 2 explores observations of hake and horse mackerel abundance in weight per hour, collected by the Autumn bottom trawl survey between 1990 and 2004, to compute covariance function parameters and geostatistical range. These estimates were used to define the range of covariance parameters used in the simulation study.

Chapter 3 analyses observations of hake abundance in weight per hour, collected in a field experience carried out during the summer of 2001 with R/V Noruega off the southwest of Portuguese

Continental shelf, to test different sampling design strategies.

In Chapter 4 the observations of hake abundance in number of individuals per hour, collected by the Autumn bottom trawl survey between 1989 and 2006, are used as a case study to illustrate the application of the methods proposed.

In Chapter 5, the database available to the ICES Working Group on the Assessment of Southern Shelf Stocks of Hake, Monk and Megrim to perform the assessment of Iberian hake in 2008 (Anon., 2008b) was used. Consisting of yearly data of:

- landings in weight per fleet from 1972 to 2007;
- stock length and age distributions in number and weight from 1982 to 2007;
- stock maturity at age from 1982 to 2007;
- stock and catch mean weight at age from 1982 to 2007;
- abundance indices of Portuguese trawlers, A Coruña trawlers, Spanish September Groundfish survey, Portuguese Autumn bottom trawl survey and Gulf of Cadiz October Groundfish survey;

Additionally, the Instituto Español de Oceanografia (IEO) made available the historical series of age compositions of the Gulf of Cadiz, consisting of landings in numbers and weight per age class for the period 1995 to 2007, as well as the discards observations of the Spanish trawl fleet for the period 1994-2007. The Instituto Nacional de Recursos Biológicos (IPIMAR) made available the discards observations of the Portuguese trawl fleet for the period 2004-2007. Discard observations were available in number of individuals per age class and mean individual weight per age class, both collected with on-board sampling programmes.

1.8 Framework

The thesis presented here aims at contributing to improve the knowledge about abundance of fish populations and its usage for fisheries management. The work focus on European hake and its abundance off the Portuguese continental coast. In particular it presents research results regarding the sampling of abundance by bottom trawl surveys, processing of abundance observations collected by bottom trawl surveys and its inclusion in Iberian hake fisheries management.

The problem was triggered in 2001 when IPIMAR decided to reduce haul duration from one hour to half hour, creating the conditions to increase the survey's sample size. The number of hauls per survey executed in the previous decade was very low (Table 1.1), due to operational constraints that limited the execution of the sampling programme. This situation was severely affecting the quality of the abundance estimates used for stock assessment and it was decided to allocate research effort to sort out the problem. The next step was to define where the new observations would be collected, raising the interest to explore alternative sampling schemes, that eventually give more insights about the abundance of demersal species and sort out problems related with over-stratification and abundance estimators (Figure 1.9). Following this line of though, it became obvious that it would also be necessary to investigate how the new estimates could be included on the stock assessment of demersal species and if it would be possible to improve the Iberian hake stock assessment.

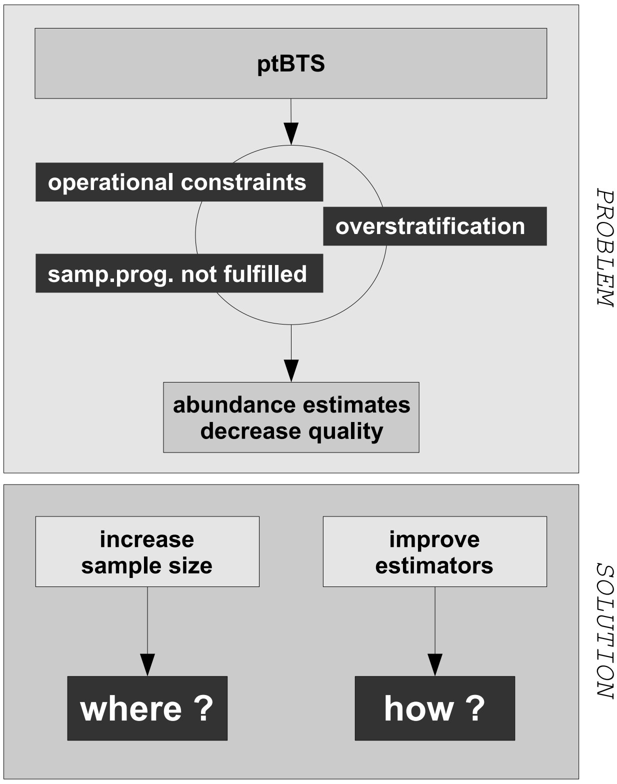


Figure 1.9: The problem addressed. Operational constraints were limiting the sampling program which, together with the overstratification of the sampling design, were decreasing the precision of abundance estimates. The solutions foreseen were the increase of sample size and the development of new statistical estimators.

The solutions were developed considering the statistical methods described in Section 1.6. These methods follow a model-based approach, which is central to this work due to the strong effort allocated to simulation methods, considered of main importance for modern fisheries science. Regarding abundance the research was centered on applications of geostatistics to take into account the spatial behaviour of fish populations when estimating abundance indicators. Regarding fisheries management it was considered the framework of Management Strategies Evaluation, a sophisticated and flexible approach to fisheries management, to test distinct management strategies inline with those proposed by the recovery plan for hake and nephrops on the Iberian peninsula, on their ability to recover hake's spawning stock biomass to a safe biological level.

The document is organized by chapters each presenting a paper published or submitted to peer reviewed journals.

The paper on sampling design (Chapter 2) was published in Fisheries Research in 2007 (Jardim and Ribeiro Jr., 2007) with the title "*Geostatistical assessment of sampling designs for Portuguese bottom trawl surveys*". The main objective of the work is to investigate proposals of new sampling designs for the Autumn Portuguese bottom trawl survey. It explores new spatial configurations and possible increases on sample size. Secondly, it describes a pragmatic procedure to build sampling designs for BTS and develops a statistical approach to compare sampling designs with different sample sizes and spatial configurations.

Sampling design testing (Chapter 3) was published by Scientia Marina in 2008 (Jardim and Ribeiro Jr., 2008) with the title "*Geostatistical tools for assessing sampling designs applied to a Portuguese bottom trawl survey field experience*". The work reports a bottom trawl survey field experience to test the sampling designs suggested in the previous work and describes a set of geostatistical tools to assess the performance of sampling designs.

The approach developed to model abundance at age (Chapter 4) was submitted to the ICES Journal of Marine Science in 2009 with the title "*Modeling Spatio-temporal Abundance at Age with Compositional Data Analysis and Bayesian Geostatistics*". The aim of this work is to propose a model-based methodology to estimate abundance-at-age time series, with a model that explicitly considers the spatial distribution and the age structure of the target population. Secondly, it reports an application to hake's abundance at age observed off the Portuguese continental coast by the Autumn bottom trawl survey. The methodology can be applied to surveys with time series of observations that were collected with distinct sampling designs and can generate simulations of the abundance at age statistical distribution suitable to be used in large simulation frameworks like MSE.

Regarding fisheries management (Chapter 5) a paper was submitted to the ICES Journal of Marine Science in 2009, with the title "*Evaluating Management Strategies to Recover the Iberian Hake (Merluccius merluccius) Stock.*" The paper evaluates management strategies to recover Iberian hake to safe biological limits and test their robustness to uncertainty on the operating model caused by the inclusion of: (i) landings and survey of the Gulf of Cadiz, and/or (ii) discards of the Spanish and Portuguese trawl fleets. The analysis used the abundance index generated from the previous chapter, illustrating its usage for stock assessment.

Figure 1.10 presents the thesis framework showing relations between chapters and major and secondary results of each chapter.

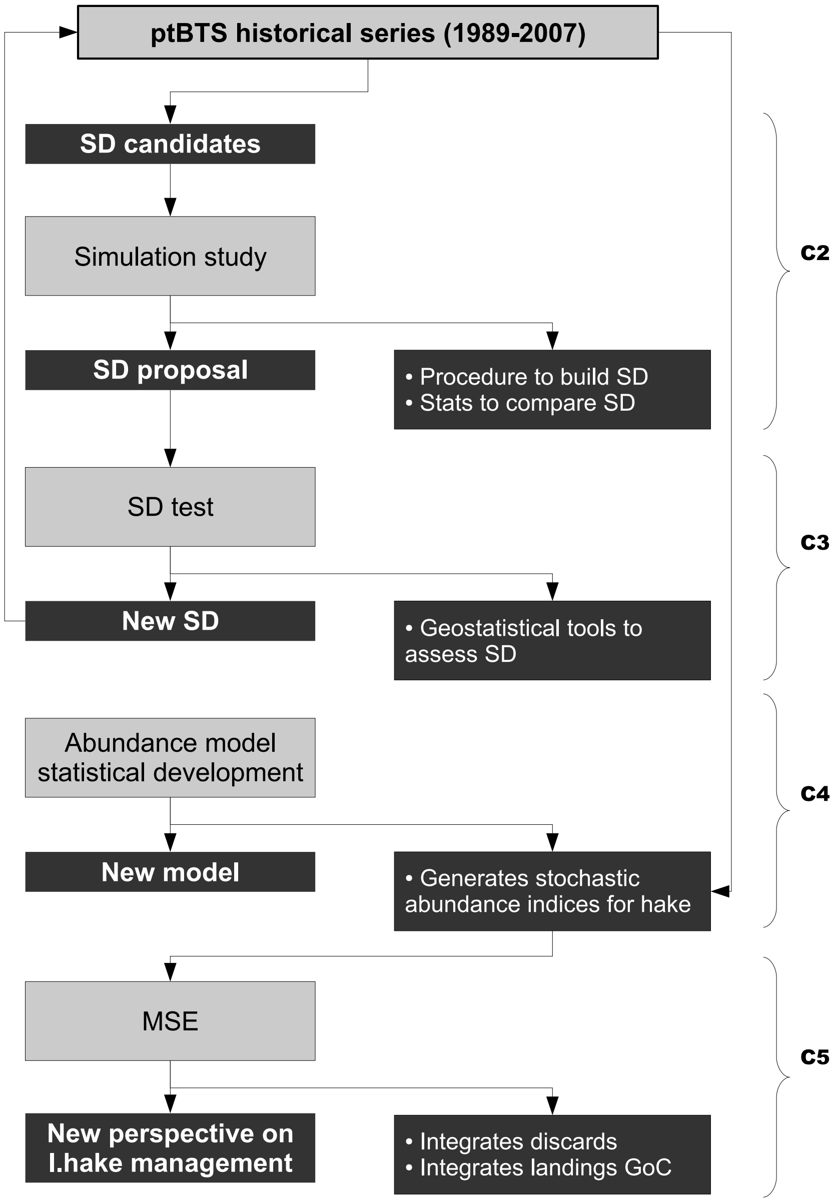


Figure 1.10: Thesis framework. Methods are represented by gray boxes and results by black boxes. Arrows represent the flow of results between chapters. The brackets entangle the chapters where the work is presented. SD=sampling design; GoC=Gulg of Cadiz.

Chapter 2

Geostatistical assessment of sampling designs

This chapter was published as a review paper in Fisheries Research with the following reference:

Ernesto Jardim and Paulo J. Ribeiro Jr. 2007. Geostatistical assessment of sampling designs for Portuguese bottom trawl surveys. Fisheries Research, 85, 239-247.

Abstract: New sampling designs for the Autumn Portuguese bottom trawl survey (ptBTS) were investigated to explore alternative spatial configurations and possible increments on sample size. The currently used stratified random design and five proposals of systematic based designs were assessed by a simulation study, adopting a geostatistical approach based on likelihood methods of inference. The construction of the designs was based on "*informal*" method to reflect the practical constraints of bottom trawl surveys. The proposed designs were a regular design with 28 locations (S28), two regular designs with extra regular added locations with 44 (S44) and 47 (S47) locations, a design which overlaps the regular and stratified random design currently used with 45 locations (S45) and an high density regular design with 108 locations (S108), used just as a benchmark. The designs were assessed by computing bias, relative bias, mean square error and coverages of confidence intervals. Additionally a variance ratio statistic between each study designs and a corresponding random design with the same sample size was computed to separate out the effects of different sample sizes and spatial configurations. The best performance design was S45 with lower variance, higher coverage for confidence intervals and lower variance ratio. This result can be explained by the fact that this design combines good parameter estimation properties of the random designs with good prediction properties of regular designs. In general coverages of confidence intervals were lower than the nominal 95% level reflecting an underestimation of variance. Another interesting fact was the lower coverages of confidence intervals computed by sampling statistics for the random designs, for increasing spatial correlation and sample size. This result illustrates that in the presence of spatial correlation, sampling statistics will underestimate variances according to the combined effect of spatial correlation and sampling density.

2.1 Introduction

Fisheries surveys are an essential sampling process for the estimation of fish abundance as they provide independent information on the number and weight of fish that exist on a specific area and period. Moreover, this information can be obtained fully disagregated along several biological dimensions like age, length, maturity status, etc. Like for any other sampling procedures, the quality of the data obtained depends greatly on the sampling design applied.

For the last 20 to 30 years, bottom trawl surveys (BTS) have been carried out in Western European waters using design-based strategies (Anon., 2002a, 2003b). However, if one assumes that the number of fish in a specific location is positively correlated with the number of fish in nearby locations, then a geostatistical model can be adopted for estimation and prediction and a model-based approach can be considered to define and assess the sampling design. On the other hand geostatistical principles are widely accepted and can be regarded as a natural choice for modelling fish abundance (e.g. see Rivoirard *et al.*, 2000; Anon., 2004c).

Thompson (1992) contrasts design-based and model-based approaches considering that under the former one assumes the values of the variable of interest are fixed and the selection probabilities for inference are introduced by the design, whereas under the latter one consider the observed properties of interest as realisations of random variables and carries out inference based on their joint probability distribution. Hansen *et al.* (1983) points the key difference between the two strategies by stating that design-based inference does not need to assume a model for the population, the random selection of the sample provides the necessary randomisation, while the model-based inference is made on the basis of an assumed model for the population, and the randomisation supplied by nature is considered sufficient. If the model is appropriate for the problem at hand there will be an efficiency gain in inference and prediction with model-based approaches, although model mis-specification can lead us to inaccurate conclusions. In our context, and with the experience accumulated over 20 years of bottom trawl surveys within the study area, a fairly complete picture exists of the characteristics of the fish assemblage in the area, so the risk of assuming an unreasonable model should be small.

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 in 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 information on 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 (Anon., 2002a).

Between 1979 and 1980, a stratified random sampling design with 15 strata was adopted. Those strata were set based on 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. Due to constraints in the vessel time available for this survey, the sample size was established to total 97 locations, which were allocated equally splited to obtain 2 locations in each stratum. The locations' coordinates 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. This sampling plan has been kept fixed since 1989. The tow duration was set until 2001 as 60 minutes and was then reduced in 2002 to 30 minutes, based on an experiment that showed no significant differences in the mean abundance and length distribution between the two tow duration.

The main objective of the present work is to investigate proposals of new sampling designs for the Autumn Portuguese bottom trawl survey (ptBTS). We aim to explore 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). Secondly, we aim to describe a pragmatic procedure to build sampling designs for BTS, develop a statistical approach to compare sampling designs with different sample sizes and spatial configurations, and provide generalized results that could be used for other surveys and species. A simulation study was performed to compare the stratified random design which is currently used against five proposals of systematic based designs, which we have called *study designs*. A model based geostatistical approach (Diggle and Ribeiro Jr., 2007) was adopted using likelihood based methods of inference and conditional simulations to estimate fish abundance on the study area.

Section 2.2 describes the framework for the simulation study starting with the model specifications followed by a description of the sampling designs and the setup for the simulation study, conducted in five steps as described in Section 2.2.3. The results of the simulation study comparing the study designs are presented in Section 2.3 and the findings are discussed in Section 2.4.

2.2 Methods

The survey area considered for this work corresponds to the Southwest of the Portuguese Continental EEZ, between S.Vicente Cape (37.00^{o}lat north) and Setubal's Canyon (38.30^{o}lat north). Locations stored using the Mercator projection were transformed into an orthonormal space by converting longitude by the cosine of the mean latitude (Rivoirard *et al.*, 2000). At Portuguese latitude (38-42^o) $1^o lat \approx 60nm$. The area has $\approx 1250nm^2$ and the maximum distance between two locations was $\approx 81nm(1.35^o lat)$.

2.2.1 Geostatistical framework

The spatial model assumed here is a log-Gaussian geostatistical model. This is a particular case of the Box-Cox Gaussian transformed class of models discussed in Christensen *et al.* (2001). The data consist of the pair of vectors (x, y) with elements $(x_i, y_i) : i = 1, \ldots, n$, where x_i denote the coordinates of a spatial location within a study region $A \subset \mathbb{R}^2$ and y_i is the measurement of the abundance at this location. Denoting by z_i the logarithm of this measurement, the Gaussian model for the vector of variables Z can be written as:

$$Z(x) = S(x) + \varepsilon \tag{2.1}$$

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'; and the terms ε are assumed to be mutually independent and identically distributed $\mathrm{Gau}(0, \tau^2)$. For the correlation function $\rho(h)$ we adopted the exponential function with algebraic form $\rho(h) = \exp\{-h/\phi\}$ where ϕ is the correlation range parameter such that $\rho(h) \simeq 0.05$ when $h = 3\phi$. Within the usual geostatistical *jargon* (Isaaks and Srivastava, 1989) $\tau^2 + \sigma^2$ is the (total) sill, σ^2 is the partial sill, τ^2 is the nugget effect and 3ϕ is the practical range.

Hereafter we use the notation $[\cdot]$ for *the distribution of* the quantity indicated within the brackets. The adopted model defines $[\log(Y)] \sim \mathrm{MVGau}(\mu\mathbf{1}, \Sigma)$, i.e $[Y]$ is multivariate log-Gaussian with covariance matrix Σ parametrised by (σ^2, ϕ, τ^2). Parameter estimates can be obtained by maximum likelihood (Diggle and Ribeiro Jr., 2007). For spatial prediction consider first the prediction target $T(x_0) = \exp\{S(x_0)\}$, i.e. the value of the process in the original measurement scale at a vector of spatial locations x_0. Typically x_o defines a grid over the study area. From the properties of the model above the predictive distribution $[T(x)|Y]$ is log-Gaussian with mean μ_T and variance σ^2_T given by:

$$\begin{aligned}
\mu_T &= \exp\{\mathrm{E}[S(x_0)] + 0.5\ \mathrm{Var}[S(x_0)]\} \\
\sigma^2_T &= \exp\{2\ \mathrm{E}[S(x_0)] + \mathrm{Var}[S(x_0)]\}(\exp\{Var[S(x_0)]\} - 1)
\end{aligned}$$

with

$$\begin{aligned}
\mathrm{E}[S(x_0)] &= \mu + \Sigma_0' \Sigma^{-1}(Z - \mathbf{1}\mu) \\
\mathrm{Cov}[S(x_0)] &= \Sigma - \Sigma_0' \Sigma^{-1} \Sigma_0
\end{aligned}$$

where Σ_0 is a matrix of covariances between the variables at prediction locations x_0 and the data locations x and $\mathrm{Var}[S(x_0)]$ are given by the diagonal elements of $\mathrm{Cov}[S(x_0)]$. In practice, we replace the model parameters in the expressions above by their maximum likelihood estimates.

Under the model assumptions, $[T|Y]$ is multivariate log-Gaussian and inferences about prediction means and variances, or other properties of interest, can be drawn either analytically or, more generally, through conditional simulations. Prediction targets can be specified as functionals $\mathscr{F}(S)$ which are applied to the conditional simulations. For instance, inferences on the global mean of a particular realisation of the stochastic process over the area are obtained by defining x_0 as a grid covering the study area at which conditional simulations of $[S(x_0)|Y]$ are taken; the simulated values are then exponentiated and averaged.

2.2.2 Sampling designs

In general, survey sampling design is about choosing the sample size n and the sample locations x from which data Y can be used to predict any functional of the process. In the case of the ptBTS some particularities must be taken into account: (i) the survey targets several species which may have different statistical and spatial behaviours; (ii) for each species several variables are collected (weight, length, number, etc.) that might be distributed differently due to age and sex-related aggregating behavior; (iii) the sampling is destructive and replicates can not be obtained; (iv) the variability of observed fish abundance is typically high, and (v) the planned sampling design may be unattained in practice due to unpredictable commercial fishing activity at the sampling area, weather conditions or other operational constraints.

Optimal designs can be obtained formally, by defining a criteria and finding the set of sampling locations which minimise some sort of loss function, as e.g. discussed in Diggle and Lophaven (2006). On the other hand, designs can be defined *informally* by arbitrarily defining locations which present a compromise between statistical principles and operational constraints. Both are valid for geostatistical inference as described in Section 2.2.1 provided that the locations x are fixed and stochastically independent of the observed variable Y. The above characteristics of the ptBTS make it very complex to set a suitable criterion to define a loss function to be minimized with relation to survey design. Additionally, vessel cost at sea is mainly day-based and not haul-based, so groups of locations instead of individual sampling points must be considered when altering sampling size. Therefore, our approach was to construct the proposed designs informally trying to accommodate: (i) historical information about hake and horse mackerel abundance distribution (Anon., 2002a; Jardim, 2004), (ii) geostatistical principles about the estimation of correlation parameters (e.g. see Isaaks and Srivastava, 1989; Cressie, 1993; Müller, 2001) and (iii) operational constraints like known trawlable grounds and minimum distance between hauls.

The *study designs* included the design currently adopted for this survey, named "ACTUAL" with 20 locations, and five systematic based sampling designs. The systematic based designs were defined based on two possible increments in the sample size: a $\approx$ 40% increment, which is expected to be achievable in practice by reducing haul time from 1 hour to 1/2 hour; and a $\approx$ 60% increment, which could be achieved in practice by adding to the previous increment an allocation of higher sampling density to this area in order to cover the highest variability of hake recruits historically found within this zone. These designs are denoted by "S" followed by a number corresponding to the sample size. For the former increment a regular design named "S28" was proposed and for the latter three designs were proposed: "S45" overlaps the designs ACTUAL and S28, allowing direct comparison with the previous designs; "S44" and "S47" are two infill designs (Diggle and Lophaven, 2006) obtained by augmenting S28 with a set of locations positioned regularly at smaller distances, aiming to better estimate the correlation parameter and, in particular, the noise-to-signal ratio. S44 was built by defining a single denser sampling zone and S47 by adding three areas with denser sampling. A sixth design "S108" was defined to be used as reference with twice the density of S28.

The designs proposed differ in both size and spatial configuration and a simple analysis of any statistic thus obtained would be confounded by these two effects. This situation motivated the development of a statistical approach to compare designs with different sample sizes and spatial configurations. We used a *ratio of variances* of the relevant estimators between pairs of study designs and random designs with the same sample size, isolating in this way the spatial configuration effect. To carry out this analysis we built six additional designs with the same sample size as the study designs and with locations randomly chosen within the study area. We denote these by "R" followed by the number of corresponding locations. Each random design contains all the locations of the previous one such that the results are comparable without the effect of the random allocation of sampling sites.

The *study* and corresponding *random* designs are shown in Figure 2.1.

2.2.3 Simulation study

The simulation study was carried out in five steps as follows:

Step 1 **Define a set of study designs.** The sampling designs described in Section 2.2.2 are denoted by $\Lambda_d : d = 1, \ldots, 12$, with $d = 1, \ldots, 6$ for the study designs and $d = 7, \ldots, 12$ for the corresponding random designs, respectively.

Step 2 **Define a set of correlation parameters.** Based on the analysis of historical data of hake and horse mackerel spatial distribution and defining $\tau^2_{REL} = \tau^2/(\tau^2 + \sigma^2)$, a set of model parameters $\theta_p : p = 1, ..., P$ was defined by all combinations of $\tau^2_{REL} = \{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$ and $\phi = \{0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4\}^o$lat. The values of σ^2 are given by setting $\sigma^2 + \tau^2 = 1$.

Step 3 **Simulate data.** For each parameter set θ_p we obtained S=200 simulations $Y_{ps} : s = 1, \ldots, S$ from $[Y]$ on a regular grid of 8781 locations under the model described in Section 2.2.1. Each simulation Y_{ps} approximates a possible realisation of the process within the study area from which we computed the mean value μ_{ps}. For each Y_{ps} we extracted the data Y_{pds} at the locations of the sampling designs Λ_d.

Step 4 **Estimate correlation parameters.** For each Y_{pds} obtain maximum likelihood estimates (MLE's) $\tilde{\theta}_{pds}$ of the model parameter.

Step 5 **Simulating from the predictive distribution.** A prediction grid x_0 with 1105 locations and the estimates $\tilde{\theta}_{psd}$ were used to obtain C=150 simulations $\tilde{Y}_{pdsc} : c = 1, \ldots, C$ of the conditional distribution $[T(x_0)|Y]$ which were averaged to produce $\bar{\tilde{Y}}_{pdsc}$.

2.2.4 Analysis of simulation results

The simulation study requires maximum likelihood estimates for the model parameters which are obtained numerically. Therefore a set of summary statistics was computed in order to check the results' consistency. We have recorded rates of non-convergence of the minimization algorithm; estimates which coincided with the limiting values imposed to the minimization algorithm ($\phi = 3$ and $\tau^2_{REL} = 0.91$); absence of spatial correlation ($\phi = 0$) and values of the parameter estimates which are considered atypical for the problem at hand ($\phi > 0.7$ and $\tau^2_{REL} > 0.67$).

The 48 parameter sets (θ_p), 12 sampling designs (Λ_d), 200 data simulations (Y_{psd}) and 150 conditional simulations ($\tilde{Y}_{psdc}$) produced 17.28 million estimates of abundance. For each design we have computed the estimator $\tilde{\mu}_{psd} = C^{-1} \sum_c \bar{\tilde{Y}}_{pdsc}$ of mean abundance μ_{ps} which has variance $\mathrm{Var}(\tilde{\mu}_{psd}) = \bar{\tilde{\rho}}_{AA} + \sum_i^n \sum_j^n w_i w_j \tilde{\rho}_{ij} - 2\sum_i^n w_i \bar{\tilde{\rho}}_{iA}$, where $\bar{\tilde{\rho}}_{AA}$ is the mean covariance within the area, estimated by the average covariance between the prediction grid locations (x_0); w are kriging weights; $\tilde{\rho}_{ij}$ is the covariance between a pair of data locations; and $\bar{\tilde{\rho}}_{iA}$ is the average covariance between each data locations and the area discretized by the prediction grid x_0 (Isaaks and Srivastava, 1989).

We used bias, relative bias, mean square error (MSE), confidence intervals coverage and ratio of variances to assess the simulation results, comparing the estimates of abundance provided by the different study designs. For each design these statistics were averaged over all the simulations (s) and parameter sets (p) or groups of parameters sets. Considering the difference between the abundance estimates $\tilde{\mu}_{psd}$ and simulated means μ_{ps}, bias was computed by the difference, relative bias was computed by the difference over the estimate $\tilde{\mu}_{ps}$ and MSE was computed by the mean square of the difference. For each estimate $\tilde{\mu}_{pds}$ a 95% confidence interval for μ_{ps}, given by $\mathrm{CI}(\tilde{\mu}_{psd}) = \tilde{\mu}_{psd} \pm 1.96\sqrt{Var(\tilde{\mu}_{psd})}$, was constructed and the coverage of the confidence intervals δ were computed as the proportion of the intervals which contained the value of μ_{ps} over all the simulations. This statistic was introduced to help assessing the quality of the variance estimates. Next, we called *ratio of variances* a statistic ξ obtained by dividing the variance $Var(\tilde{\mu}_{psd})$ of each study design by the random design with the same size. Notice that the single difference among

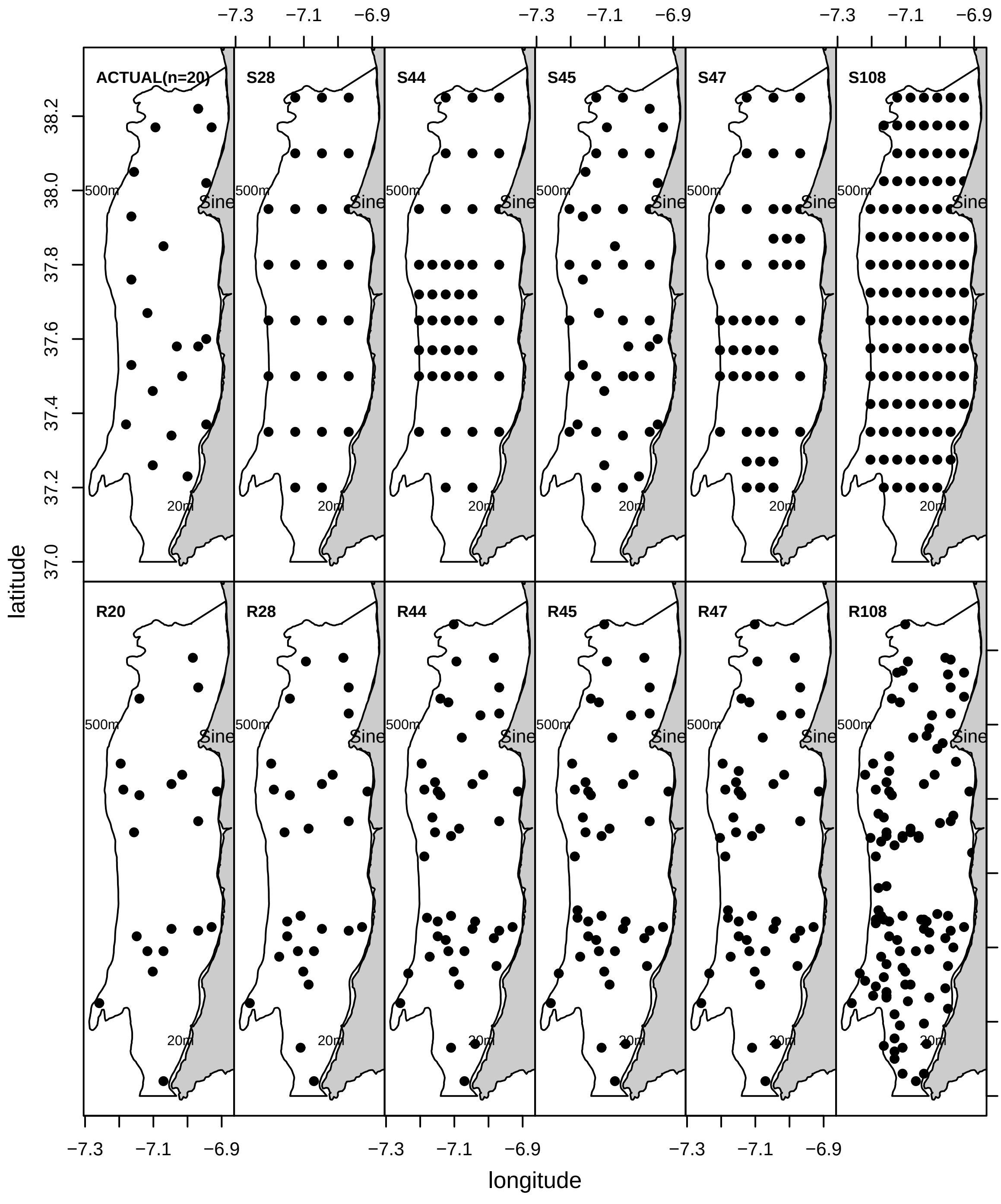


Figure 2.1: Sampling designs and the study area (southwest of Portugal). Each plot shows the sample locations, the bathymetric isoline of 500m and 20m and the coast line. The sampling design name is presented on the top left corner of the plots. The top row shows the *study* designs and the bottom row the random designs.

each pair of designs with the same size was the spatial configuration of the locations and ξ isolated this effect. Finally we used the results from the six random designs to contrast sampling design based and geostatistical based estimates.

All the analysis were performed using the R software (R Development Core Team, 2008) and the add-on packages geoR (Ribeiro Jr. and Diggle, 2001) and RandomFields (Schlather, 2001).

2.3 Results

Table 2.1 summarises the analysis of historical data showing parameter estimates for a sequence of years. This aims to gather information on reasonable values for the model parameters. Notice that units for ϕ are given in degrees and, for the adopted exponential correlation model, the practical range in nautical miles (r) is given by 3ϕ. The values of $\tau^2_{REL} = 1$ estimated in some years indicate an uncorrelated spatial process and for such cases estimates of ϕ equals to zero. For most cases τ^2_{REL} was estimated as zero due to the lack of nearby locations in the sampling plan and the behaviour of the exponential correlation function at short distances. Given that there is no information in the data about the spatial correlation at distances smaller than the smallest separation distance between a pair of location, this parameter can not be estimated properly and the results depend on the behaviour of the correlation function near the origin.

Table 2.2 presents results used for checking the reliability of the parameter estimates and the possible impact on prediction results. The highest rate of lack of convergence was 0.6% for designs ACTUAL and R20. Estimates of ϕ constraint by the upper limit imposed to the algorithm were, in the worst case, 0.9% for R28 and R47 while for τ^2_{REL} it was 1.2% for R28. In general there was a slightly worst performance of the random designs but this is irrelevant for the objectives of this study. The above simulations were not considered for subsequent analysis. Lack or weak spatial correlation given by $\phi = 0$ and/or $\tau^2_{REL} > 0.67$ were found in about 35% of the simulations for the designs with fewer number of locations. This rate decreases as the sample size increases down to below 10% for the largest designs. For both statistics the study designs showed slightly higher values than the corresponding random designs. Identification of weakly correlated spatial

Table 2.1: Exponential covariance function parameters ($\phi, \tau^2_{\mathrm{REL}}$) and the geostatistical range (r) estimated yearly (1990-2004) for hake and horse mackerel abundance. The values of ϕ are presented in degrees of latitude and range in nautical miles. The maximum distance between pairs of locations was 63nm.

	Hake			Horse mackerel		
	ϕ (^{o}lat)	r(nm)	τ^2_{REL}	ϕ (^{o}lat)	r(nm)	τ^2_{REL}
1990	0.05	9.1	0.01	0.42	76.4	0.00
1991	0.14	24.4	0.63	0.49	88.9	0.43
1992	0.00	0.0	1.00	0.22	39.3	0.05
1993	0.05	9.3	0.00	0.00	0.0	1.00
1995	0.05	8.8	0.00	0.08	14.4	0.00
1997	0.14	24.8	0.00	0.21	38.6	0.42
1998	0.02	3.4	0.00	0.09	16.5	0.00
1999	0.10	17.8	0.00	0.09	16.0	0.00
2000	0.03	4.6	0.00	0.16	29.5	0.00
2001	0.07	12.9	0.00	0.42	75.7	0.06
2002	0.00	0.0	1.00	0.05	8.9	0.00
2003	0.33	59.0	0.00	0.34	62.0	0.00
2004	0.09	15.4	0.00	0.09	17.0	0.00

processes in part of the simulations was indeed expected to occur given the low values of ϕ (0.05 and 0.1) and high values of τ^2_{REL} (0.5) used in the simulations. The number of cases that presented $\phi > 0.7$ were slightly higher for random designs, with a maximum of 2.6% for R44 and R45, but were considered to be within an acceptable range given the high variability of the estimator. Our overall conclusion was that the estimation procedure and algorithms produced parameter estimates which can be trusted for subsequent analysis.

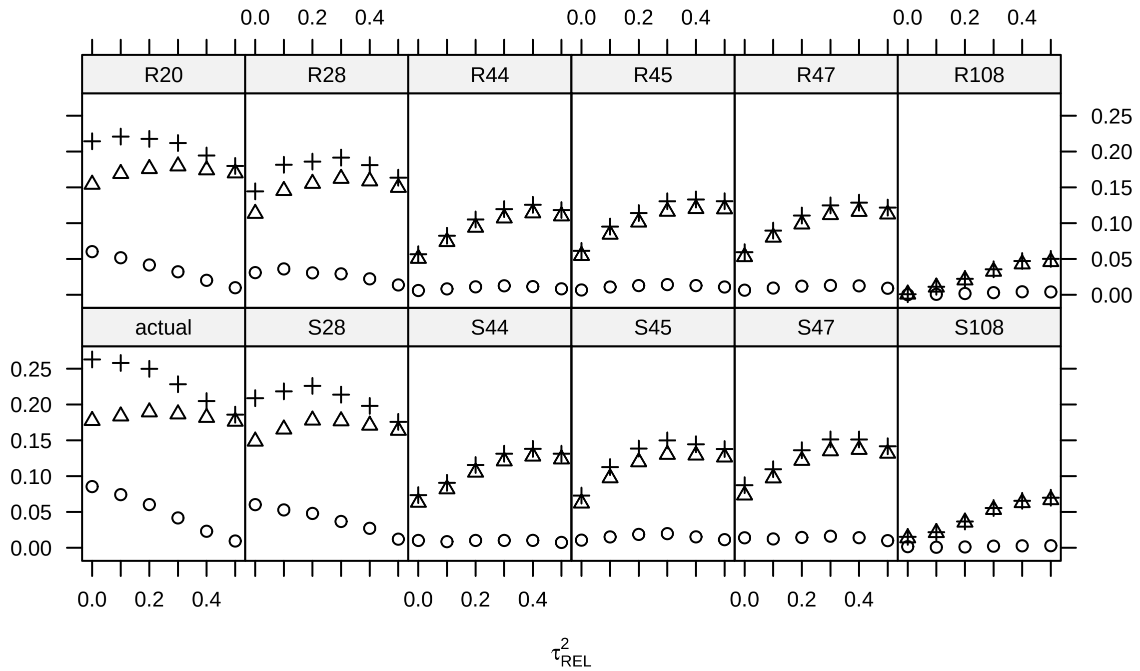
Figure 2.2 shows square bias, variance and MSE obtained from the estimates of correlation parameters ϕ and τ^2_{REL}. For τ^2_{REL} the majority of the designs presented similar patterns with a small contribution of bias to the MSE and increasing values of MSE for higher parameter values. The designs ACTUAL, S28 and R20 behaved differently with higher values of bias at low values of τ^2_{REL} that pushed MSE to higher values. As an effect of the sample sizes, the absolute values of MSE define 3 groups composed by designs with 20 and 28 locations, designs with 44, 45 and 47 locations, and designs with 108 locations; with decreasing values of MSE among them, respectively. MSE increases with the increase of the true value of ϕ and its absolute value decreases slightly with the increasing sample sizes. All designs presented a similar pattern with the vari-

Table 2.2: Simulations quality assessment statistics (in percentages) for both design sets and all sample sizes: non-convergence of the minimization algorithm (non-conv); cases truncated by the limits imposed to the minimization algorithm ($\phi = 3$ and $\tau^2_{\mathrm{REL}} = 0.91$); uncorrelated cases ($\phi = 0$); and atypical values of the correlation parameters ($\phi > 0.7$ and $\tau^2_{\mathrm{REL}} > 0.67$).

statistic	design	sample size					
		20	28	44	45	47	108
non-conv	study	0.6	0.5	0.2	0.2	0.2	0.1
	random	0.6	0.4	0.2	0.2	0.2	0.1
$\phi = 3$	study	0.7	0.5	0.7	0.7	0.5	0.2
	random	0.6	0.9	0.8	0.8	0.9	0.1
$\tau^2_{\mathrm{REL}} = 0.91$	study	0.7	0.7	1.0	0.9	0.8	0.4
	random	0.8	1.2	1.1	1.1	1.1	0.2
$\phi = 0$	study	36.3	33.0	20.7	20.6	18.0	5.3
	random	32.8	28.5	18.1	17.2	16.2	3.3
$\phi > 0.7$	study	1.3	1.6	1.9	1.9	1.8	1.4
	random	1.8	2.2	2.6	2.6	2.4	1.7
$\tau^2_{\mathrm{REL}} > 0.67$	study	38.5	35.8	24.2	24.7	21.8	10.0
	random	35.0	31.6	22.1	21.1	20.3	7.6

ance contributing more than bias to the MSE. The study designs showed a slightly higher relative contribution of the variance to MSE compared with the random designs.

Table 2.3 shows geostatistical abundance estimates ($\tilde{\mu}$) and their bias, relative bias, variance, MSE and 95% confidence interval coverage for both sets of designs. Additionally the table also shows design-based statistics for random designs. For subsequent analysis the designs S108 and R108 were regarded just as benchmarks since they are unrealistic for practical implementation. Bias was quite small in all situations and can be considered negligible; the highest relative bias value was 0.014 for S28. All random designs showed a negative bias whereas all study designs showed a positive one. Variances estimated by study designs were lower than the ones for the corresponding random designs. For random designs the variance decays with increasing sample sizes, whereas study designs behaved differently with S45 presenting the lowest variance followed by S47, S44, S28 and S20. MSE showed the same pattern since bias was small, supporting our claim that bias is not relevant for the purpose of this work. The coverages of confidence intervals (δ) were lower than the nominal level of 95% except for S108 and R108, reflecting a possible underestimation of variance. Considering the designs individually it can be seen that underestimation using ACTUAL,



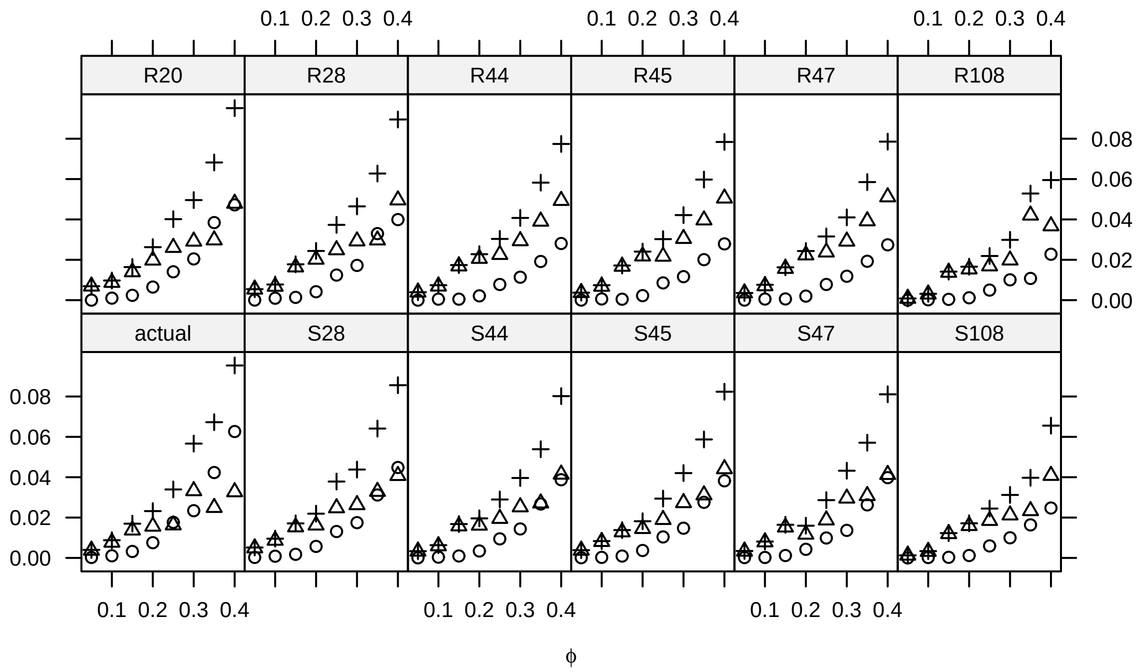


Figure 2.2: Summary statistics for the covariance parameters estimation by sampling design as a function of the true parameter values. bias^2 (○), variance (△) and mean square error (+). Top figure presents τ^2_{REL} results and bottom figure ϕ.

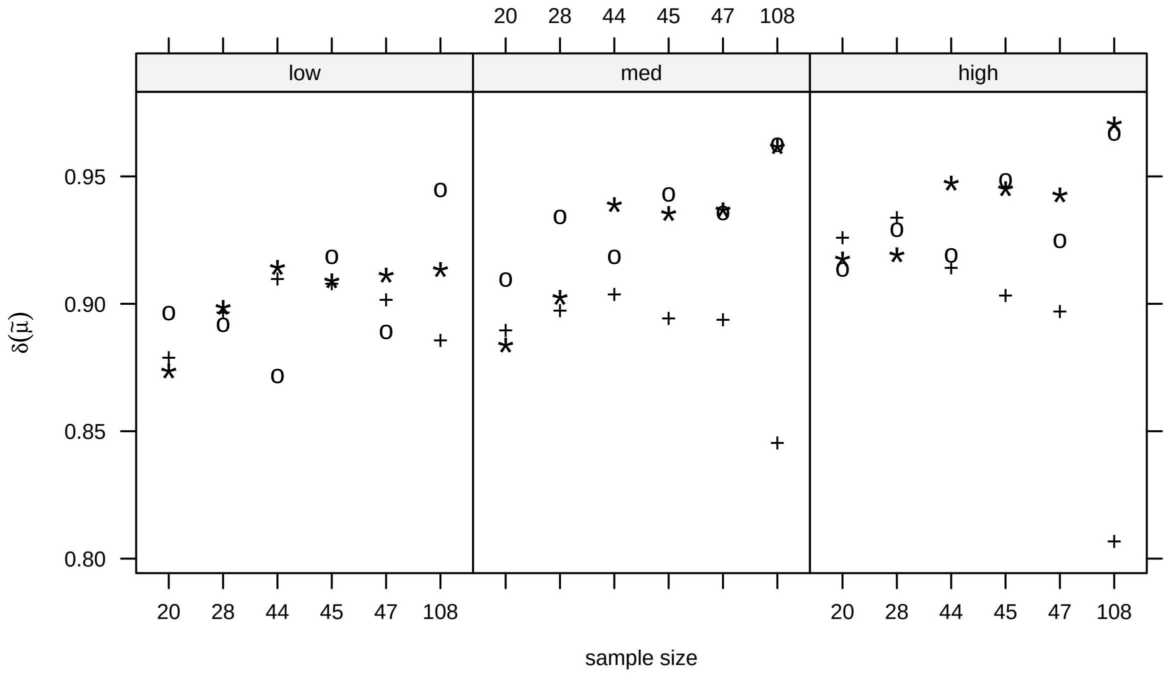


Figure 2.3: Coverage of the confidence intervals (δ) for different ϕ levels (low $= \{0.05, 0.1\}$, med$\{0.15, 0.20, 0.25\}$ high $= \{0.30, 0.35, 0.40\}$) for estimates of abundance by sampling statistics for the random designs ($+$) and by geostatistics for the study (o) and random designs ($*$).

S28 and S45 was actually lower than with the equivalent random designs. To better investigate this, Figure 2.3 presents values of δ splitted by three levels of correlation (low={0.05, 0.1}, med={0.15, 0.20, 0.25}, high={0.3, 0.35, 0.4}). The estimates of δ with geostatistical methods increased with higher correlation levels and larger sample sizes, whereas with sampling statistics there is a decrease in confidence interval coverage with higher levels of correlation and larger sample sizes, reflecting a more pronounced underestimation of variance.

Logarithms of the variance ratios between corresponding “S” and “R” designs are presented in Table 2.3. Without considering S108 for the reasons stated before, the best result was found for S45 (-0.208) and the worst for S28 (-0.108). This must be balanced by the fact that S45 showed a lower variance underestimation than R45, with the opposite happening for S44/R44 and S47/R47, so, in reality, the value of ξ is smaller for S45 than for S44 and S47.

Table 2.3: Summary statistics per sets of sampling designs and sample size. Geostatistical abundance estimates ($\tilde{\mu}$) in kg/hour, bias (bias$(\tilde{\mu})$), relative bias (bias$_r(\tilde{\mu})$), variance (var$(\tilde{\mu})$), mean square error (MSE) and 95% confidence interval coverage ($\delta(\tilde{\mu})$). Mean log variance ratios per sampling design type (ξ) measures the relative log effect of the systematic based designs configuration with relation to the random designs. The last six rows present the same statistics estimated for random designs by sampling statistics.

method	statistic	design	number of locations					
			20	28	44	45	47	108
geostatistics	$\tilde{\mu}$	study	1.658	1.662	1.649	1.657	1.651	1.641
		random	1.631	1.624	1.625	1.624	1.625	1.625
	bias$(\tilde{\mu})$	study	0.025	0.030	0.016	0.026	0.019	0.008
		random	-0.001	-0.008	-0.007	-0.009	-0.008	-0.007
	bias$_r(\tilde{\mu})$	study	0.012	0.014	0.003	0.012	0.005	0.001
		random	-0.004	-0.008	-0.005	-0.006	-0.005	-0.005
	var$(\tilde{\mu})$	study	0.136	0.108	0.092	0.086	0.089	0.081
		random	0.168	0.129	0.113	0.112	0.112	0.097
	MSE$(\tilde{\mu})$	study	0.272	0.196	0.164	0.144	0.154	0.104
		random	0.321	0.230	0.173	0.171	0.171	0.124
	$\delta(\tilde{\mu})$	study	0.908	0.922	0.907	0.939	0.920	0.960
		random	0.895	0.909	0.937	0.934	0.934	0.954
	ξ	stu/rnd	-0.128	-0.107	-0.150	-0.208	-0.179	-0.228
sampling statistics	Y	random	1.615	1.619	1.618	1.616	1.618	1.622
	bias$(\bar{Y})$	random	-0.017	-0.014	-0.014	-0.017	-0.015	-0.010
	bias$_r(\bar{Y})$	random	-0.017	-0.014	-0.013	-0.014	-0.014	-0.006
	var$(\bar{Y})$	random	0.197	0.146	0.091	0.088	0.085	0.037
	MSE$(\tilde{\mu})$	random	0.380	0.296	0.192	0.188	0.192	0.108
	$\delta(\bar{Y})$	random	0.900	0.910	0.908	0.900	0.896	0.840

2.4 Discussion

The choice of sampling designs for BTS is subject to several practical constraints and this has motivated the adoption of *informally* defined designs which accommodated several sources of information like fishing grounds, haul duration, previous knowledge of the spatial distribution of hake and horse mackerel, among others, which could not be incorporated into a design criteria in an objective way. The fact that this can generate designs with different sample sizes is a drawback of this approach. However, implementation of systematic designs on irregular spatial domains is likely to provide different sample sizes, depending on the starting location. On the other hand, costs of hauling are relatively small when compared with the fixed costs associated with a vessel's working day and increasing sample sizes for a BTS should consider sets of locations which can be sampled in one working day. For these reasons the different sample sizes of each design are not just a feature of the adopted approach but also a result of the BTS particularities.

The confounding effects of sample size and spatial configuration of the proposed designs jeopardized the comparison of their ability in estimating abundance. To overcome this limitation a methodology to compare designs with different sample sizes and spatial configurations was required. To deal with this issue we have introduced a mean abundance variance ratio statistic, between the study designs and a simulated random design with the same sample size.

Spatial analysis in fisheries science is mostly concerned with: (i) predicting the distribution of the marine resource, aiming, for instance, to define areas of high abundance of a given age, sex or maturity status, for the purpose of protection; and (ii) to compute abundance indices for stock assessment models (Anon., 2004c). For such situations the model parameters are not the object of study, but just a device to better predict abundance. Müller (2001) points out that the optimality of spatial sampling designs depends on the given objectives, showing that ideal designs to estimate covariance parameters of the stochastic process are not the same that would best predict the value of the stochastic process in a specific location and/or estimate global abundance. We have not compared the various study designs with respect to their estimates of the covariance parameters as our main concern was spatial prediction of abundance.

The choice of the parameter estimation method was a relevant issue in the context of this work. The absence of a formal criteria to identify the “best” design naturally led to the use of geostatistical simulations to compare the proposed designs. To carry out a simulation study it is useful to have an objective method capable of producing single estimates of the model parameters. Within traditional geostatistical methods (Isaaks and Srivastava, 1989; Cressie, 1993; Goovaerts, 1997; Rivoirard *et al.*, 2000) estimation usually involves the subjective intervention of the analyst to define some empirical variogram parameters such as lag interval, lag tolerance and an estimator for the empirical variogram. Likelihood based inference produces estimates of the covariance parameters without a subjective intervention of the data analyst, allowing for automatization of the estimation process, which makes it suitable for simulation studies. For this work we have also tested other model fitting methods such as restricted maximum likelihood (REML) and weighted least squares, but they have produced worse rates of convergence in the simulation study. In particular REML was highly unstable with a high frequency of atypical results for ϕ. An aspect of parameter estimation for geostatistical models which is highlighted when using likelihood based methods concerns parameter identification due to over-parametrized or poorly identifiable models (see e.g. Zhang, 2004). To avoid over-parametrization we used log-transformation, and the process was considered isotropic, avoiding the inclusion of three parameters on the model: the box-cox transformation parameter (Box and Cox, 1964) and the two anisotropy parameters, angle and ratio. The choice of the log transformation was supported by the analysis of historical data and does not impact the comparison of the designs, given that the relative performance of each design will not be affected by the transformation. A point of concern with the log transformation was the existence of zero values which, in the analysis of the historical data, were treated as measurement error and included in the analysis by adding a small amount to all observations. However, it must be noted this is not always recommended and, in particular, if the stock is concentrated on small schools that cause discontinuities on the spatial distribution, these transformations will not produce satisfactory results. Concerning anisotropy, a complete simulation procedure was carried out considering a fixed anisotropy angle on the north-south direction and an anisotropy ratio of 1, 1.5 or 2. As expected, the absolute values obtained were different but the overall relative performance was the same, supporting our decision to report results only for the isotropic model.

A major motivation for performing a simulation study was the possibility to use a wide range of covariance parameters that reflect different spatial behaviours. We used, to define the range of the parameters for simulation, two species with different aggregation patterns, hake and horse mackerel: the first an ubiquitous species not usually found in dense aggregations, the second a schooling species. The similarities found suggest that these results can be extended to other species with spatial behavior compatible with the covariance parameters used here.

From a space-time modeling perspective, one of the most interesting analysis for fisheries science is the fluctuation of the stochastic process over time contrasted with the specific realization in a particular time. Therefore the comparison of individual results with the mean of the realisations (μ_{ps}) was considered more relevant than to the mean of the underlying process (μ) for the computation of bias and variability. The results showed higher bias for study designs when compared with random designs, but in both cases showing low values which were considered negligible for the purposes of this work.

Apart from design S108, which was introduced as a benchmark and not suitable for implementation, the design that performed better was S45, which presented lower variance, confidence interval coverages closer to the nominal level of 95% and lower variance ratio (Table 2.3). One possible reason is the balance between good estimation properties given by the random locations and good predictive properties given by the systematic locations, however the complexity of the BTS objectives makes it impossible to find a full explanation for this results. A possible indicator of the predictive properties is the average distance between the designs and the prediction grid locations, which reflects the extrapolation needed to predict over a grid. We found that S45 had an average of 2.61*nm* whereas for S47 the value is 2.72*nm*, explaining in part the S45 performance. These results are in agreement with Diggle and Lophaven (2006) who showed that *lattice plus closed pairs* designs (similar to S45) performed better than *lattice plus in-fill* designs (similar to S44 and S47) for accurate prediction of the underlying spatial phenomenon. The combination of random and systematic designs like S45 is seldom considered in practice and we are not aware of recommendations of such designs for BTS.

It was interesting to notice that most designs presented a coverage of confidence intervals below the nominal level of 95% indicating that variances were underestimated. It was not fully clear how to use such results to correct variance estimation and further investigation is needed on the subject. Care must be taken when looking at variance ratios since underestimated denominators will produce higher ratios which can mask the results. This was the case of S45 when compared to S47 and S44, thus supporting our conclusions about S45.

Another result of our work was the assessment of abundance estimates from random designs by sampling statistics, the most common procedure for fisheries surveys (Anon., 2004c), under the presence of spatial correlation. In such conditions an increase in sample size may not provide a proportional increase in the quantity of information due to the partial redundancy of information under spatial correlation. Results obtained for coverages of confidence intervals illustrated this (Table 2.3 and Figure 2.3), with smaller coverages for larger sample sizes and higher spatial correlation. In our opinion this is due to an overestimation of the degrees of freedom that lead to an underestimation of prediction standart errors producing the smaller coverages. These findings support claims to consider geostatistical methods to estimate fish abundance so that correlation between locations is explicitly considered in the analysis.

Chapter 3

Geostatistical Tools for Assessing Sampling Designs

This chapter was published as a research paper in Scientia Marina with the following reference:

Ernesto Jardim and Paulo J. Ribeiro Jr. 2008. Geostatistical tools for assessing sampling designs applied to a Portuguese bottom trawl survey field experience. Scientia Marina, 72, 623-630.

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 which implement an hybrid random-systematic and a systematic sampling strategy. We used a common base regular grid covering the survey area and overlapped 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*) abundance and model-based geostatistics to compute measures 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 π (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.

3.1 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., 2005c). 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.

Several authors discussed the advantages of systematic designs over random designs to sample spatial correlated variables like fish abundance (Cochran, 1963; Ripley, 1981; Thompson, 1992; Cressie, 1993; Chilès 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 (Müller, 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 (Müller, 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 suggest designs that mix a set of locations covering the area with additional locations at short distances (Müller, 2001; Diggle and Lophaven, 2006; Zhu and Stein, 2006) to balance between both objectives. Such designs applied to bottom trawl surveys had a limited attention (Selzenmuller *et al.*, 2005) although fish abundance characteristics fit well in the assumptions of these proposals.

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 usage of geostatistics to optimize fisheries survey designs is not new (e.g. Simard *et al.*, 1992; Petitgas, 2001), although there are some limitations due to the high variability and the complex spatial structure of fish distribution. Associated to a small sampling effort and usual operational constraints on the full acomplishement of the sampling plan, caused by bad sea conditions or other fishing activities on the zone.

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., 2002a, 2003b, 2004a, 2005a, 2006a; 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.

3.2 Material

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: 20-100 m, 101-200 m, 201-500 m 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 south-west of Portuguese Continental shelf (Fig. 3.1) using a Norwegian Campbell Trawl 1800/96 (NCT) with a codend of 20 mm, mean vertical opening of 4.8 m and mean horizontal opening between wings of 15.5 m. 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 20 m depth isoline and on the west by the 500 m isoline. The survey area had approximately 4300 km^2 and the maximum distance within the area was approximately 150 km. 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.

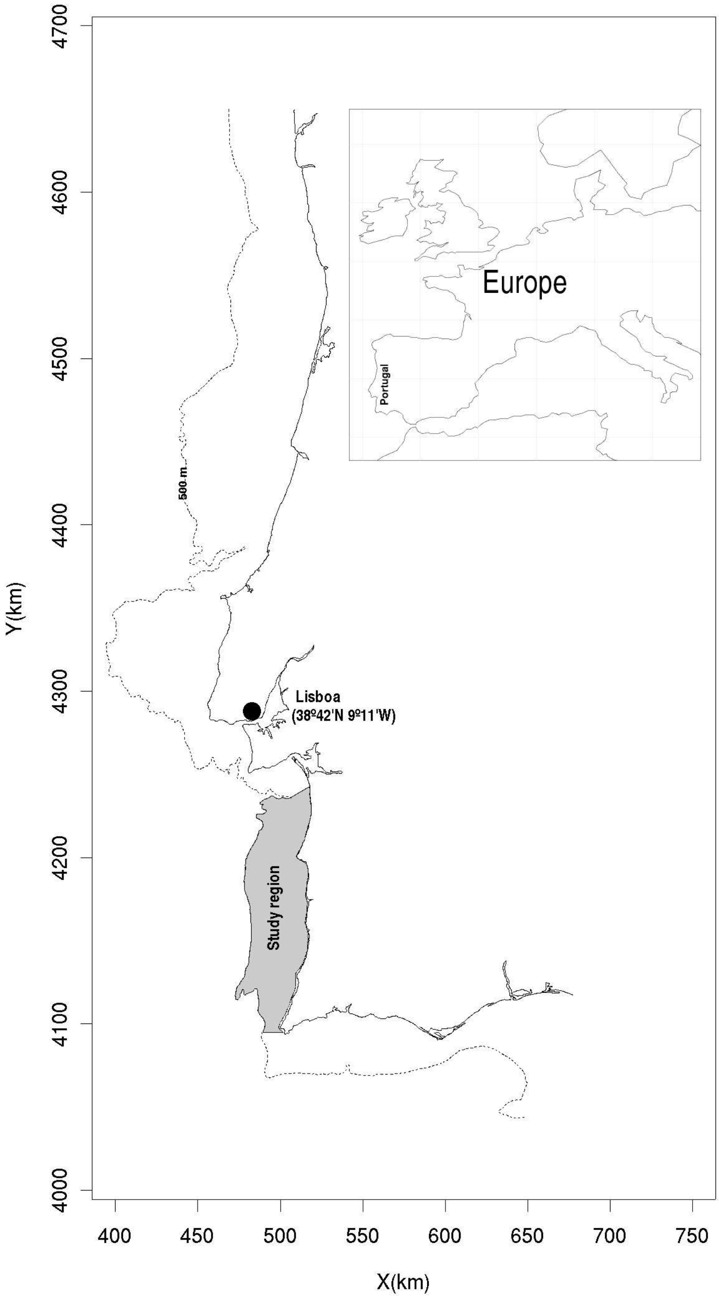


Figure 3.1: Survey area on the southwest of the Portuguese Continental shelf between 20 m and 500 m.

3.3 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.

3.3.1 Sampling designs

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.

The sampling effort available for the candidate design was 36 locations. We built two candidate designs using as basis a regular grid with 19 locations, covering the survey area, and added seventeen additional at shorter distances. Two candidate designs were built, an *hybrid design* that allocated the additional locations randomly and a *systematic design* that allocated them at regular locations. The hybrid design overlaps the regular grid with the existent random design, keeping some continuity with the survey historical records (top-left plot in Fig. 3.2). The systematic design includes regular locations at smaller distances, creating 4 denser sampling areas (bottom-left plot in Fig. 3.2). The vessel time available did not allowed to test other possibilities.

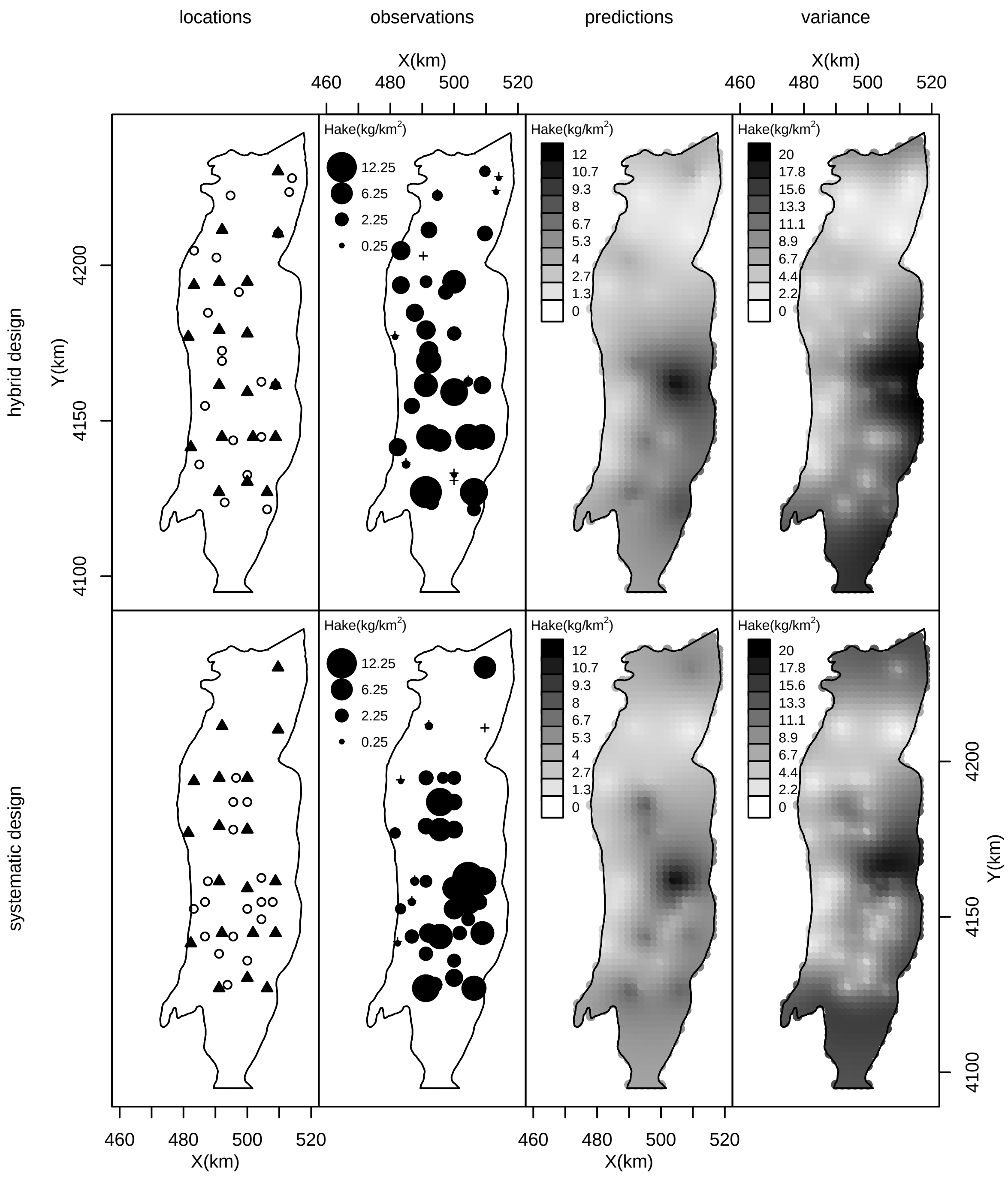


Figure 3.2: Study area on the Portuguese southwest coast. The top panels show information about the hybrid random-systematic design and the bottom panels about the systematic design. The leftmost plots show the sampling designs locations, the black triangles represent the regular grid common to both designs, and the open circles the additional locations. Follows the observations of hake abundance (kg/km^2) and the predictions obtained by kriging, both on the square root scale. The rightmost plots present the kriging variance

3.3.2 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 $Z(x) = S(x) + \varepsilon$, 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, $\varepsilon \sim \text{Gau}(0, \tau^2)$. 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

(Chilès 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 2×2 km 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.

3.3.3 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 mean 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, ξ, and the generalised cross validation index, π, 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 $\pi = n^{-1}\sum_i(S^{-1}\sum_s(t_s(x_i) - y(x_i))^2)$, the average of the mean quadratic error on each location estimated using the full set of conditional simulations.

3.4 Results

The two sampling designs and the observations of hake abundance are presented in the leftmost panels of Figure 3.2 where the base regular design is represented by the black triangles. The abundance of hake observed showed that the distribution of abundance 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 sensitivity 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 3.1). The total variance $\hat{\sigma}_T^2$ 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 $\hat{\sigma}_T^2 = 3.20$, with $\hat{\tau}^2 = 0.61$ and $\hat{\sigma}^2 = 2.59$; and $\hat{\phi} = 10.21$. Looking at τ^2_{REL}, that computes the relationship between the random variability and the spatially structure variability, and $\sigma^2\phi^{-1}$, that give information about the "size" of the spatial process, both designs showed similar relative nuggets. However, 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 $\approx 50\,km$ for hybrid and $\approx 30\,km$ for the systematic design.

Table 3.1: Sampling statistics, estimates of model parameters and performance statistics by design. Sampling statistics are: n, the sample size; $\bar{y}$, the sampling mean; $s^2_{\bar{y}}$, the variance of the sampling mean. Model parameters are: τ^2, the short distance variance or nugget effect; σ^2 the variance of the spatial process; σ^2_T 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^2_{REL}, 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 $\sigma^2_{\bar{\mu}}$, the mean and variance of the global abundance; $\hat{p}_{95}$ and $\hat{\sigma}^2_p$, the mean and variance of the 95th percentile of the global abundance; π, the generalised cross validation index and ξ, the coverage of the prediction confidence interval with nominal level of 0.95.

	parameter	hybrid	systematic
sampling statistics	n	36	36
	$\bar{y}$	4.21	4.41
	$s^2_{\bar{y}}$	0.35	0.35
	cv	14.05	13.41
model parameters	τ^2	0.75	0.61
	σ^2	3.00	2.59
	σ^2_T	3.75	3.20
	ϕ	16.64	10.21
	τ^2_{REL}	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
	$\hat{\sigma}^2_{\mu}$	0.23	0.31
	cv	11.89	13.25
	$\hat{p}_{95}$	11.01	10.78
	$\hat{\sigma}^2_p$	1.55	1.43
	cv	11.31	11.09
	ξ	0.94	0.94
	π	16.32	18.82

The rightmost panels of Figure 3.2 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, $\mathrm{CV}_{\mu} = 13.25\%$. Sampling statistics computed for these designs showed a similar pattern (Table 3.1). 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 would 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.

3.5 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.

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. It would not be surprising if similar results are found for other species, once that the principles behind the construction of the sampling designs tested are quite generic and can be applied to most fish species.

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.

Chapter 4

Estimating Abundance at Age

This chapter was submitted as a research paper to the ICES Journal of Marine Science:

Ernesto Jardim and Paulo J. Ribeiro Jr. 2009 (submitted). Modeling Spatio-temporal Abundance at Age with Compositional Data Analysis and Bayesian Geostatistics. ICES Journal of Marine Science.

Abstract: This work presents a methodology to estimate abundance-at-age by a space-time-age model combining the spatio-temporal distribution of abundance and the age structure of the population. The join distribution of abundance-at-age is modelled through the elements of the product between the distribution of age aggregated abundance and the conditional distribution of age proportions. The spatial behavior of the population is described by a geostatistical sub-model and the age structure of the population by a sub-model for compositional data. Inferences on abundance-at-age are based on the product of Monte Carlo simulations generated from both sub-models. The proposed model takes into account the major sources of variability in abundance, space-time variability and population structure variability. The factorization provides flexibility of using distinct approaches in the analysis of each sub-model. The methodology produces abundance indicators that provide an overview of abundance along distinct viewpoints. The analysis of age compositions provides an insight on how the population structure evolves over time. The geostatistical sub-model returns abundance indicators for both, space and time dimensions. The proposed approach is applied in the analysis catches of Hake (*Merluccius merluccius*) by the Portuguese Bottom Trawl Survey.

4.1 Introduction

Estimates of abundance are important indicators of stock size and space-time distribution of marine populations. Such indicators provide valuable fisheries-independent information for stock assessment, and, more generally, for fisheries advice and ecological management. Scientific literature on abundance estimation adopts either design-based techniques (Cochran, 1963; Thompson, 1992; Smith and Gavaris, 1993) or model-based approaches such as generalized linear models (Chen *et al.*, 2004; Sousa *et al.*, 2007), generalized additive models (Piet, 2002), geostatistics (Rivoirard *et al.*, 2000; Roa-Ureta and Niklitschek, 2007; Jardim and Ribeiro Jr., 2008) or hierarchical models (Mendes *et al.*, 2007). Abundance can be modelled by different statistical distributions as the log-normal (Smith, 1990; Dingsor, 2005), 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 *et al.*, 2007).

Most literature dealing with spatial analysis adopts univariate methods either by modeling each age independently, age aggregated abundance or abundance of specific age groups, like recruits. Multivariate space-time models require long time series and large sample sizes rarely available for fish abundance. However, there is scope for further development of space-time-age joint modeling strategies in marine and fisheries sciences.

Specific difficulties are added in the case of demersal species sampled with bottom trawl surveys (BTS): (i) BTS are expensive operations and vessel time availability tend to be limited, which constrains sampling effort, (ii) sampling programmes are often incomplete because of bad sea conditions or fishing activity on the sampling locations, (iii) replicates are not feasible since trawling is a destructive sampling mechanism, and (iv) observations tend to be asymmetric and over-dispersed, with large number of null catches (Martin *et al.*, 2005; Maunder and Punt, 2004) possibly combined with very large catches (Smith, 1997; Kappenman, 1999).

The aim of this work is to propose a model-based methodology to estimate abundance-at-age time series with a model that explicitly considers the spatial distribution and the age structure of the target population. The approach suggested here builds the space-time-age model from two sub-models, one dealing with space-time patterns of abundance and another with the age structure of the population. The development of this model is motivated by the need of estimating abundance indices for stock assessment. Modern advice about fisheries management requires uncertainty and risk about the proposed management actions to be reported, and under such conditions it is paramount to compute the variability of input parameters like abundance indices properly. An example application is presented for hake (*Merluccius merluccius*) abundance off the Portuguese continental coast, used for tuning the stock assessment of the Southern stock of European hake (Anon., 2008b). in which abundance is expressed in numbers of individuals, whereas the methodology remains valid for abundance expressed in weight.

4.2 Material and Methods

Model specification uses the notation "$[\cdot]$", to denote *the distribution of* the variable inside the square brackets. The random variables are distinguished from their observations by using upper and lower cases, respectively. Consider the following subscripts: $i = 1,\dots,I$ for years, $j = 1,\dots,J$ for ages, $h = 1,\dots,H$ for hauls and $r = 1,\dots,R$ for simulations. The following observable random variables are defined: C_j for abundance in numbers of individuals per age, hereafter abundance-at-age, Y for age aggregated abundance ($Y = \sum_j C_j$), Z for the transformed age aggregated abundance, P_j for the proportions-at-age or compositions ($P_j = C_j/Y$) and D_j for the transformed proportions at age.

Abundance-at-age is given by the product of age aggregated abundance and age proportions reflecting space-time patterns and the age structure of the population, respectively. The joint distribution of abundance-at-age is then factorized by the distribution of age aggregated abundance and the conditional distribution of proportions-at-age $[C_1,\dots,C_J] = [P_1,\dots,P_J|Y][Y]$.

A model-based geostatistical approach (Diggle *et al.*, 1998; Diggle and Ribeiro Jr., 2007) is adopted for the analysis of age aggregated abundance. The distinctive characteristic of model-based geostatistics is the full parametric specification of the spatial model, which allows for maximum likelihood and Bayesian inference.

Total abundance is described by a Box-Cox transformed Gaussian model with transformation parameter λ (Christensen *et al.*, 2001) such that $g_{\lambda}(Y) = Z$. The model for Z at locations x, where x denotes the geographic coordinates within a study region $A \subset \mathbb{R}^2$, can be written as a linear model $Z(x) = S(x) + \varepsilon$. S is a stationary Gaussian stochastic process, with $E[S(x)] = \beta$, $Var[S(x)] = \sigma^2$ and an isotropic exponential correlation function $\rho(u) = Corr[S(x), S(x')] = \exp\{-u/\phi\}$, where $u = \|x - x'\|$ is the Euclidean distance between locations x and x'. The terms ε are assumed to be normal, mutually independent and identically distributed, $\varepsilon \sim \mathrm{N}(0, \tau^2)$. Following usual geostatistical terminology (Isaaks and Srivastava, 1989), $\sigma_T^2 = \tau^2 + \sigma^2$ is the total sill, σ^2 the partial sill, τ^2 the nugget effect and 3ϕ corresponds, for the assumed exponential correlation function, to the practical range, defined as the distance u for which $\rho(u) \simeq 0.05$. Geometric anisotropy (Isaaks and Srivastava, 1989; Cressie, 1993) is considered an extension of this model adding extra parameters $\psi = \{\psi_A, \psi_R\}$, where ψ_A is the anisotropic angle and ψ_R is the anisotropic ratio. Anisotropy considers directional effects with correlation decaying with distance depending on the orientation between pairs of locations, which may be relevant to model abundance.

To estimate the model parameters Bayesian methods were adopted to account for parameters' uncertainty (Diggle *et al.*, 1998; Diggle and Ribeiro Jr., 2007). For the mean and variance parameters the prior is set to $[\beta, \sigma^2|\phi, \tau^2] \sim 1/\sigma^2$. This is a vague prior frequently adopted for mean and variance parameters in Bayesian analysis of linear models (O'Hagan, 1994). Regarding $[\phi, \tau^2]$, there is no standard or computationally convenient prior and, for numerical tractability, we use a discrete prior as suggested by Gelman *et al.* (2004) and adopted in Diggle *et al.* (2003) for geostatistical models. In practice, τ^2 is re-parametrized as $\tau_{REL}^2 = \tau^2/\sigma^2$, and *a priori* probabilities for ϕ and τ_{REL}^2 are set proportionally to a chosen distribution on a discrete support.

Under the above model specification β reflects mean abundance over the study area in the Gaussian scale. The Bayesian approach produces samples from the posterior distributions of β_i, τ_i^2 and σ_i^2 which are used to compute replicates of the empirical distribution of mean abundance in the original scale, y_{ir}. Spatial distribution of abundance is described by predicting at a grid of unsampled locations, x_0, defined over the study area. Conditional simulations are obtained from the predictive distributions $[Z(x_0)|Y, \phi, \tau^2, \sigma^2]$, back transformed to the original scale $y(x_0)$.

The age structure of the population, given by $[P|Y]$, is modeled using compositional data analysis (Aitchison, 1982, 2003), a statistical framework that models multinomial probabilities, where compositions are given by numerical proportions of parts of a whole. The major advantage regarding modelling the population age structure is the usage of the full covariance structure of proportions-at-age for simulation.

Considering the compositions to represent the population age structure, the vector of proportions-at-age in year i and haul h represents a composition of ages with J components $p_{ijh} = c_{ijh}/y_{ih}$. This operation called the "closure" by Aitchison (1982, 2003), is central to compositional data analysis and operates as the conditioning mechanism in the proposed model. Aitchison (1982, 2003) showed that the additive log-ratio, $D = \log(P_j/P_a)$ with $j \neq a$, where "a" is the component chosen for denominator, transforms compositions into a $J-1$ vector of multivariate normal distributed variables, $D \sim N_{J-1}(\mu, \Sigma)$. Note that the distribution of D is conditioned on Y due to the closure operation and so the estimators of μ have to take into account the value of Y to assure unbiasedness. Considering the weights $w_h = y_h/\sum_h y_h$, the moments estimator of μ and the associated covariance matrix are given by:

$$
\begin{aligned}
\hat{\mu} &= \textstyle\sum_h^H w_h log(p_{hj\neq a}/p_{hj=a}) \\
\hat{\Sigma}_\mu &= H^{-1} \textstyle\sum_{h=1}^H w_h log(p_{hj\neq a}/p_{hj=a}) log(p_{hj\neq a}/p_{hj=a}) \\
&\quad - \textstyle\sum_{h=1}^H w_h log(p_{hj\neq a}/p_{hj=a}) \sum_{h=1}^H w_h log(p_{hj\neq a}/p_{hj=a})
\end{aligned}
$$

For each year i, a set of replicates are generated by randomly sampling from the distribution of $\hat{\mu}$. These values are back-transformed and subject to the closure operation, providing replicates of proportions-at-age, p_{ijr}.

Simulations generated from both sub-models are used to compute the empirical distribution of C_{ij} with $c_{ijr} = p_{ijr} y_{ir}$ for inferences on abundance-at-age. The flowchart in Figure 4.1 summarizes the methodology.

This work was fully performed with open source software. Data analysis, figures and implementation of the methodology were carried out in R (R Development Core Team, 2008) and code for

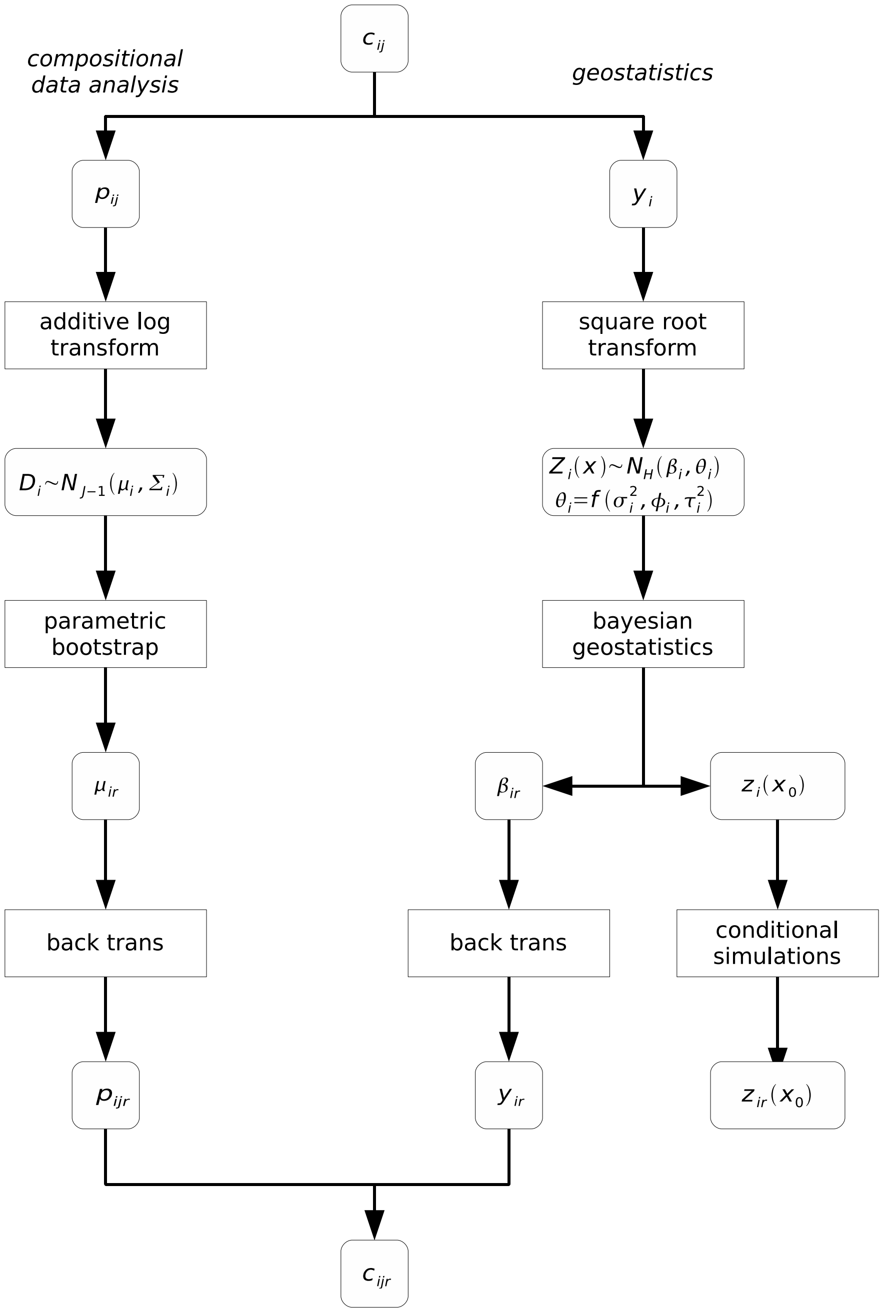


Figure 4.1: Graphical representation of the algorithm showing a clear separation of yearly abundance at age, c_{ij}, in two sub-models. On the the left the age structure, p_{ij}, is analyzed with compositional data analysis, and on the write the spatial distribution y_i is analyzed with model-based geostatistics. The simulations of both variables are combined to compute the stochastic distribution of the abundance-at-age per year. The round boxes represent data and the sharp boxes represent methods. d is the transformed compositional data; N_k=multivariate normal distribution of order k; μ and Σ are parameters of d; p_{ijr} are the replicates of the average composition; $z(x)$ is a stationary spatial process; β and θ are parameters of the spatial models with $\sigma^2 =$ sill, $\phi =$ correlation range and $\tau^2 =$ nugget; y_{ir} are the replicates of the mean abundance over the area; x_0 is a grid of unsampled locations; i indexes years, j indexes ages and r indexes simulations.

analysis makes usage of the add-on packages geoR (Ribeiro Jr. and Diggle, 2001), compositions (van den Boogaart *et al.*, 2006), MASS (Venables and Ripley, 2002) and VGAM (Yee, 2007).

4.3 Application to hake abundance indices collected by the Portuguese bottom trawl survey

Hake is a widely distributed specie in the northeast Atlantic from Norway to Iceland (62^{o}N) to Mauritania (21^{o}N), expanding through the Mediterranean (Alheit and Pitcher, 1995). It is mainly found between 50m and 500m over mud, sand and rocky substrates (Casey and Pereiro, 1995).

Hake's eggs are pelagic and are more frequent near the continental shelf edge close to the spawning grounds at depths between 100m and 250m (Casey and Pereiro, 1995). Larvae are transported to the continental shelf by wind-induced currents (Alvarez *et al.*, 2001), after which individuals start migrating in the water column to depths between 50m and 100m for feeding, mainly on small crustaceans (Casey and Pereiro, 1995; Mahe *et al.*, 2007). When reaching the bottom grounds near the coast, juveniles stay at those depths until the first maturity (Casey and Pereiro, 1995). During this period the diet is constituted of small crustacean and small pelagic fish which are caught during night vertical migrations (Papaconstantinou and Stergiou, 1995). As individuals grow larger they migrate to deeper grounds near the edge of the continental platform. Their diet becomes less generalized to be mostly composed of small pelagic fish and hake juveniles (Mahe *et al.*, 2007). Cannibalism may play an important role on adult hake diet depending on the abundance of juveniles and the spatial overlap between different age groups. Cardador (1988) reported $\approx 7\%$ cannibalism off the Portuguese Continental coast, while Casey and Pereiro (1995) and Mahe *et al.* (2007) reported $\approx 20\%$ on the Bay of Biscay. Velasco and Olaso (1998) reports $< 3\%$ cannibalism off the Cantabrian coast. The growth of European hake is not clearly known but there is information supporting a faster growth rate than considered currently (de Pontual *et al.*, 2006; Piñeiro *et al.*, 2007, 2009).

Hake's spawning season off the Iberian coast starts in December and extends through May (Casey and Pereiro, 1995; Piñeiro and Sainza, 2003). Recruitment occurs mainly during the Autumn in three main areas, the southeast of the Gulf of Cadiz, southwest of the Portuguese coast and northwest of the Spanish coast(Anon., 2006a, 2007c).

The Portuguese Autumn BTS has been carried out in Portuguese continental waters since 1979 on board the RV "Noruega" and RV "Capricórnio". One of the main objectives of this survey is to estimate abundance indices for hake to be used in stock assessment (Anon., 2008b). 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 (Anon., 2002a). The survey has been conducted for a period of one month between September and December. Hauling is carried out during daylight.

A stratified sampling design was used from 1989 until 2004. The stratification was defined by 12 sectors along the Portuguese continental coast subdivided into 4 depth ranges: 20-100m, 101-200m, 201-500m and 501-750m, with a total of 48 strata. Constraints in vessel time limited the target sample size to 97 locations, evenly distributed to obtain two locations within each stratum. The coordinates of the sampling locations were randomly selected within each stratum area, constrained by the historical records of clear tow positions and information on the sea floor. In 2005 a new sampling design composed by a regular grid with a set of additional random locations was introduced (Jardim and Ribeiro Jr., 2007, 2008). The tow duration was 60 minutes until 2001 and reduced to 30 minutes for the subsequent years, based on results of an experiment showing no significant differences in the mean abundance and length distribution between the two tow durations (Cardador personal communication, 2007).

The application data set refers to haul-by-haul information of hake catch-at-age observations in number of individuals per hour. It included haul duration (minutes), haul time, haul date and geographic coordinates (UTM, Zone 29) for all valid hauls executed during the Autumn survey between 1989 and 2006. Ages were determined using age-length-keys obtained from otolith readings of a sub-sample of the survey catch. Observations collected with RV "Capricórnio" (1996, 1999, 2003 and 2004) were calibrated to RV "Noruega" using factors by age estimated in a calibration exercise in 2006 (Azevedo personal communication, 2007). Figure 4.2 shows the map of

Table 4.1: Age aggregated abundance estimates in number of individuals per hour by design-based statistics and model-based geostatistics. The design statistics were the stratified mean, $\hat{y}$, its standard deviation, $\sigma_{\hat{y}}$, and coefficient of variation, $CV_{\hat{y}}$. The geostatistics summaries were the median, $\tilde{Y}$, the median absolute deviation, $MAD_{\tilde{Y}}$, the relative median absolute deviation, $RMAD_{\tilde{Y}}$, the 0.025 percentile, $Q_L(\tilde{Y})$, the 0.975 percentile, $Q_U(\tilde{Y})$, and the inter-quartile range, $IQR_{\tilde{Y}}$.

		Design-based			Model-based geostatistics					
Year	hauls	$\hat{y}$	$\sigma_{\hat{y}}$	$CV_{\hat{y}}$	$\tilde{Y}$	$MAD_{\tilde{Y}}$	$RMAD_{\tilde{Y}}$	$Q_L(\tilde{Y})$	$Q_U(\tilde{Y})$	$IQR_{\tilde{Y}}$
1989	130	59.2	1.7	0.03	54.5	6.4	0.12	41.4	77.4	13.3
1990	108	157.0	9.7	0.06	123.3	13.4	0.11	92.2	162.3	26.9
1991	80	194.1	12.2	0.06	177.1	24.7	0.14	122.8	263.0	49.3
1992	44	65.3	3.2	0.05	70.1	10.8	0.15	49.5	106.3	21.9
1993	58	54.1	4.5	0.08	48.0	7.7	0.16	32.6	73.6	15.9
1994	76	95.9	4.7	0.05	100.2	9.5	0.10	78.6	127.7	19.2
1995	80	85.2	4.1	0.05	81.2	11.3	0.14	57.4	120.2	23.3
1996	63	44.6	2.3	0.05	47.8	7.2	0.15	32.8	74.3	14.6
1997	51	207.2	21.5	0.10	182.2	34.1	0.19	119.9	318.7	69.1
1998	64	139.8	7.8	0.06	131.4	18.5	0.14	94.5	192.5	37.5
1999	71	71.2	2.5	0.04	89.9	14.7	0.16	57.8	137.0	29.6
2000	65	102.2	5.8	0.06	107.6	14.7	0.14	77.3	159.1	29.8
2001	58	164.0	15.3	0.09	180.3	20.7	0.11	138.2	237.2	41.5
2002	66	117.5	7.9	0.07	103.6	15.9	0.15	67.3	157.4	32.4
2003	72	55.3	2.0	0.04	60.6	8.9	0.15	42.2	91.5	17.9
2004	79	124.4	6.3	0.05	129.8	20.4	0.16	85.8	198.7	41.4
2005	87	214.0	9.4	0.04	235.1	35.6	0.15	161.3	366.6	74.1
2006	88	125.9	4.4	0.03	136.0	17.3	0.13	100.9	201.7	36.8

hake catches in total number of individuals per hour observed during the study period. The number of hauls, the design-based estimates of mean abundance, its standard deviation and coefficient of variation per year are presented in the first five columns of Table 4.1. Design-based estimates of abundance at age and its coefficient of variation per year are showed on the top panel of Table 4.2. In those years that the sampling plan was not fully accomplished due to operational constraints, variance for strata with a single observation was estimated using a linear relation between variance and mean, computed for the strata with two observations.

In accordance with Jardim and Ribeiro Jr. (2008) and the visual inspection of histograms and density estimation plots of abundance data per year, a Box-Cox transformation parameter $\lambda = 0.5$ corresponding to a square root transformation was used. The back transformed values of β_{ir} are

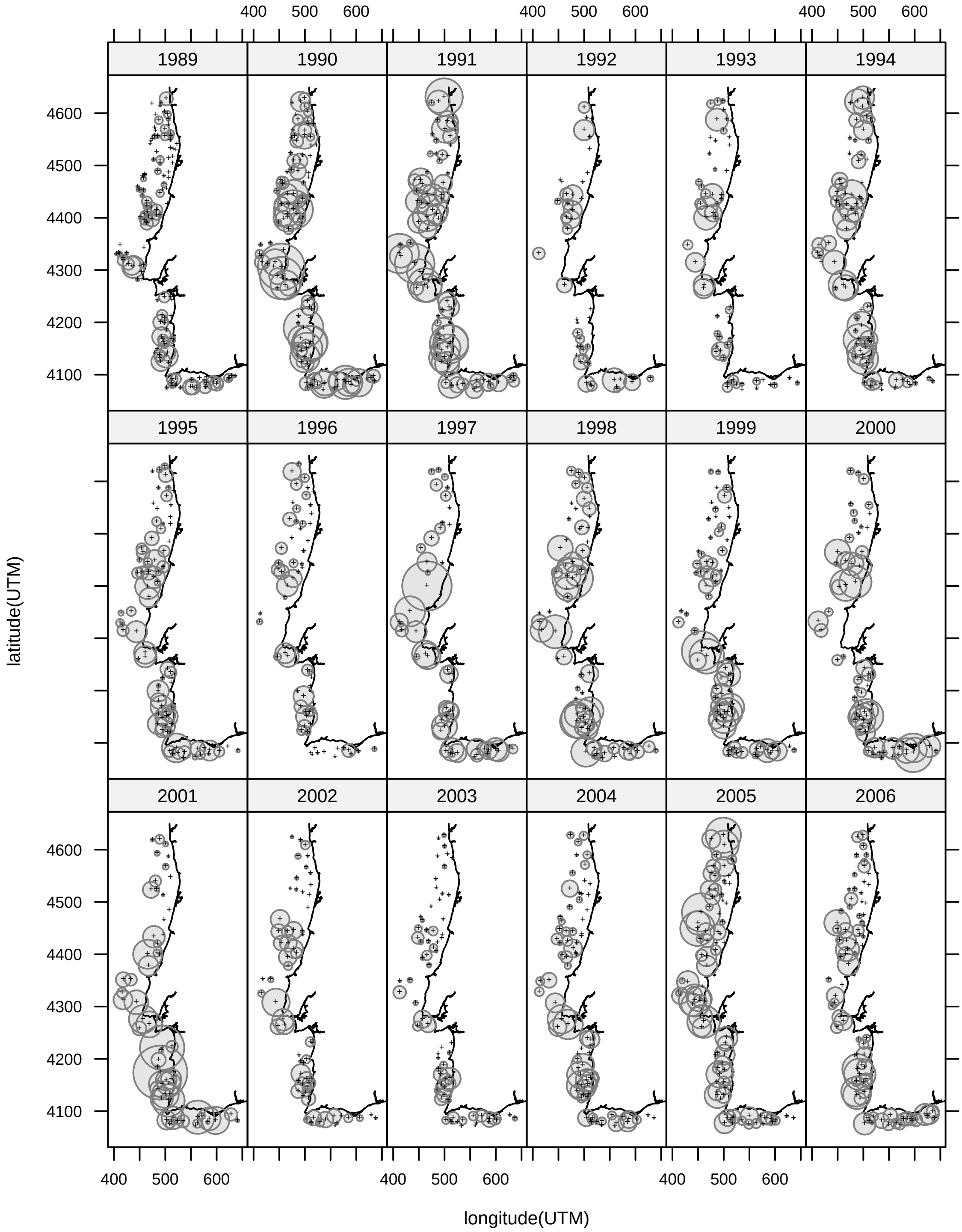


Figure 4.2: Yearly maps with locations of hauls (+) and observed catches of Hake (*Merluccius merluccius*) by the Portuguese bottom trawl survey. The gray circles are proportional to the logarithm of the numbers of individuals caught per hour. The full line represents the Portuguese continental coast.

Table 4.2: Abundance at age estimates in number of individuals per hour by design-based statistics on the top panel and model-based statistics computed with the combined model proposed by this study on the bottom panel. The design statistics are the stratified mean and its coefficient of variation between brackets. The estimates provided by this study are the median and the relative median absolute deviation between brackets.

Estimator	Year	Age					
		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)
Model-based	1989	5.3 (0.18)	22.2 (0.12)	19.7 (0.13)	6.6 (0.15)	0.7 (0.18)	0.1 (0.16)
	1990	45.0 (0.16)	56.6 (0.12)	15.1 (0.18)	4.7 (0.19)	1.1 (0.19)	0.1 (0.20)
	1991	34.5 (0.21)	89.8 (0.15)	37.2 (0.21)	11.0 (0.22)	1.5 (0.24)	0.4 (0.22)
	1992	2.0 (0.38)	17.0 (0.25)	30.0 (0.17)	17.6 (0.19)	2.6 (0.24)	0.2 (0.31)
	1993	14.5 (0.21)	18.9 (0.18)	10.4 (0.22)	2.6 (0.26)	0.7 (0.27)	0.1 (0.24)
	1994	12.2 (0.17)	65.0 (0.10)	14.2 (0.17)	6.4 (0.17)	1.3 (0.17)	0.1 (0.18)
	1995	0.4 (0.20)	30.9 (0.16)	40.0 (0.15)	8.0 (0.17)	1.8 (0.18)	0.2 (0.17)
	1996	5.7 (0.21)	20.9 (0.18)	11.3 (0.18)	7.4 (0.19)	1.7 (0.21)	0.9 (0.21)
	1997	8.2 (0.29)	64.8 (0.21)	96.3 (0.20)	9.9 (0.22)	2.3 (0.22)	1.2 (0.26)
	1998	56.4 (0.21)	46.2 (0.17)	16.2 (0.23)	8.7 (0.24)	2.1 (0.23)	0.7 (0.24)
	1999	6.3 (0.23)	32.5 (0.19)	38.5 (0.18)	9.9 (0.19)	1.7 (0.22)	0.3 (0.20)
	2000	11.8 (0.24)	44.0 (0.16)	36.5 (0.17)	12.2 (0.20)	1.8 (0.21)	0.9 (0.21)
	2001	49.1 (0.16)	101.6 (0.13)	17.3 (0.22)	8.3 (0.25)	0.9 (0.23)	0.5 (0.21)
	2002	26.6 (0.20)	35.8 (0.18)	31.3 (0.18)	7.3 (0.19)	1.5 (0.21)	0.2 (0.21)
	2003	4.2 (0.19)	33.6 (0.15)	16.0 (0.16)	5.2 (0.19)	1.0 (0.20)	0.2 (0.18)
	2004	40.3 (0.18)	60.2 (0.17)	22.4 (0.18)	4.8 (0.21)	0.9 (0.20)	0.4 (0.20)
	2005	112.6 (0.17)	90.3 (0.17)	23.4 (0.21)	5.7 (0.20)	1.1 (0.20)	0.4 (0.20)
	2006	29.7 (0.22)	53.0 (0.14)	37.7 (0.16)	12.4 (0.17)	2.5 (0.19)	0.5 (0.18)

given by $y_{ir} = (1-0.5\beta_{ir})^2 + 0.25(\tau_{ir}^2 + \sigma_{ir}^2)$.

Profiled likelihoods (Diggle and Ribeiro Jr., 2007) were used to inspect for anisotropic effects but the curves are too flat to identify anisotropy parameters and an isotropic spatial process was assumed.

Priors for the correlation parameters are set based on hake's biology, a non schooling species widely distributed at all depths, and the shape of the Portuguese coast, rectangular with depth increasing parallel to the coast and a strong steepness of the continental shelf. Prior choice is crucial for the Bayesian analysis and a particularly delicate issue in geostatistical models with inferences being sensitive to usual choices. Berger *et al.* (2001) explores the topic of objective prior specification for geostatistical models in greater detail. The prior for ϕ is based on an exponentially decaying distribution with expected value 20km, reflecting higher beliefs on short correlations. The prior for τ_{REL}^2 was set based on the zero inflated Poisson distribution. Our choice is based on the prior belief that the random noise τ^2 should not be higher than the spatial structure variability σ^2 and τ_{REL}^2 is *a priori* expected to be small. More accurate information on τ^2 would require duplicated observations or pairs of observations at very short distances, which is operationally not feasible for BTS. The same priors were adopted for all years. Table 4.3 summarises the adopted prior distributions.

Prior and posterior distributions of ϕ and τ_{REL}^2 are shown in Figure 4.3. The posterior distributions of ϕ showed modes approximately between 10 and 20 km, reflecting a practical correlation range between 30 and 60 km, compatible with the length of the Portuguese coast. For τ_{REL}^2 the posterior distributions show a peak slightly below 0.5, reflecting a process with $\approx$ 30% unstructured variability. However, in 1990 and between 1992 and 1997 the posteriors are very similar to the priors, indicating little information on the data to identify this parameter for those years.

Sensitivity analysis performed using reciprocal, uniform and exponential distributions for ϕ and τ_{REL}^2, with distinct parameter choices, showed posteriors influenced by the choice of priors, in particular on the tail. An heavy tail on correlation parameters would imply the existence of information on large distances, which is not available on the data due to the size of the study area. The

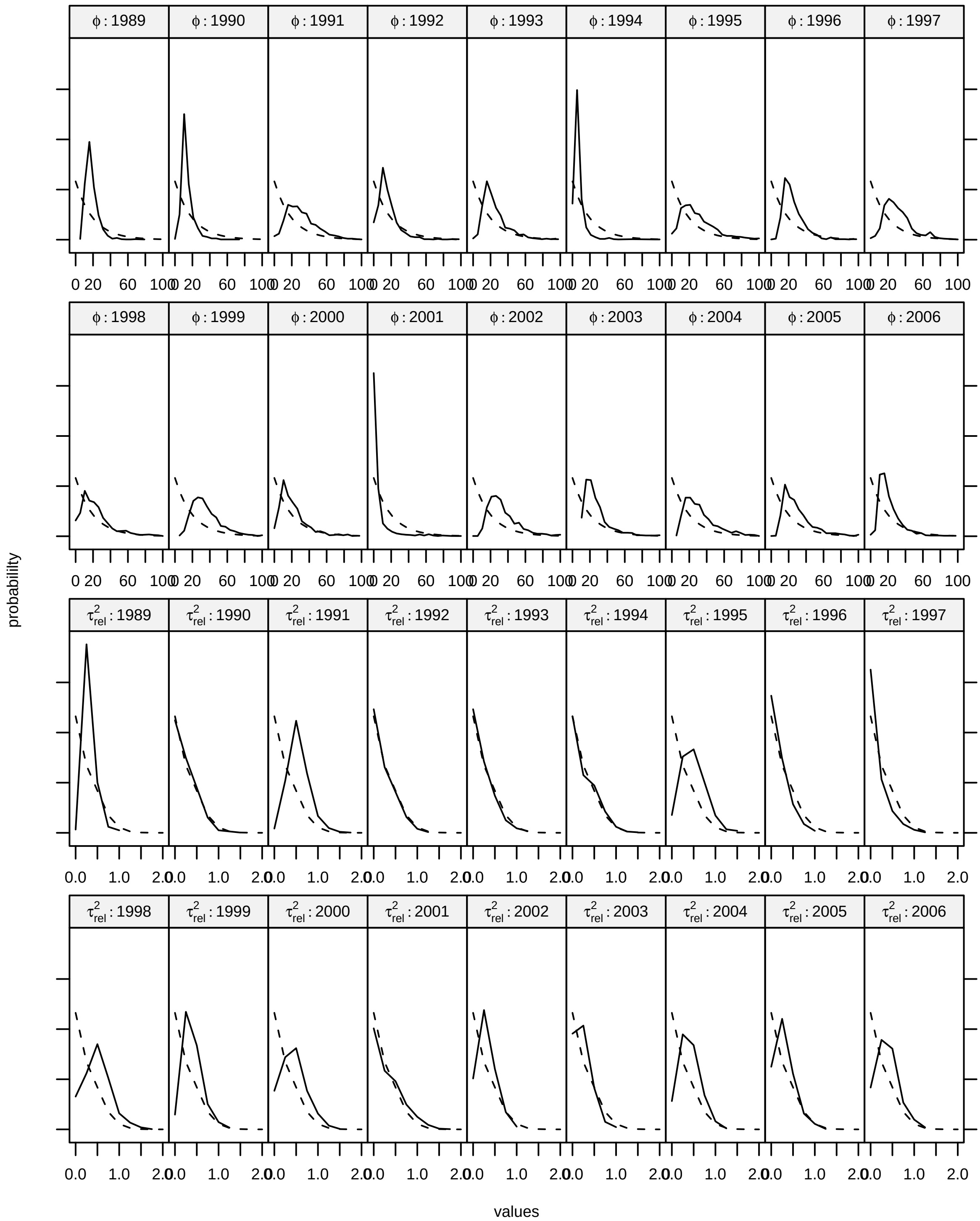


Figure 4.3: Priors and posteriors for the correlation range ϕ and the relative nugget τ^2_{REL} used for the geostatistical analysis. The dashed line represents the priors for each parameter, kept constant for all years. The full line represents the posteriors obtained per year.

Table 4.3: Prior distributions for the Bayesian analysis.

parameter	a priori distribution	
	probabilities proportional to	description
ϕ	exponential	$P[\phi] \propto \frac{1}{20}\exp(-\frac{1}{20}\phi)$
τ^2_{REL}	zero inflated Poisson	$\left\{\begin{array}{ll} \tau^2_{REL} & P[\tau^2_{REL}] \\ 0.00 & 0.46458 \\ 0.25 & 0.26860 \\ 0.50 & 0.16787 \\ 0.75 & 0.06995 \\ 1.00 & 0.02186 \\ 1.25 & 0.00546 \\ 1.50 & 0.00114 \\ 1.75 & 0.00020 \\ 2.00 & 0.00003 \end{array}\right\}$
σ^2	reciprocal	$P[\sigma^2 \vert \phi, \tau^2_{REL}] \propto 1/\sigma^2$
β	flat	$P[\beta \vert \phi, \tau^2_{REL}, \sigma^2] \propto 1$

information on the sample is not enough to attenuate the heavy tail of the priors, an expected result for geostatistical models which reinforces the importance of prior choice based on knowledge of the study region, the population biology and experience with similar data.

Figure 4.4 presents the spatial distribution of hake over the study area standardized by the maximum in each year, so that year effects were removed highlighting spatial patterns. 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.

Modelling proportions-at-age requires a choice of an age class for the additive log-ratio transformation denominator and a procedure to deal with null observations. The chosen second age class is widely abundant over the sampling locations and therefore reducing the number of fractions with zero denominator. Null observations were replaced following the multiplicative replacement strategy proposed by Martín-Fernández *et al.* (2003) with the minimum observed proportion on the relevant year as constant.

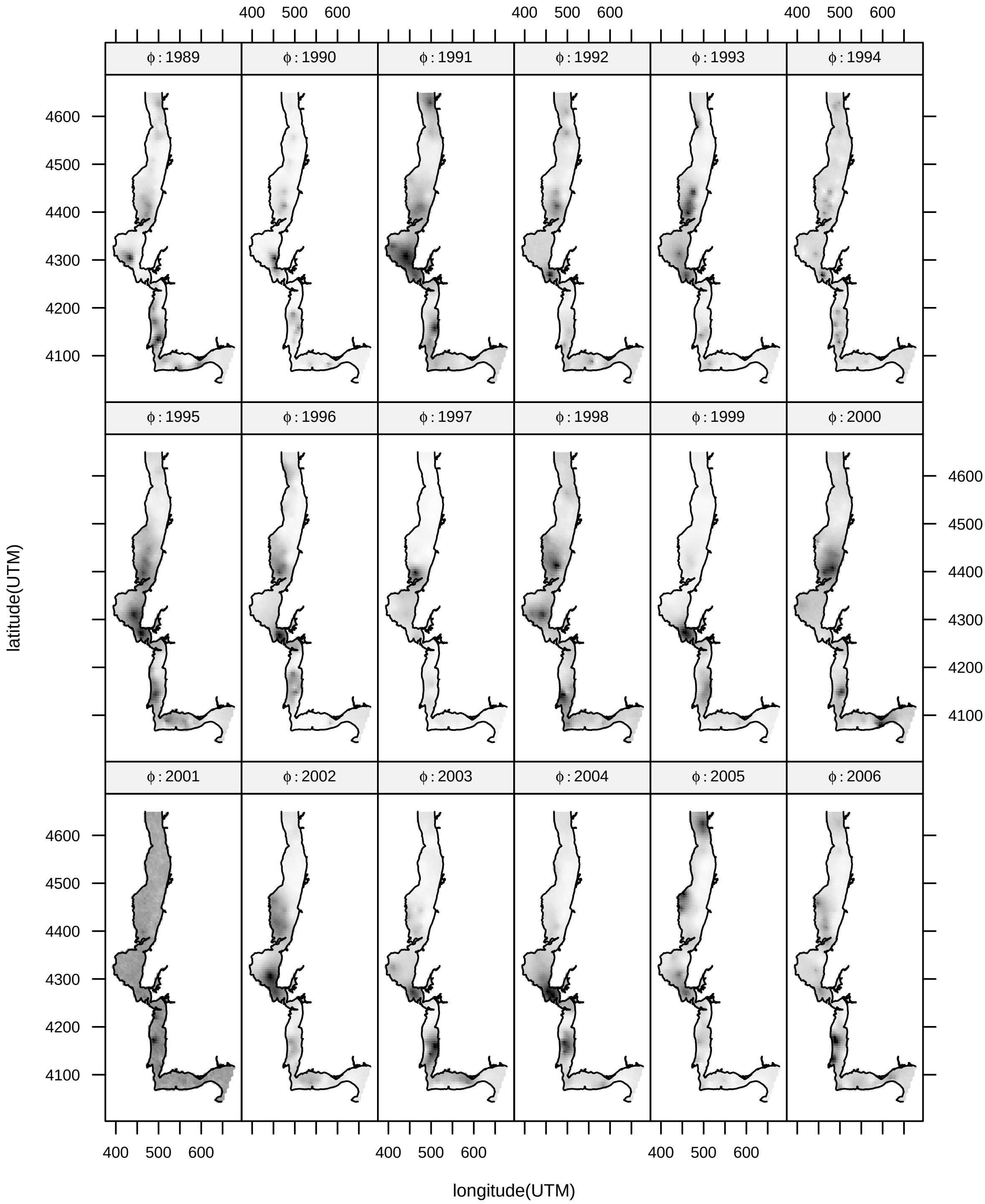


Figure 4.4: Spatial distribution of age aggregated abundance per year. The gray degrees are proportional to the number of individuals caught by unit effort, rescaled to the maximum estimate within each year. The black color represent 1 and the white color represents 0.

Figure 4.5 shows the age compositions per year and the 95% confidence intervals estimated by the 0.025 and 0.975 percentiles. The estimates show a dome shape with maxima at ages 1 and 2. Changes in age proportions can reflect shifts in abundance at age for different years, although ageing classification errors can also affect this result. The integration of this source of error is outside the scope of the paper, however, the model can accommodate developments in compositional data analysis to do it. Simulating and obtaining p_{ijr} from the resulting submodel, allows for the integration into the abundance-at-age model.

Table 4.1 and Figure 4.6 present age aggregated abundance results, contrasting several metrics computed using design statistics and geostatistics. The relative median absolute deviation, RMAD, is used as a measure of precision to be compared with the coefficient of variation. Both abundance estimates are similar showing the same cyclic pattern with high values in 1991, 1997, 2001 and 2005; and low values in 1993, 1996, 1999, 2003 and 2006. The credibility intervals obtained from back-transformed values are asymmetric and include design based estimates within their range. Geostatistical results present a relative median absolute deviation between 10% and 19%, in agreement with other studies (*e.g.* see Smith and Gavaris, 1993; Dingsor, 2005; Sousa *et al.*, 2007; Roa-Ureta and Niklitschek, 2007), whereas design-based estimates show coefficients of variation between 3% and 10%.

Abundance-at-age estimated by the median per year are presented in the bottom panel of Table 4.2 with the relative median absolute deviation between brackets. Figure 4.7 shows yearly median estimates by age and 95% confidence intervals computed by the 0.025 and 0.975 percentiles. The estimates of both procedures are similar showing similar trends on time and the model-based confidence intervals include most design-based estimates. As with age aggregated abundance the precision of the combined model is lower, between 10% and 38%, than the design-based ones, between 5% and 32%.

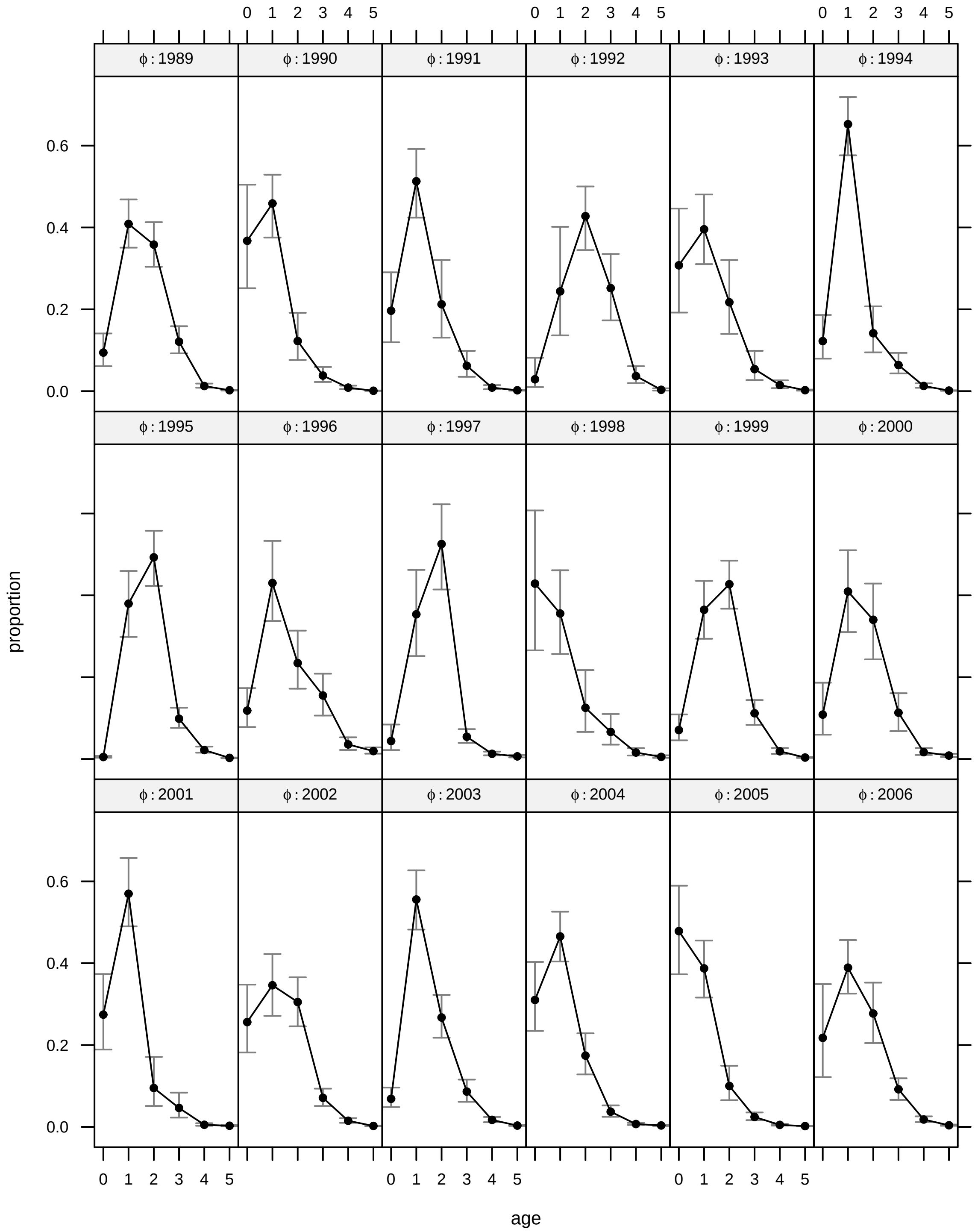


Figure 4.5: Age compositions empirical distribution obtained by parametric bootstrap. The full circle represents the median proportion and the gray lines represent the confidence interval computed by the 0.025 and 0.975 percentiles.

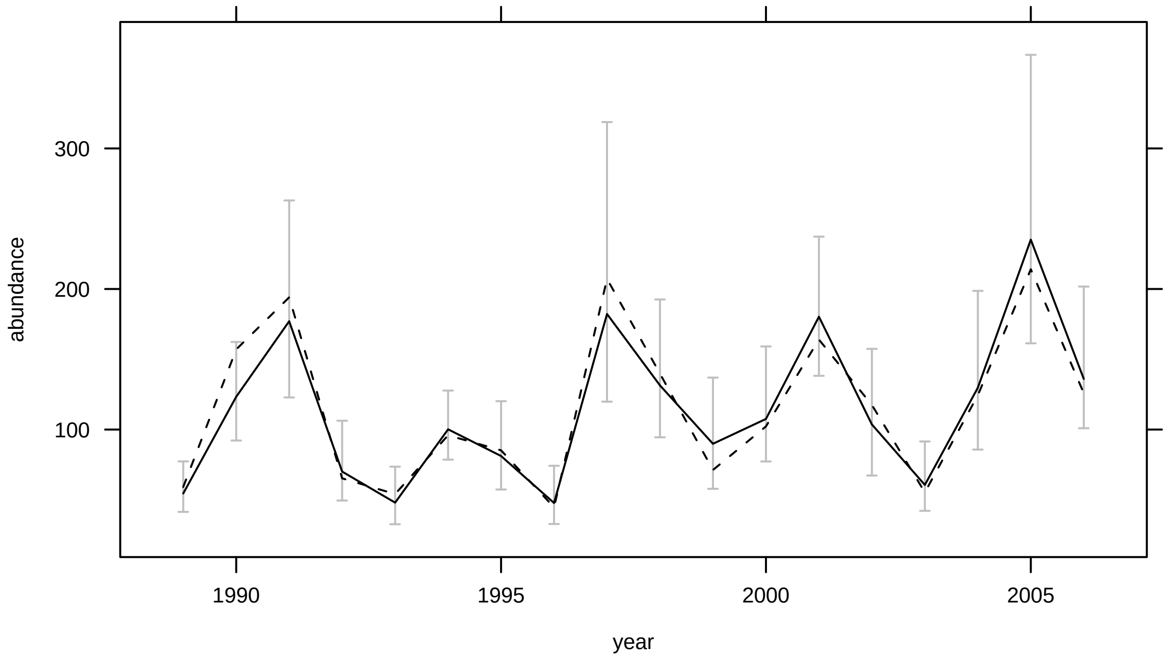


Figure 4.6: Yearly abundance estimates. The full black line represents the median abundance and the gray lines represent the confidence interval computed by the 0.025 and 0.975 percentiles obtained with the model-based approach proposed by this study. The dashed line represents the design-based estimates.

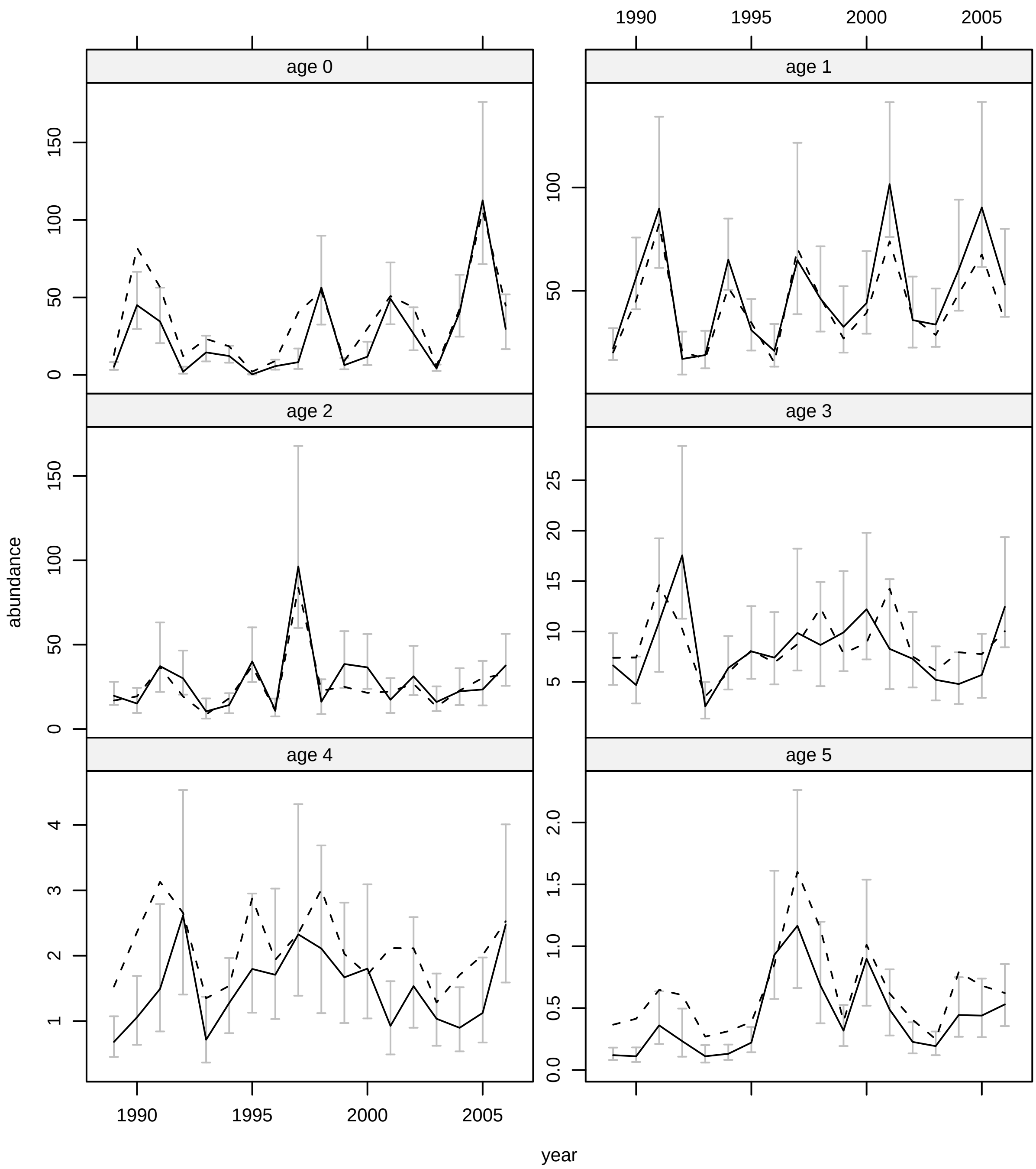


Figure 4.7: Abundance-at-age estimates per year. The full black line represents the median abundance and the gray lines represent the confidence interval computed by the 0.025 and 0.975 percentiles obtained with the model-based approach proposed by this study. The dashed line represents the design-based estimates.

4.4 Discussion

The proposed approach models abundance-at-age by the product of two sub-models, one for space-time distribution of abundance in numbers and another for the conditional distribution of the population's age structure. A model accounting for the complete specification of abundance-at-age could in principle provide more insights about the underlying stochastic process. However, such a model would require a lot more information or, in its absence, strong assumptions would be necessary to allow for parameter estimation. Considering the small sample sizes of marine surveys and the large observation variability, modeling abundance-at-age with such a model is not possible without making strong assumptions about cross-correlations between ages.

Although not considering the full characteristics of the join distribution of abundance-at-age, the proposed model takes into account the major sources of variability, space-time variability and population structure variability. The methodology is simpler and has less parameters than modeling all the cross-correlations between abundance-at-age time series. The factorization in sub-models increased the model flexibility allowing distinct approaches to be used in each sub-model analysis. It is worth noting that the induced flexibility does not constraint the complexity of each sub-model, allowing the integration of more sophisticated approaches such as adopting non-separable space-time covariance functions (Gneiting, 2002) for the geostatistical model.

The Bayesian approach is introduced simple through the spatial modeling. It reflects a pragmatic choice of relying on the good results obtained with simple stochastic sampling and not substantially increasing the complexity of the model by setting priors for the compositional correlation structure. Tjelmeland and Lund (2003) explores the Bayesian inference for correlated compositions which adds issues on prior choices, Monte Carlo Markov Chain settings and spatial prediction is not addressed.

Another alternative and simpler model would be to assume independence between ages, adjusting the geostatistical model to each age individually. This model allows the estimation of the spatial behavior of each age, however, it is likely to produce conflicting spatial covariance parameters which may lead to inconsistent spatial predictions. In extreme situations, due to a large number of null observations for ages not well represented on the sample, it would be impossible to estimate the model parameters. The proposed approach has the advantage of modeling a single spatial process per year, avoiding such inconsistencies, and deals with less represented ages through compositional data analysis borrowing information from other ages.

Design-based approaches have the shortfall of considering independence between observations which is hardly verifiable when dealing with fish abundance. The mean estimates are unbiased if the observations are fairly symmetric but the variance may be biased depending on the strength of the association between ages and/or locations. Barber and Gelfand (2007) and Jardim and Ribeiro Jr. (2007) argue that the amount of information contained in each sample is over estimated when ignoring the correlation between samples, leading to an underestimation of uncertainty.

The case study showed design based estimates with higher precision than model based estimates. To assess the above mentioned effect the ratio between the average distance between locations within each stratum and ϕ were computed per year. The percentage of pairs lying between 0 and 1 was 33%, between 1 and 2 was 37%, between 2 and 3 was 16% and higher than 3 was 15%. Considering that the practical range is 3ϕ most of the pairs are in fact correlated in space, which means that the values are more similar than expected if the locations were independent and so the variance is likely to be underestimated. On the other hand, design-based techniques depend on the sampling design which is not the case of model-based techniques, an important advantage since BTS sampling design may change over the years.

Another feature of the methods advocated in this paper is the production of several abundance indicators, providing an overview of abundance along distinct viewpoints. The analysis of age compositions provides an insight on how the population structure evolves over time and the geostatistical sub-model returns abundance time series and abundance maps. Finally, the full parametric specification of the model allows the usage of Monte Carlo simulation methods and provide stochastic distributions of all parameters and estimates, which can be used in larger simulation frameworks like MSE.

Chapter 5

Management Strategies Evaluation

This chapter was submitted as a research paper to the ICES Journal of Marine Science:

Ernesto Jardim, Santiago Cervino and Manuela Azevedo. 2009 (submitted). Evaluating Management Strategies to Implement the Recovery Plan for Iberian Hake (*Merluccius merluccius*) - impact of censored catch information. ICES Journal of Marine Science.

Abstract: Iberian hake assessment showed an increase of fishing mortality (F) despite enforcement of the recovery plan. Recent landings are above the TAC and discards rates are high. Management strategies (MS) likely to recover the Iberian hake stock are (i) evaluated with respect to their ability to recover spawning stock biomass to safe levels and drive the fishery wealthier state, and (ii) tested regarding robustness to uncertainty on catch information and stock dynamics. Due to difficulties rebuilding the time series of discards and the landings at age in the Gulf of Cadiz area, these information is not included on the current assessment. The results obtained show that censured catch data, excluding the Gulf of Cadiz and discard, may drive to inappropriate conclusions. Reducing fishing mortality is an absolute requirement to recover the stock, while simultaneously reducing discards will lead the fishery to a higher profit profile. A Fmax strategy with discard reduction showed the highest probability of rebuilding the stock and drive the fishery to a sustainable exploitation, leading %SPR in 2025 to 30%-40%, mean individual weight in the landings to raise to 450g in 2015, and yield to increase more than 20%, leading the fishery to more valuable landings associated with lower exploitation costs. Keep fishing at the present level stabilizes spawning stock biomass and recruitment above 20 000t and 140 million individuals, respectively. Nevertheless, the size of the spawning stock is forecast to be less than 10% of virgin biomass, yield increases until 2010 supported by recent high recruitment but is expected to decline afterwards to levels below 2007. Mean weight in the landings will be marginally above the current estimate, which combined with decreasing landings indicate that income is likely to decrease in the future. Due to uncertainty in maximum sustainable yield biological reference points MS based on Fmsy showed the worst performance in terms of robustness. All MS looked robust to distinct S/R models, which had a minor influence on the results during the study period 2008-2015.

5.1 Introduction

The Iberian hake (*Merluccius merluccius*) stock is distributed along the continental shelf of Spain and Portugal (Figure 5.1), from the south area of the Bay of Biscay to the Gulf of Cadiz (GoC). It is an important species for trawl, gillnet and long line fleets of both countries, as well as some small scale fisheries using gillnets and trammel nets.

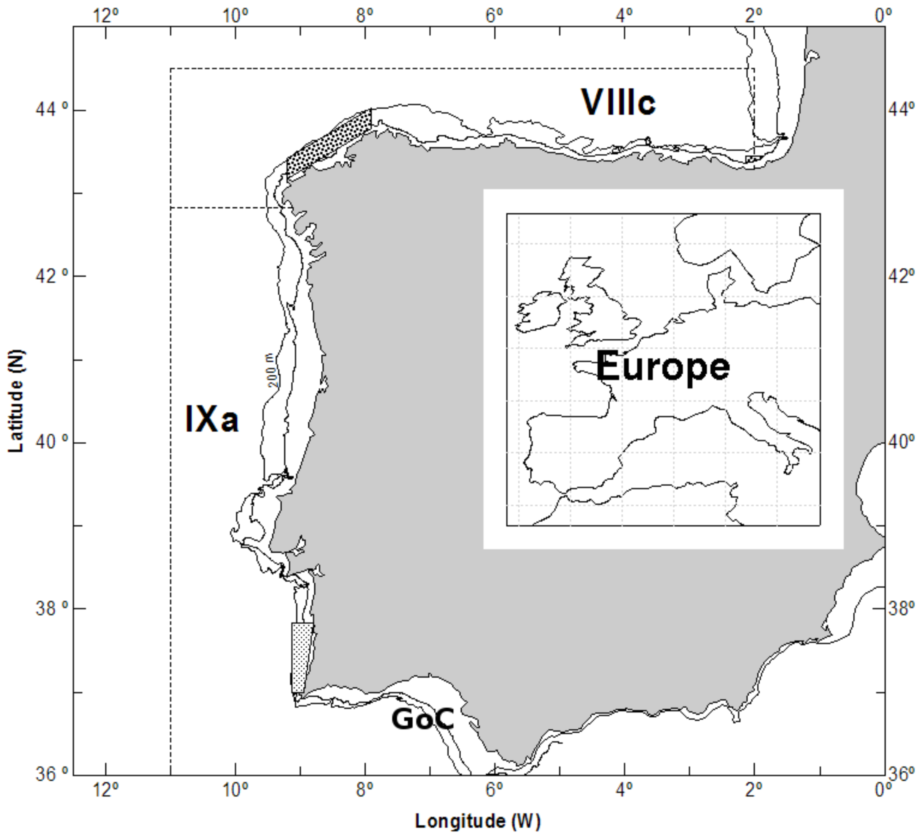


Figure 5.1: Iberian hake area of distribution off the Spanish and Portuguese continental coast including the two closed areas defined by the recovery plan. On the Northeast in Division VIIIc the Galicean box, closed from the first of October until the first of January and on the Southeast in Division IXa the Arrifana box closed from the first of December until the last day of February. The Gulf of Cadiz location on the south of the Iberian peninsula is signed with “GoC”.

In 2003 the International Council for the Exploitation of the Sea (ICES), who is responsible for the provision of annual scientific advice to the European Commission (EC), classified the stock as being outside safe biological limits and advised a rebuilding plan aiming at a rapid and safe recovery of the spawning stock biomass (Anon., 2004b). Accordingly, a recovery plan (RP) was introduced by the EC in 2006 (Reg. EC No 2166/2005) with the aim of rebuilding the spawning stock biomass to 35 000t, the precautionary spawning stock biomass (B_{pa}) estimated by ICES. The time frame for recovery was set in ten years, following the compromise of exploring fish stocks at a level able to produce the maximum sustainable yield (MSY) in 2015, agreed at the Johannesburg World Summit on Sustainable Development in 2002.

The RP foresees a strategy based on reductions of fishing mortality of 10% per year towards a target fishing mortality, that must be implemented by reductions of total allowable catches (TAC) and number of days at sea allocated for each vessel catching Iberian hake. Due to uncertainty on the stock dynamics, the fishing mortality (F) that produces MSY, F_{msy}, was poorly estimated and the fishing mortality giving the maximum yield on a yield per recruit curve, F_{max}, was used as target. F_{max} was estimated in 2004 to be 0.27 (Anon., 2004b). Additionally, the RP enforces a constraint on the maximum change of the TAC between years of 15% in order to assure catch stability.

The RP harvest control rule (HCR) to set the annual total allowable catches (TAC) can be expressed as:

$$\text{if } F_{y-1} > 0.3 \text{ then } TAC_{y+1} \sim F_{y+1} = 0.9 F_y$$

$$\text{if } F_{y-1} \leq 0.3 \text{ then } TAC_{y+1} \sim F_{y+1} = 0.27$$

$$\text{if } TAC_{y+1} > 1.15\, TAC_y \text{ then } TAC_{y+1} = 1.15\, TAC_y$$

$$\text{if } TAC_{y+1} < 0.85\, TAC_y \text{ then } TAC_{y+1} = 0.85\, TAC_y$$

where y is the year when the assessment is carried out, $y-1$ is the last year with observations, $y+1$ is the year for which the advice is being provided and $\sim$ stands for "set in accordance with".

Complementary to catch and effort control, the management of Iberian hake include technical measures to protect juveniles like a minimum landing size (MLS) of 27cm, area/season closures (Figure 5.1) and mesh size constraints.

Table 5.1 shows TACs, landings and discards by fleet estimated by Anon. (2008b) for Spain and Portugal. France caught a very small fraction of the stock until early nineties and was excluded from the analysis. Historical yields (column TOTAL in Table 5.1) show a decline from values

$\approx$ 30 000t at the beginning of the 70's to a minimum of $\approx$ 6 700t in 2002, increasing thereafter to $\approx$ 15 000t in 2007. Since 2004 landings have been estimated to be above the TAC, 17% in 2004, 40% in 2005, 60% in 2006 and 113% in 2007, largely due to Spanish landings, where trawls represent $\approx$ 80% of the landings in recent years.

Discard rates, computed as the weight discarded over the weight retained, are estimated to be quite high in the Portuguese trawl fleet with an average of 1.76 between 2004 and 2007. The Spanish trawl fleet discard rate is estimated to be 0.15 during the same period. Overall, preliminary estimates of discards were approximately 3 000t in 2007, representing approximately 20% of the total landings, concentrated on ages 0 to 2 (Anon., 2008b).

The trawl fleet in the Gulf of Cadiz is responsible for $\approx$ 10% of the stock landings (Anon., 2008b). However, due to a failure on the enforcement of the MLS until recently, this fleet showed a different selection pattern from other trawl fleets acting on the Iberian Peninsula, concentrated on smaller individuals. Until 1995, no sampling programme for length frequencies of the landings was carried out, and the short time series available for this region provided limited information to be included on stock assessment. In 2003 it was decided to remove the GoC from the assessment (Anon., 2004b).

The aim of this work is the evaluation of management strategies to implement the recovery plan of Iberian hake and test their robustness to uncertainty on catch information and the stock dynamics. Secondly it presents a simple procedure to reconstruct the time series of discards and landings in GoC. Finally, metrics and risks indicators were developed with the aim of comparing the multiple scenarios with regards to stock conservation and exploitation.

5.2 Knowledge base

Iberian hake's knowledge base was built from the data available to the ICES Working Group on the Assessment of Southern Shelf Stocks of Hake, Monk and Megrim (WGHMM) in 2008 (Anon., 2008b).

Table 5.1: Iberian hake landings of the Spanish and Portuguese gillnets (GN), longlines (LL), trawl (TR) and polivalent (PV) fleets, total allowable catches (TAC) and discards of the Spanish (SPTR) and Portuguese (PTTR) trawl fleets. All figures are in thousands of tonnes.

Year	Spanish fleets				Portuguese fleets				Stock		Discards	
	GN	LL	TR	PV	GN	LL	TR	PV	TOTAL	TAC	SPTR	PTTR
1972			10.20	7.10			4.10	4.70	26.10			
1973			12.30	8.50			7.30	6.50	34.60			
1974	2.60	2.20	8.30	1.00			3.50	5.10	22.70			
1975	3.50	3.00	11.20	1.30			4.30	6.10	29.40			
1976	3.10	2.60	10.00	1.20			3.10	6.00	26.00			
1977	1.50	1.30	5.80	0.60			1.60	4.50	15.30			
1978	1.40	2.10	4.90	0.10			1.40	3.40	13.30			
1979	1.70	2.10	7.20	0.20			1.90	3.90	17.00			
1980	2.20	5.00	5.30	0.20			2.30	4.50	19.50			
1981	1.50	4.60	4.10	0.30			1.90	4.10	16.50			
1982	1.25	4.18	4.41	0.27			2.48	5.01	17.59			
1983	2.10	6.57	5.87	0.37			2.86	5.18	22.95			
1984	2.27	7.52	6.54	0.33			1.22	4.30	22.18			
1985	1.81	4.42	6.12	0.77			2.05	3.77	18.94			
1986	2.07	3.46	5.84	0.83	0.92	0.27	1.79	1.97	17.15			
1987	1.97	4.41	4.45	0.53	1.00	0.27	1.33	2.20	16.16	25.00		
1988	1.99	2.97	4.96	0.70	0.73	0.77	1.71	2.81	16.63	25.00		
1989	1.86	1.95	4.82	0.56	0.51	0.09	1.85	2.13	13.77	20.00		
1990	1.72	2.13	5.33	0.59	0.57	0.03	1.14	1.66	13.16	20.00		
1991	1.41	2.20	4.84	0.42	0.73	0.23	1.25	1.75	12.82	18.00		
1992	1.48	2.05	4.76	0.40	1.71	0.47	1.32	1.59	13.80	16.00		
1993	1.25	2.74	3.21	0.37	1.43	0.36	0.87	1.25	11.49	12.00		
1994	1.90	1.47	3.04	0.38	1.00	0.13	0.79	1.17	9.87	11.50	0.29	
1995	1.59	0.96	5.73	0.37	1.26	0.16	1.03	1.15	12.24	8.50		
1996	1.15	0.97	4.61	0.24	1.15	0.15	0.89	0.71	9.88	9.00		
1997	1.04	0.77	3.98	0.35	0.82	0.11	0.91	0.58	8.54	9.00	1.13	
1998	0.75	0.62	3.35	0.36	0.84	0.14	0.91	0.69	7.67	8.20		
1999	0.60	0.25	3.02	0.41	0.96	0.14	1.09	1.02	7.50	9.00	0.36	
2000	0.85	0.15	3.39	0.27	0.92	0.24	1.16	0.93	7.91	8.50	0.62	
2001	0.58	0.11	3.38	0.35	0.93	0.20	1.20	0.87	7.62	8.90		
2002	0.60	0.14	3.01	0.19	0.81	0.20	0.97	0.80	6.72	8.00		
2003	0.43	0.17	3.68	0.50			0.96	1.15	6.89	6.96	0.34	
2004	0.42	0.13	3.85	0.48			0.80	1.31	6.98	5.95	0.24	1.06
2005	0.63	0.23	4.80	0.59			0.96	1.12	8.35	5.97	0.32	1.73
2006	0.71	0.35	7.14	0.50			0.88	1.14	10.70	6.66	2.65	1.03
2007	1.80	0.89	9.28	0.83			0.72	1.44	14.96	7.05	0.87	1.99

Since 1972 landings in weight are estimated from Portuguese sales notes, Spanish sales notes and Spanish Owners Associations data.

Since 1982 length and age compositions, as well as maturity and length-weight information, are available for stock assessment. In the GoC the sampling programme for length frequencies of the landings started in 1995, for growth and reproduction started in 2000 and discards in 2004.

To rebuild the historical series of landings at age on the GoC, the average percentage landings at age between 1995 and 2003 was applied to the period 1982-1994. Individual mean weight at age in the landings between 1982 and 1994 were computed by the average individual weight of the period 1995 to 2003.

Given that variance estimates were unavailable for landings, variability was introduced by adding Gaussian random variability with variance at age estimated by Jardim *et al.* (2004). Replicates of the total landings in weight were computed by multiplying the landings numbers at age replicates and mean weight at age in the landings.

Discarding from this fishery is mainly carried out by the trawl fleets driven by the 27cm MLS enforced in 1991. Discards in numbers at age and mean weight at age are available for the Portuguese and Spanish trawl fleets collected with on-board sampling programmes. Portuguese data were available for the 2004-2007 period, segmented into a fleet targeting round fish operating with 65mm mesh size and a fleet targeting Nephrops in the southern area of Portugal operating with 55mm or 70mm mesh size. The Spanish data were available for the period 1994-2007 with gaps in 1995, 1996, 1998, 2001 and 2002. The sampling programme was segmented by baca trawls operating with 65mm mesh size, pair trawls operating with 45-55mm mesh size and high vertical opening trawls operating with 65mm mesh size, operating in the north and northwest Spanish Atlantic coast. More information about the discards sampling programmes and results can be found in Anon. (2007e, 2008b) and related working documents. There is no information about hake discarding by other fleets although it is supposed to be low compared with trawls, since the mean length of the catches is higher for gill nets and longlines.

The relationships between discards at age, survey abundance at age and trawl landings at age were

Table 5.2: Generalised Linear Models adjusted to rebuild the historical series of discard data including the model formula and link functions by age and country for the trawl fleets. Sampling variance in CV used for generating replicates and percentage of variance explained by the model also included. D_{ij} represents discards in numbers; C_{ij} represents catches in numbers of the commercial fleet; U_{ij} represents abundance index in numbers caught per hour by scientific surveys; i indexes fleets; j indexes ages; B represents a covariate that splits the period before 2000 and the period after and including 2000; f represents ratio; $\sim$ represents "dependent of" for a GLM adjustment; P = Portugal; S = Spain; $*$ represents multiplicative factors; $+$ represents additive factors.

Country	Age	Model	link function	Samp. CV	% Var
Portugal	0	$D_{P0} = 0.63 D_{P1}$	-	0.1	-
	1	$D_{P1} \sim U_{P1}$	identity	0.1	97
	2	$D_{P2} \sim U_{P2}$	identity	0.1	68
	3	$D_{P3} = 0.06 D_{P2}$	-	0.2	-
Spain	0	$D_{S0} \sim B * D_{S1} + U_{S0}$	identity	0.1	98
	1	$D_{S1} \sim B * C_{S1} + B * U_{S1} + C_{s1} * U_{s1}$	identity	0.1	99
	2	$D_{S2} \sim B + U_{S2}$	square root	0.1	98
	3	$D_{S3} \sim B * U_{S2}$	square root	0.2	79

modelled with GLMs (McCullagh and Nelder, 1991) assuming Gaussian errors and identity or square root link functions, to comply with the linear models assumptions. The fitted parameters were used to predict discards of the period without observations from survey abundance at age or trawl landings at age observed in the missing years. A summary of the models used is shown in Table 5.2. Variability was generated bootstrapping the residuals' variance of the fitted models, for the predicted years, or the sampling variance, for the sampled years. Model selection was done by inspecting plots of residuals, Cook's distance plots, F tests and R^2. The Portuguese discards data presented a good fit between discards of ages 1 and 2 and the Portuguese bottom trawl survey abundance estimates at ages 1 and 2, with a percentage of variance explained of 97% and 68%, respectively. However, ages 0 and 3 showed poor model fittings and discards at ages 0 and 3 before 2004 were calculated by the average ratio of the period 2004-2007 between ages 0 and 1, and, ages 2 and 3, respectively. The Spanish discards data presented a clear change in the exploitation pattern in 2000 and an extra covariate was introduced to reflect the two periods. All Spanish ages showed good GLM fit with a percentage of variance explained between 79% and 99%.

There were five abundance indices available, two from commercial data and three from surveys.

The cpue series were from the Portuguese trawlers (pTr) and A Coruña trawlers (sTrC), and the three survey indices from the Spanish September Groundfish survey (sGFS) that covers the north and northwest of the Spanish continental shelf, the Portuguese October Groundfish survey (pGFS) that covers the Portuguese continental shelf, and the GoC October Groundfish survey (sGFScad) that covers the GoC area. Variability for pGFS indices was generated using Monte Carlo techniques, Bayesian geostatistics and compositional data analysis (Jardim and Ribeiro Jr., 2009). For the remaining indices there was no information available for variability and a log normal distribution with a coefficient of variation of 30%, the average CV at age of pGFS, was assumed.

Other biological parameters required for the analysis were obtained from WGHMM (Anon., 2008b), namely, natural mortality fixed at 0.2 per year, stock weights, catch weights and proportion mature at age for combined sexes, assumed to be exact. A summary of the Iberian hake knowledge base used in this study is presented in Table 5.3.

5.3 Methods

Management Strategies Evaluation (MSE) was used to evaluate the suggested management strategies to recover Iberian hake along the lines set by the RP. MSE are simulation frameworks that aim to test different management strategies regarding their success on achieving a management objective and investigate the robustness of such strategies to uncertainty on the underlying dynamics, data, models or management implementation. MSE consists of two modules, the operating model (OM) and the management procedure (MP). The OM is composed of several statistical sub-models that represents the "true" population and fishery dynamics. Its ability to represent the truth depends on existing knowledge about the stock and fishery and the parametrization of its sub-models, also called *conditioning*. The MP contains an assessment model and a decision algorithm, which implements a management strategy that triggers specific management actions based on the perception of the stock condition given by the assessment model, *i.e.* the relation between the stock status and the management reference points. The MP will constrain the fishery driving the population towards predefined goals. The linkages between both models are (i) the observation error model

Table 5.3: Iberian hake knowledge base describing for specific parameters the period for which estimates existed, the period rebuilt with predictions, the Monte Carlo (MC) method used and the source of uncertainty used. Parameters' codes are: L = landings, D = discards, U = abundance index, W = mean individual weight, M = natural mortality and P = proportion mature. Subscripts *a* indexes ages and *w* weight.

Parameter	area/fleet	Estimates	Predictions	MC method	MC source
L_a	stock without GoC	1982-2007	-	bootstrap	Jardim *et al.* (2004)
L_w		1982-2007	-	-	-
L		1982-2007	-	-	$f(L_a)$
L_a	GoC	1995-2003	1982-1994;2004-2007	bootstrap	Jardim *et al.* (2004)
L_w		1995-2003	1982-1994;2004-2007	-	-
L		1995-2003	1982-1994;2004-2007	-	$f(L_a)$
D_a	pTr	2004-2007	1990-2003	bootstrap	GLM residuals
D_a	sTr	1994, 1997, 1999, 2000, 2003-2007	1983-1993, 1995, 1996, 1998, 2001, 2002	bootstrap	GLM residuals
D_w	stock	1994, 1997, 1999, 2000, 2003-2007	1983-1993, 1995, 1996, 1998, 2001, 2002	-	-
D	stock	1994, 1997, 1999, 2000, 2003-2007	1983-1993, 1995, 1996, 1998, 2001, 2002	-	$f(D_a)$
U_a	pGFS	1985-2007		Bayesian	Jardim and Ribeiro Jr. (2009)
U_a	sGFS	1983-2007		bootstrap	Jardim and Ribeiro Jr. (2009)
U_a	sGFScad	2000-2007		bootstrap	Jardim and Ribeiro Jr. (2009)
U_a	pTr	1995-2007		bootstrap	Jardim and Ribeiro Jr. (2009)
U_a	sTrC	1985-2007		bootstrap	Jardim and Ribeiro Jr. (2009)
W_a	stock	1982-2007	-	-	-
M_a	stock	1982-2007	-	-	-
P_a	stock	1982-2007	-	-	-

(OEM) that generates a distinct view of the stock used for management; and (ii) the implementation error model (IEM) that generates differences between the management actions foreseen by the MP and the actions executed. MSE has its genesis in the International Whaling Commission (for a quick summary see Punt and Donovan, 2007) in the 90's and is widely used (*e.g.* Butterworth *et al.*, 1997; Cooke, 1999; Butterworth and Punt, 1999; Kell *et al.*, 2005).

Regarding Iberian hake, the major sources of uncertainty which are expected to have a large impact on our perception of the stock and consequently on the advice provided are (Anon., 2008b):

- the lack of discards information which are estimated to be high (Table 5.1), driven by the MLS and high-grading in the Portuguese fleets due to the implementation of individual quotas;
- the exclusion of the information from the GoC due to difficulties rebuilding the historical series;
- a possible biased growth pattern, estimated at lower growth rates than observed in recent tagging experiments (de Pontual *et al.*, 2006; Piñeiro *et al.*, 2007), which is not considered in this work.

The MSE developed for Iberian hake is shown in Figure 5.2. The OM conditioning integrates stochastic variability on landings, discards and abundance indices, that will be carried on through the MSE. The OEM subsets the OM to provide input data for assessment corresponding to a censored view of the catches.

The TAC overshoot estimated in recent years and the high discard rate are clear indicators that the current management system does not control the fishing mortality of the fleet, in particular when its stressed by decreasing fishing opportunities. On the other hand, the large fluctuations in recruitment induce a high variability in stock size that may originate distinct catches from those foreseen. To overcome these problems the MPs developed are based on controlling fishing mortality leaving catches to result from natural fluctuations of stock size. The MP defines a fishing mortality trajectory by a linear decrease in F towards a target F, from 2009 to 2015, which is kept

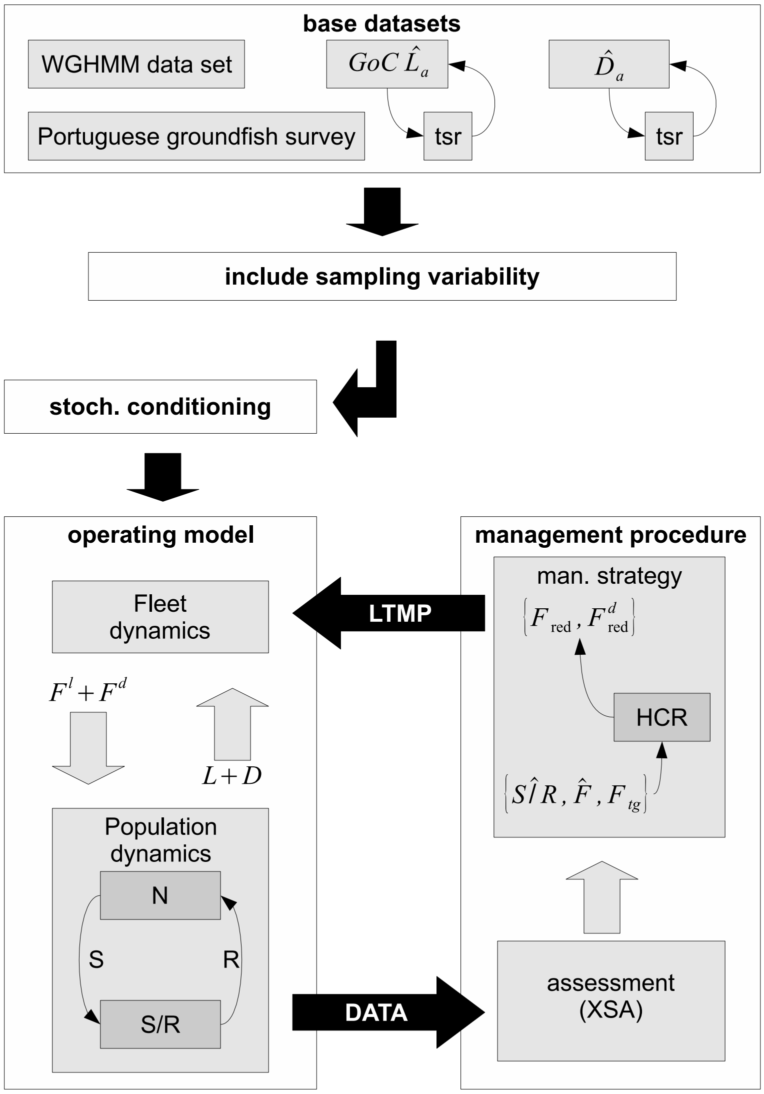


Figure 5.2: Analysis workflow including the Management Strategies Evaluation framework. F = fishing mortality, L = landings, D = discards, S = spawning stock biomass, R = recruitment, S/R = stock-recruitment model, HCR = harvest control rule, XSA = extended survival analysis. Superscripts l and d stand for "landings" and "discards", respectively. Subscripts a, red, tg stand for "age", "reduction" and "target", respectively.

constant thereafter. The fishing mortality trajectory is set in 2008, depending of the estimates of fishing mortality in 2007 and the target F, which is based on biological reference points estimates. The resulting management strategy can be viewed as a long term management plan (LTMP) that will constrain the fishery and drive the population to the management objectives. Such approach does not require yearly assessments to set the TAC once that the fishery is managed through fishing mortality control.

Under a F control system the IEM shall deal with mis-matches between the F trajectory foreseen by the MP and the effective F deployed by the fleets, taking into account: (i) a bias in fishing mortality to mimic smaller decreases in F than expected, and/or (ii) additional variability on the fishing mortality to include uncertainty about the implementation of management actions. The key variable on such procedure is catchability, that reflects the relation between F and fishing effort, which is the characteristic that can be controlled by management actions. However, due to the lack of information about catchability, the bias introduced would simply result in distinct recovery perspectives of the stock, most likely to be between the most drastic fishing mortality reductions and fishing at 2007 levels. Moreover uncertainty would be added as random noise that will not contribute to understand the management dynamics, simply widen the confidence intervals of the performance statistics. In face of these options it was decided not to introduce implementation error.

Variability is introduced in two ways: (i) by adding variability in the knowledge base, estimated from sampling and prediction error, that is carried through the OM, OEM and MP, (ii) by introducing random variability on recruitment from S/R model residuals. For each of these variables 1000 replicates were generated.

This work was carried out with open source software. Data analysis, figures and implementation of the methodology were carried out with R (R Development Core Team, 2008) and FLR packages (Kell *et al.*, 2007).

5.3.1 Operating model

Having introduced variability in the base parameters, the conditioning of the operating models was implemented to integrate such variability by running a stock assessment in each replicate, which are constituted of a full set of input parameters. The assessment model used to estimate Fishing mortality (F_{ay}) and population size (N_{ay}) was XSA - eXtended Survivor Analysis (Shepherd, 1999) with the settings defined by WGHMM (Anon., 2008b). The subscripts a and y index "age" and "year", repectively. Running the assessment model in each replicate will produce 1000 replicates of F_{ay} and N_{ay} that carry the variability of the base parameters.

Two stock-recruitment (S/R) models were adjusted, a Ricker model, $N_0 = aS\exp(-bS)$, and a segmented regression model, $N_0 = \begin{cases} S \leq b & aS \\ S > b & ab \end{cases}$, where S is the spawning stock biomass, a and b are model parameters. The former accounts for over compensatory effects likely to occur due to hake's cannibalism at high levels of S. The later considers recruitment independent of the spawning stock biomass except when it is at a very low level reflecting complex and poorly understood hatching and larval phases. To avoid the influence of the 2007 recruitment estimate, S/R models were adjusted for the period 1982-2006, and replicates were taken as observations of the same stochastic process.

Projections were based on the common catch-at-age and survival equations for cohorts. Each year the catch is removed from the population taking into account the fishing mortality applied that year with $C_{ay} = N_{ay}F_{ay}Z_{ay}^{-1}(1-\exp(-Z_{ay}))$, where y indexes years, a indexes ages, N is the population in numbers, F is the fishing mortality and Z is the total mortality. The population is projected to the end of the year with $N_{a+1,y+1} = N_{ay}\exp(-Z_{ay})$. The survivors in the plus group, set at age 8, are estimated with $N_{a=8,y+1} = N_{a=7,y}\exp(-Z_{a=7,y}) + N_{a=8,y}\exp(-Z_{a=8,y})$. Recruitment, considered at age 0, is generated using S/R models, $N_{0,y+1} = f(S_y)$ with $S_y = \sum_a P_{ay}N_{ay}W_{ay}$, where P denotes the proportion of mature individuals and W the mean individual weight. Recruitment variability is included by bootstrapping the residuals of S/R models.

Discards are projected splitting fishing mortality into landings fishing mortality and discards fishing mortality, using the average ratio of the number of individuals at age in discards over catches between 2004 and 2007, the period with regular discard sampling. The ratio is computed by $r_a = 0.25\sum_{y=2004}^{2007} D_{ay}C_{ay}^{-1}$, where D is the number of individuals discarded and C is the number of individuals caught. Note that $C = D + L$ where L is the number of individuals landed. To compute partial fishing mortality it was considered $F_a = F_a^l + F_a^d$ and $F_a^l = F_a(1 - r_a)$ where superscripts l and d stand for "landings" and "discards", respectively.

To smooth the influence of last year's F estimates on the exploitation pattern used to start the projections, an average over the last four years was computed, considering the period for which there are discards observations. Accordingly, both proportion mature at age and weight at age were smoothed with a four year average.

The above procedures produce two OM, one for each S/R model, that entangle all the information available about the fishery and the stock biology, with the exception of the growth pattern which was not addressed by this work.

5.3.2 Observation Error Model

The observation error model was implemented by censoring the input data for assessment following likely data set to be assembled by WGHMM:

- ALL - perfect assessment, OEM uses all available information (WGHMM data set, GoC information and discards),
- WG - replicates WGHMM assessment, OEM censures GoC information and discards;
- GoC - inclusion of GoC on WGHMM assessment, OEM censures discards estimates;
- DISC - inclusion of discards on WGHMM assessment, OEM censures GoC information.

No random variability is introduced at this stage so that the variability introduced at the knowledge base construction, used to conditioned the OM, is carried on to the MP.

5.3.3 Management procedure

Stock assessments are carried out for each data set produced by the OEM using XSA with the settings defined by WGHMM (Anon., 2008b). Considering the variability introduced in the OM and carried on by the OEM, the fishing mortality (F_{ay}) and population size (N_{ay}) in the management procedure were estimated for each replicate. To estimate biological reference points the exploitation pattern, maturity at age and weight at age were averaged over the last four years. Ricker models were adjusted for the period 1982-2006 to compute MSY related reference points.

Management strategies were built following the principles of the RP, reduce fishing mortality to a target fishing mortality until 2015, in two ways: (i) reducing overall fishing mortality which could be enforced by effort reductions, and (ii) reduce discards, which can be implemented by a change in the selection pattern induced by changes in gear selectivity, implementation of closed areas/seasons or decommissioning of trawlers.

The harvest control rule below represents the decision algorithm to implement the above strategies:

if $F_{y-1} > F_{tg}$ then $F_{y+1} = F_y - a$ where $a = \frac{F_{07} - F_{tg}}{2015-2007}$

if $F_{y-1} \leq F_{tg}$ then $F_{y+1} = F_{tg}$

if $y = 2009$ then $D_{2009} = mD_{2007}$

An important feature of the HCR proposed is that it has only two variables, F_{tg} and F_{07}, that will be estimated by the 2008 assessment. The assessments run on each OEM will provide distinct estimates of these parameters, and each pair will define distinct trajectories for fishing mortality. The discard reduction defined by the multiplier m depends on a management decision and is not estimated from the data It will act as an extra F reduction, implemented through a shift in F_a.

Note that the 15% constrain in TAC variation between years is not considered, once that the MS principles do not constrain catches. Catch fluctuations are monitored as a performance statistic, described below.

Taking into account the objective of driving the fishery to MSY, two F targets were considered, F_{max} and F_{msy}, being the first a proxy to the former, used when the stock dynamics are uncertain.

For comparison purposes it was also considered fishing at the present level, F_{sq}. The discard reduction is implemented considering two options: (i) keeping at the same level as 2007 (m=1), or (ii) reducing 100% of the 2007 level (m=0), simulating a discard ban. The reduction is introduced in 2009, and continued for the remaining years to determine the effects of discarding. The different combinations of the two management actions corresponds to six management strategies to be tested, coded as "F target: discard multiplier":

- F_{max} : 1 - linear reduction on fishing mortality from the present level to F_{max} in 2015,
- F_{max} : 0 - linear reduction on fishing mortality from the present level to F_{max} in 2015 and discard ban in 2009,
- F_{msy} : 1 - linear reduction on fishing mortality from the present level to F_{msy} in 2015,
- F_{msy} : 0 - linear reduction on fishing mortality from the present level to F_{msy} in 2015 and discard ban in 2009,
- F_{sq} : 1 - keep fishing at the present level, F_{sq},
- F_{sq} : 0 - keep fishing at the present level, F_{sq}, and discard ban in 2009.

The combination of the six management strategies, four observation error models and two operating models produce 48 scenarios to be analysed.

5.3.4 Metrics

To summarise information about the stock and fishery dynamics, allowing the comparison of multiple scenarios, a group of metrics are chosen that reflect conservation, exploitation and risk viewpoints:

- conservation:
  - P[S15 $\geq$ 35 000t] - probability of the spawning stock biomass in 2015 being above the target spawning stock biomass defined in the RP, 35 000t,

  - %SPR25 - percentage of virgin spawning biomass per recruit in 2025.

- exploitation:
  - Y15/Y07 - yield ratio between 2015 and 2007,
  - MWL15 - mean weight in the landings in 2015

- risk:
  - P[Yloss] - risk of loosing fishing opportunities due to 15% TAC constrain,
  - P[Ylow] - risk of having low catches.

Risk measures are defined as the probability of occurrence of a negative event during the period, computed by the number of years such event occurred during the eight years period, 2008 to 2015. The "loosing fishing opportunities" event (P[Yloss]) was defined as having a probability higher than 0.1 of the catches raising above 15% of the previous year catches. This metric reflects the risk of loosing catches due to the implementation of the 15% catch constrain rule. The negative event "low catches" (P[Ylow]) was defined as having a probability higher than 0.1 of the catches falling below 15% of the previous year catches. For example, if P[Ylow]=0.375 it implies that in 3 out of 8 years the probability of catches being less than 15% the previous year catches was more than 0.1.

5.4 Results

5.4.1 Conditioning the operating model and stock perception

Taking into consideration that the OEM ALL induces a perfect assessment on the MP, the results of the assessment carried out for conditioning are not explicitly presented, once that both use the same data set. Conditioning will use the same parameters as presented for OEM ALL.

The assessment procedures carried out for each OEM provide the MP with a specific perception about the stock status. Based on this perception the MS will be defined depending on the decision about the target fishing mortality and an additional discard ban in 2009, as described in the MP's HCR. For the sake of simplicity the results will mention OEMs in a wide perspective, including the stock perception derived from them, although such results should already be mentioned has belonging to the MP.

Figure 5.3 shows landings, recruitment, spawning stock biomass, catches, mean fishing mortality over ages 2 to 5 and mean discards mortality over ages 0 to 3, estimated by XSA for each OEM. Only median values are shown to simplify the analysis. Landings and catches showed the expected differences between data sets due to GoC and discards data integration. Fishing mortality show similar trends but different levels. Until mid nineties F was ≈ 0.45. In 1995 the highest value was observed, ≈ 0.8, and until 2001 F was kept at a high level. A sharp decline was observed on the next three years but this trend was reversed and in 2007 fishing mortality was estimated ≈ 0.6. Discards mortality showed an increasing trend since 1990, reflecting our assumption that discards resulted from the enforcement of the MLS, with a peak in the second half of the nineties. Spawning stock estimates do not show any relevant differences due to the fact that the main differences among OEMs are in ages 0 to 2, which have a small contribution to the spawning stock. Recruitment levels are quite different although time trends are similar, with high values in the beginning of the series, a decrease until early nineties followed by a stable period and an increase since 2000. The exception was the GoC that showed a strong decrease in recruitment in 2007.

The impact of recruitment scaling without significant changes in spawning stock size had a major effect on the perceived stock-recruitment dynamics. The segmented regression model clearly shows that merging all information suggests a perspective of higher production ($\approx 25\%$) than when excluding such information (Figure 5.4). The WG break point is more than twice higher than ALL's, indicating a lower resilience to low S levels. The DISC data set shows similar productivity to that of WG, whilst GoC presented a low productivity, about 2/3 of ALL. Both show a break point closer to ALL's estimate. Regarding the Ricker model (Figure 5.4) the same productivity scaling exists. The main contrast is in the over compensatory zone of the curve, with WG showing a flatter

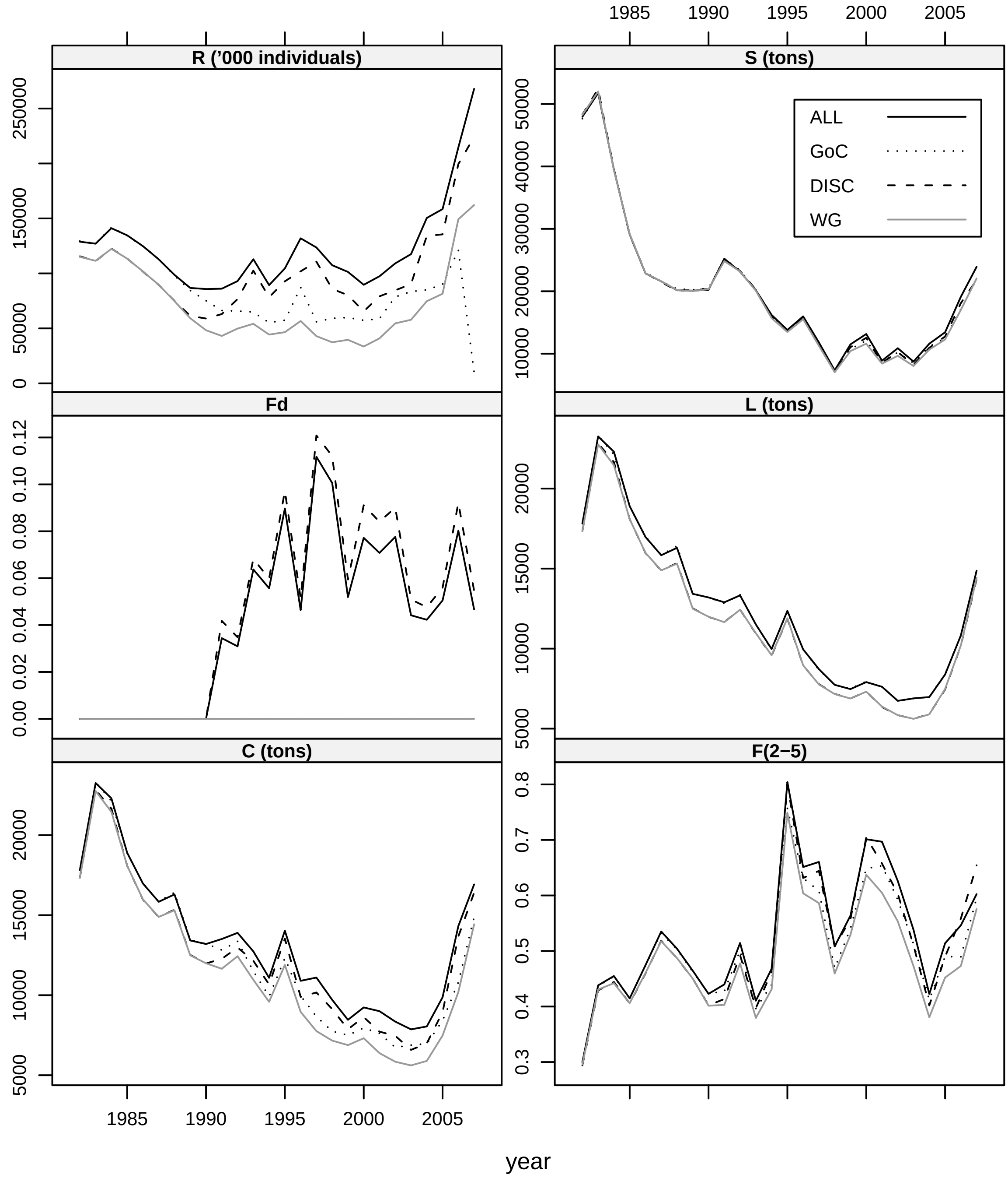


Figure 5.3: Assessment results for each observation error model. The figure shows landings (L), recruitment (R), spawning stock biomass (S), catches (C), average fishing mortality of ages 2 to 5 (F(2-5)) and discards mortality (Fd).

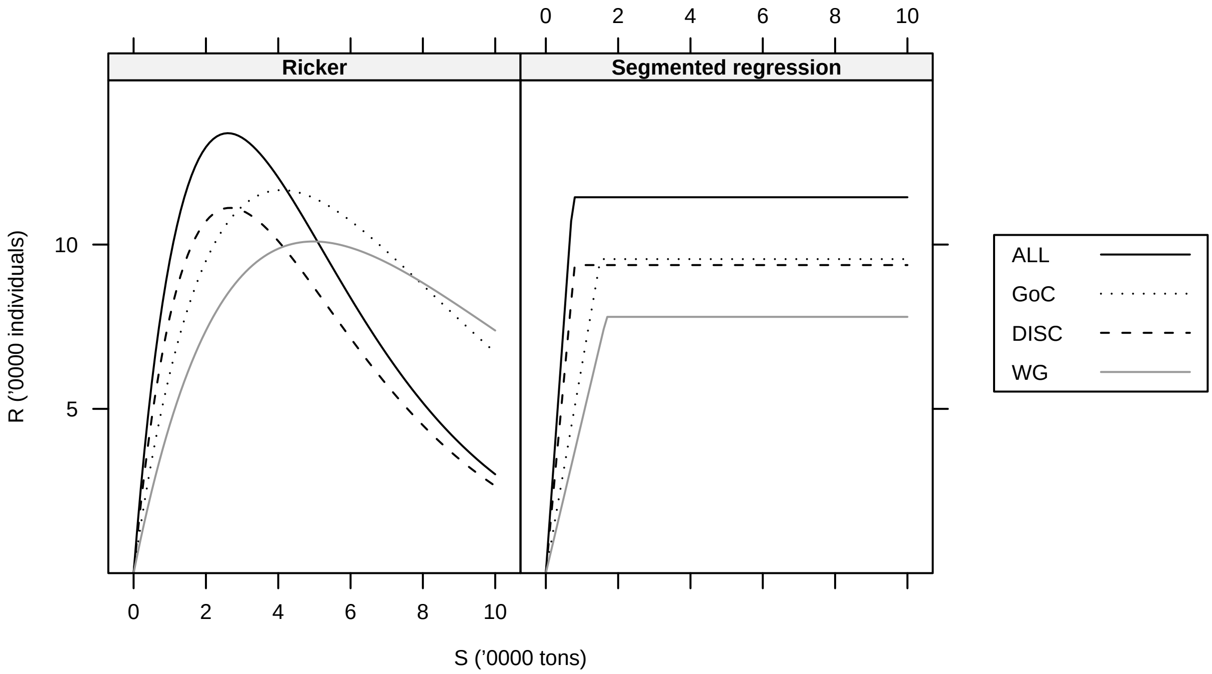


Figure 5.4: Ricker and segmented regression stock-recruitment models adjusted for each observation error model. R = recruitment, S = spawning stock biomass.

curve and ALL a steeper one, while GoC and DISC show intermediate results. The perspectives estimated for OEMs ALL and WG are opposite. ALL shows a stock with higher productivity and a strong density dependent effect, while WG showed lower productivity, less constrained by density dependent effects. Recent high recruitment at low levels of spawning stock corroborate a stock with a high productivity, hence more in agreement with the perspective given by the OEM ALL. A note of caution is however required since the over compensatory zone of the Ricker model is outside the range of observed S, $\approx$ 40 000t, and is estimated with little information.

The distinct stock dynamics estimated for each OEM are summarized by the biological reference points presented in Table 5.4. F_{max} is lower (≈ 0.25) for both models considering discards, ALL and DISC, than for models without discards, WG and GoC, caused by the change in selectivity estimated for different OEMs. This is in agreement with Chen *et al.* (2007) that found overestimation of F_{max} and $F_{0.1}$ when discards are not considered. The distinct Ricker curves show distinct over-compensatory effects that lead F_{msy} estimates to be higher than F_{max}, as well as distinct F_{msy}

Table 5.4: Biological reference points (BRP) estimated for the different observation error models (OEM). Points based on maximum sustainable yield (MSY) are estimated for the Ricker S/R model. F_{07} = fishing mortality estimate in 2007, F_{max} = fishing mortality giving the maximum yield on a yield per recruit curve, F_{msy} fishing mortality that provides MSY, B_{msy} spawning stock biomass at MSY.

BRP	OEM			
	ALL	WG	GoC	DISC
F_{07} ($year^{-1}$)	0.602	0.576	0.595	0.654
F_{max} ($year^{-1}$)	0.252	0.292	0.281	0.25
yearly reduction (%)	7.3	6.2	6.6	7.7
F_{msy} ($year^{-1}$)	0.444	0.316	0.372	0.397
yearly reduction (%)	3.3	5.6	4.7	4.9
B_{msy} ($'000t$)	32.81	51.93	46.91	32.74
MSY ($'000t$)	20.22	20.07	21.80	17.54

estimates for each OEM (Figure 5.4). In particular, the higher F_{msy} for ALL and DISC result of the higher productivity observed at low S levels.

Concentrating on OEMs ALL and WG, the most interesting for our analysis, its worth noting the distinct fishing mortality trajectories induced on the MPs through the MS definition. If a F_{max} strategy is considered ALL will require a F reduction per year 18% higher than WG, due to the fact that the target is estimated to be lower, 0.252 against 0.292, and F_{07} is estimated to be higher, 0.602 against 0.576. However, if a F_{msy} strategy is implemented ALL will require a F reduction per year 41% lower than WG, once that the target is estimated to be higher, 0.444 against 0.316. Such differences raises due to the large change on productivity dynamics estimated by both MPs, which also has a large impact on B_{msy}, $\approx 33\,000$t for ALL and $\approx 52\,000$t for WG. The reason for such behaviour is the steeper fall of recruitment in ALL showing that high levels of S, resulting from low F, are expected to produce low recruitment. The maximum sustainable yield is not so different among the distinct MPs, around 20 000t, which is inside the observed range.

5.4.2 Projections and recovery perspective

Each management strategy was projected for 25 years in each OM for the 1000 replicates generated during the conditioning phase.

Table 5.5: Average relative differences in spawning stock biomass in 2015 between operating models, by observation error model (OEM) and management strategy (MS). MS are coded as "Ftarget:discard multiplier".

OEM	MS					
	fmax:1	fmax:0	fmsy:1	fmsy:0	fsq:1	fsq:0
ALL	-0.110	-0.083	-0.105	-0.123	-0.120	-0.124
WG	-0.087	-0.083	-0.107	-0.119	-0.124	-0.110
GoC	-0.101	-0.089	-0.111	-0.125	-0.125	-0.121
DISC	-0.118	-0.101	-0.119	-0.135	-0.114	-0.128
average	-0.110	-0.089	-0.121	-0.104	-0.121	-0.125

To look for the impact of OM uncertainty on the perception of the stock in 2015, the average relative differences of S in 2015 between OMs for each combination of OEM and MS were computed (Table 5.5). The average relative differences were computed like $\delta = 1000^{-1} \times \sum_i^{1000} (S_i^{(s)} - S_i^{(r)})/S_i^{(r)}$, where s and r refer to the distinct OMs, with segmented regression or Ricker S/R, respectively, and i indexes replicates. The results show that the segmented regression model predicts lower spawning stock biomass than the Ricker model in all MPs, with a minimum of -0.083 and a maximum of -0.135. In average, the F_{max} strategy with discards reduction shows lower values than the other MSs, which can be interpreted has being the most robust MS to uncertainty on the S/R model.

To evaluate the best management strategy the metrics described above were computed for each combination of OEM and OM. Table 5.6 presents the results obtained for OEMs ALL and WG, the most interesting for this analysis and the most extreme cases. The criteria used to highlight these results are shown on the bottom row of Table 5.6.

Overall, the F_{max} strategy with discards reduction shows the best results, with a high probability of rebuilding the stock above 35 000t in 2015, driving S in 2025 to %SPR above 30%, increase landings in 2015 between 1.1 and 1.3 times those estimated in 2007, increase the mean individual weight in the landings in 2015 more than 50% the observed in 2015 (0.3kg), and showing a low risk of having years with low catches.

An F_{max} strategy without discards reduction shows a high probability of recovering the stock combined with a %SPR close to 30% and fairly high increase in mean weight in the landings. However,

Table 5.6: Performance metrics by management strategy (MS), observation error model (OEM) and operating model (OM). MS are coded as "Ftarget:discard multiplier". MP presented are ALL and WG. OM include the Ricker (r) and segmented regression (s). P[S15≥35 000t] - probability of the spawning stock biomass in 2015 being above the target spawning stock biomass defined in the RP, 35 000t; %SPR25 - percentage of virgin spawning biomass per recruit in 2025; Y15/Y07 - yield ratio between 2015 and 2007; MWL15 - mean weight in the landings in 2015; P[Yloss] - risk of loosing fishing opportunities due to 15% TAC constrain; P[Ylow] - risk of having low catches. Values below the adopted criteria, described in the last row, are shown with smaller font.

MS	OEM	OM	Metrics					
			conservation		exploitation		risk	
			P[S15≥35000t]	%SPR25	Y15/Y07	MWL15	P[Yloss]	P[Ylow]
Fmax:1	ALL	r	0.98	29.9	0.95	0.44	0.125	0.000
		s	0.90	33.2	0.84	0.44	0.125	0.125
	WG	r	0.94	26.0	1.01	0.43	0.250	0.000
		s	0.78	27.3	0.90	0.43	0.250	0.125
Fmax:0	ALL	r	1.00	33.9	1.22	0.48	0.125	0.000
		s	1.00	41.4	1.13	0.45	0.125	0.000
	WG	r	1.00	31.4	1.31	0.46	0.375	0.000
		s	1.00	34.8	1.22	0.44	0.250	0.000
Fmsy:1	ALL	r	0.14	14.7	1.06	0.37	0.125	0.000
		s	0.01	14.5	0.91	0.38	0.125	0.125
	WG	r	0.90	23.7	1.04	0.42	0.250	0.000
		s	0.63	24.3	0.91	0.42	0.250	0.125
Fmsy:0	ALL	r	0.96	21.0	1.51	0.39	0.375	0.000
		s	0.81	20.7	1.34	0.39	0.125	0.000
	WG	r	1.00	29.7	1.36	0.45	0.375	0.000
		s	1.00	31.8	1.25	0.43	0.250	0.000
Fsq:1	ALL	r	0.01	08.7	1.00	0.34	0.125	0.125
		s	0.00	08.5	0.86	0.34	0.125	0.125
	WG	r	0.05	09.4	1.03	0.35	0.250	0.000
		s	0.01	09.3	0.88	0.35	0.250	0.125
Fsq:0	ALL	r	0.43	14.0	1.56	0.35	0.375	0.000
		s	0.17	14.0	1.37	0.35	0.125	0.000
	WG	r	0.54	14.7	1.57	0.36	0.500	0.000
		s	0.25	14.6	1.38	0.36	0.250	0.000
criteria			≥0.9	≥30%	≥1	≥0.45	≤0.250 & =0.000	

landings in 2015 are predicted to be lower than in 2007.

On the other side of the spectrum is the F_{sq} strategy. The probability of recovery in 2015 is close to zero, the %SPR in 2025 is below 10%, there are signs that the landings in 2015 will be lower than in 2007, individual mean weights in the landings are slightly above 2007 and the risks of having one year of low catches is consistently estimated across OEMs and OMs.

An interesting perspective arises from a F_{sq} strategy with discard reduction. The probability of recovery is ≈ 0.35 although showing some inconsistencies between OMs. However, S in 2015 is seldom at its equilibrium level and more biomass is expected to develop if fishing mortality is controlled, which gives a fairly good perspective of recovery. Also interesting in this strategy is the expected growth in landings, which is very consistent and the highest of all MSs.

Regarding robustness to uncertainty on the OEM a note of caution is required for the F_{msy} strategy without discards reduction. It shows the most inconsistent estimates, with a particular problem in the probability of recovery. The OEM ALL suggests a very low recovery probability, 0.14 and 0.01, for the Ricker or the segmented regression OM, respectively, while WG suggests a quite high recovery probability, 0.90 and 0.63, under the same conditions. This situation results from the different perspectives about the stock dynamics computed in each MP. Using the ALL data set the MP estimates $F_{msy} = 0.444$ and $F_{07} = 0.602$, which sets the MS reduction to 3.3% every year and drives the stock to $B_{msy} = 32\,800$t. S is seldom at B_{msy} in 2015, once that it will take a few more years to rebuild S to B_{msy} level. When comparing with 35 000t it will hardly show any signs of recovery. The WG perspective is very different, $F_{msy} = 0.316$ and $F_{07} = 0.576$, the MS decision will be to reduce fishing mortality by 5.6% each year, trying to achieve 51 900t, the estimated B_{msy}. Although not yet at equilibrium, S in 2015 will be quite higher and the projects will show a higher chance to recover.

If discards reduction is added to the F_{msy} strategy, the results are more robust with the interesting feature of providing a strong increase in landings in 2015 when compared to 2007, combined with high probability of rebuild the stock above 35 000t.

With the aim of showing the large differences between the best MS, F_{max} with discard reduction, and the worst, F_{sq}, Figure 5.5 presents the time series of spawning stock biomass, recruitment and catch for OEMs ALL and WG, and both OMs. In general results are robust to OEM uncertainty, with the exception of S after 2015 that starts diverging although showing similar trends. Regarding spawning stock biomass, the large differences between both strategies are paramount for both OM. Recruitment estimated by the segmented regression is equal for all scenarios, once that it is independent of stock size. The Ricker model estimates show a decrease reflecting the high spawning stock biomass that lies on the over compensatory side of the curve. Projected catches show that the F_{sq} strategy may raise yield on the first years, opposed to F_{max}, mainly due to the high recruitment estimated in 2006 that will contribute to the fishery until 2010/2011. However, early 2010's catches are expected to decline sharply if the fishery keeps deploying the same level of mortality as now, while driving the fishery to F_{max} is expected to result in a increase in catches on the medium term.

5.5 Discussion

The management strategy proposed by the recovery plan for hake and nephrops (Reg.EC 2166/2005) took into account the worries of the fishing industry, implementing a slow decrease in fishing mortality along a period of ten years, without allowing drastic changes in TAC. Similar management strategies have been suggested for recovery and long term management plans of other stocks (Anon., 2007b; Penas, 2007). In spite of such concerns, the latest assessment of Iberian hake (Anon., 2008b) showed that the fishing mortality reduction aimed by the RP was not achieved. Recent landings are well above the TAC and discards rates of the trawl fleets are high, showing that the current management system was not able to constraint fishing mortality. On a multispecies fishery like the demersal fisheries targeting hake in Iberian waters, catches should not be the main focus of management. Under these conditions, TAC enforcement is hardly successful and very likely to generate discards. Likewise, any over production generated by high recruitment can not be landed by the fleet, increasing discards practices or under reporting, a major criticism made by stakeholders to the current RP. The decision to focus management strategies on fishing mortality

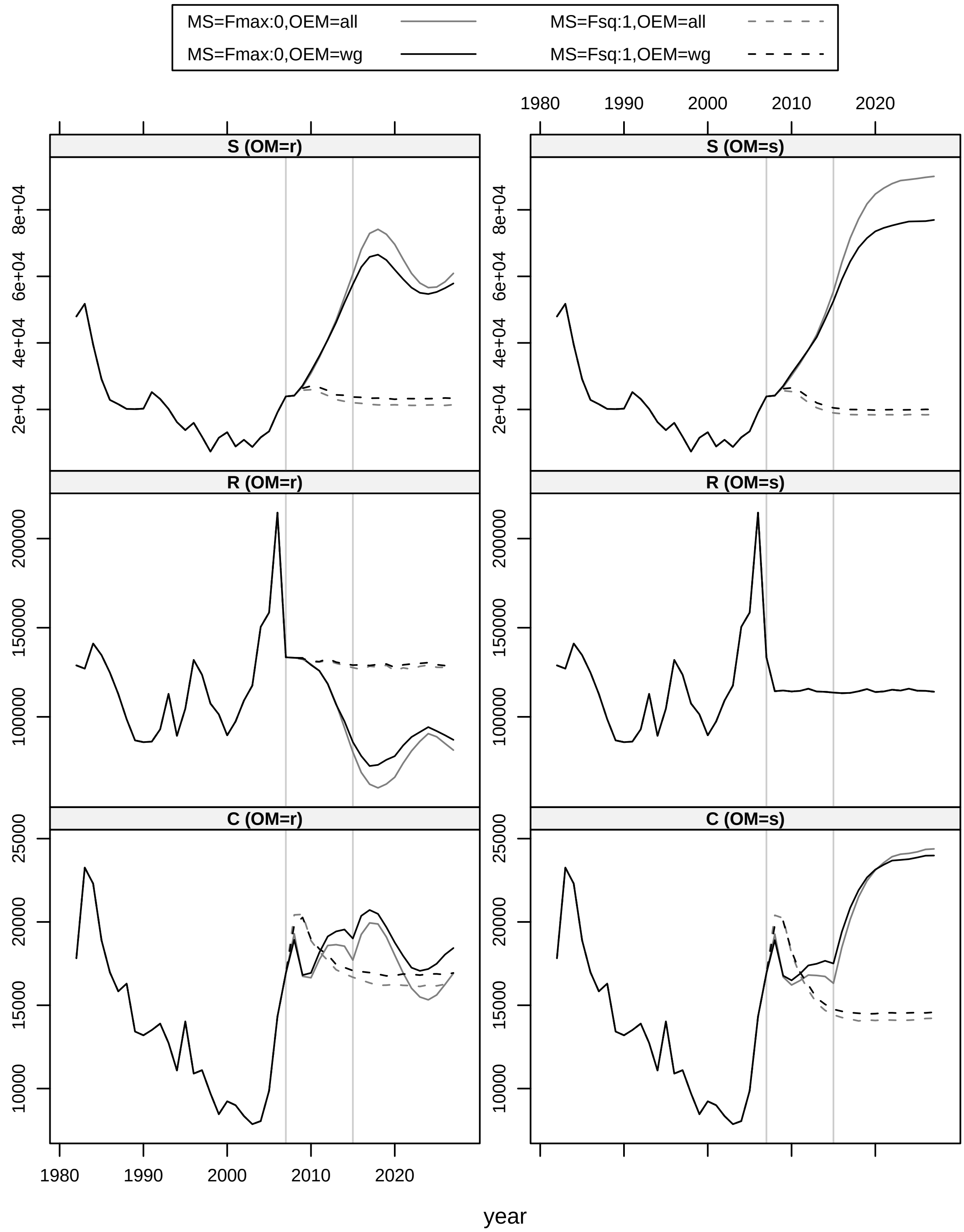


Figure 5.5: Time series of spawning stock biomass (S), recruitment (R) and catches (C) by management strategy (MS), observation error model (OEM) and operating model (OM). MS coded as "Ftarget:discard multiplier", OEM include only ALL and WG, OM include the Ricker (r) and segmented regression (s). Vertical lines refer to 2007, the last year with real data, and 2015, the year set by the recovery plan to have the spawning stock biomass above 35000t.

control is based on this reality. On the other hand, it opens the possibility to focus on managing fishing effort which is expected to be more effective controlling fishing mortality than TACs.

Scientific advice provided by ICES to the European Commission excluded the GoC information and discards from the assessment due to difficulties in rebuilding the time series. Such practice was expected to bias the advice, but until now it was unclear how much it influenced the results. The main impact occurred on the estimation of S/R models' parameters, with a large impact on the BRPs. Not considering discards resulted in the overestimation of F_{max}, caused by a biased estimation of the selection pattern that suggests less mortality at younger ages, and the underestimation of F_{msy}, induced by the estimation of smoother over compensatory effects that imply higher recruitment to be produced at high levels of spawning biomass levels.

Nevertheless, the differences among F_{msy} estimates are larger than among F_{max} or F_{07}. Not surprisingly MSs based on F_{msy} showed the worst performance in terms of robustness. Although all MSs looked fairly robust to distinct S/R models, which had a minor influence on the results during the study period 2008-2015.

A F_{max} strategy with discard reduction showed the highest probability of rebuilding the stock and drive the fishery to a sustainable exploitation. This strategy will lead %SPR in 2025 to be between 30% and 40% (Table 5.6), which Caddy and Agnew (2004) considered safe for groundfish stocks. Reducing discards will raise mean weight in the landings from the actual 300g to more than 450g in 2015, combined with an increase in yield likely to be superior to 20%. This shift in landings' weight and composition is expected to lead the fishery to more valuable landings associated with lower exploitation costs, which eventually will provide higher income and drive the fishery to a wealthier situation than today.

Discards reduction is a sound measure both in conservation and exploitation perspectives. The percentage of virgin biomass, mean weight in the landings and yield showed additional gains in average for all scenarios, respectively 39%, 4% and 42% higher than those predicted without discards. These strategies impose a larger reduction in overall fishing mortality, although not necessarily due to effort reduction. Closed areas/seasons, change in mesh size, inclusion of escape devices on the gear or a combination of all can have the same consequence. Nevertheless, it must be born in mind that there is a risk of allocating fishing mortality from juveniles to large spawners which may have a negative impact in the sustainability of the stock.

Discard management was simulated in a way that is hardly possible to implement, a discard ban. Still it gives an excellent perspective of what could happen if discarding practices are reduced. Results are likely to be less sharp but the overall perspective is valid.

The results obtained support claims that it may be sustainable to keep fishing at the present level. Spawning stock biomass and recruitment are stable, above 20 000t and 140 million individuals, respectively. Nevertheless, spawning stock biomass is around the area of maximum productivity on the Ricker model estimated for this stock, and it was already showed that the S/R model parameters may not be robust. The size of the spawning stock is forecast to be less than 10% of virgin biomass, which keeps the population at a high risk of collapse if a recruitment failure occurs, as observed in the late 90's. Yield forecasts until 2010 are supported by the recent high recruitment but are expected to decline afterwards to levels below those estimated in 2007. Mean weight in the landings will be marginally above the current estimate, which combined with decreasing landings indicate that income is likely to decrease in the future. Considering these results a F reduction strategy is an absolute requirement to drive the fishery to a sustainable level.

The results obtained show that censured catch data in the current assessment, excluding the Gulf of Cadiz and discard, may drive to inappropriate conclusions regarding predictions and probability of recovery. Although this information is scarce before 2000, good recent data are available and the risk of introducing bias in the past is largely exceeded by the improved ability to estimate the present as well as predict the future, providing better advice to managers.

The work presented here moved from the traditional "assessment plus projections" approach carried out by ICES to a MSE approach testing a set of management strategies likely to recover the Iberian hake stock. The results obtained are essential to understand the Iberian hake stock and fishery dynamics in a context of over-exploitation and recovery. Future developments should focus on other relevant sources of uncertainty like growth rates, weight-at-age and maturity-at-age. From a modelling perspective it will be relevant to expand the model and include the spatial dynamics of the fleet and the stock. From a management perspective it would be interesting to explore the multispecies nature of the fishery.

Chapter 6

Conclusions

The analysis carried out to identify the best sampling design showed that a hybrid systematic/random design performs better, both in the simulation study as well as in the field test. Hybrid designs balance good estimation properties provided by the random locations and good predictive properties given by the systematic locations. It is worth noting 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 abundance estimates.

Hybrid designs are seldom considered, if ever, for bottom trawl surveys. However, the results obtained can be applied to other species and the procedures described can be used to develop designs for other surveys. The methodology used to build candidate designs, both for simulation and field testing, is supported by generic principles and can be applied to most fish species. Furthermore, the simulation study considered a wide range of covariance parameters that reflect different aggregation patterns, which can be used for species showing spatial behaviours compatible with the covariance parameters used.

The informal approach adopted to build sampling designs allowed merging promising strategies with the sampling design implemented previously, keeping the continuity with the historical time series. The adoption of a formal criteria and loss function to find an optimum design seems unrealistic due to the multidimensionality of the data, operational constraints and conflicting objectives of inference and prediction. Once that there was not a single criteria, the evaluation of candidate designs relied on spatial modelling and explored several aspects of the same data set looking for consistency among statistics.

The confounding between the sample size effect and the spatial configuration effect, arising from the implementation of systematic designs on irregular spatial domains and the informal approach used to build the sampling designs, was sorted out by introducing the mean abundance variance ratio. This statistic was computed between each candidate design and a simulated random design with the same sample size. The results support its usage for other situations dealing with similar confounding effects.

A set of performance statistics were introduced to reflect relevant characteristics and different aspects of spatial prediction with the objective of analysing the field test results. These metrics were able to distinguish between candidate designs and can be used for other purposes dealing with spatial prediction.

It was shown that computing sampling statistics of abundance for random designs under the presence of spatial correlation underestimates the variance of the overall mean abundance. The partial redundancy between each location of the sampling design is not considered and the quantity of information on the data is over estimated. These findings support claims to consider geostatistical methods to estimate fish abundance so that correlation between locations is explicitly considered in the analysis.

The combined model for abundance-at-age time series, described in Chapter 4 is a full parametric model given by the product of age aggregated abundance and age proportions, reflecting space-time patterns and the age structure of the population, respectively. The example presented for hake abundance off the Portuguese continental coast, used model-based geostatistics with Bayesian methods to model the space-time patterns and compositional data analysis to model the age structure of the population. The factorization in sub-models increases the model flexibility, allowing distinct approaches to be used in each sub-model which promotes the integration of sophisticated methods.

From a modelling perspective the proposed model is simpler and has less parameters than a full specified model, still taking into account the major sources of variability, space-time variability and population structure variability. In comparison with single-age spatial models, the model suggested overcomes difficulties regarding the estimation of spatial parameters. Estimating spatial parameters for all ages with a single-age approach is likely to generate conflicting estimates, which may lead to inconsistent spatial predictions. In extreme situations, due to a large number of null observations for ages not well represented on the sample, it would be impossible to estimate the parameters using single-age models.

In contrast with design-based techniques, the combined model has the advantage of considering spatial correlation as well as demographic dynamics. Furthermore, it can deal with time series of distinct sampling designs along the survey history, an important advantage once that it is not uncommon to change the sampling design along the survey history.

The method advocated produces several abundance indicators, providing an overview of abundance along distinct viewpoints. The analysis of age compositions provides an insight on how the population structure evolves over time and the geostatistical sub-model returns abundance time series and abundance maps.

The parametric specification of the model allows the usage of stochastic simulations and Bayesian methods to generate distributions of all parameters and estimates, suitable to be included in large simulation frameworks like management strategies evaluation.

Chapter 6 presents the evaluation of strategies to implement the recovery plan for Iberian hake, considering the complete removals estimates in weight and numbers of Iberian hake. Discards and landings in the Gulf of Cadiz fishery were rebuild for the first time.

Results showed that a strategy combining reductions of fishing mortality with strong reductions of discard practices is absolutely essential to recover the stock until 2015.

However, recent landings well above the TAC and the high discards rates of the trawl fleets showed that the current management system was not able to constraint fishing mortality. On a multispecies fishery like the demersal fisheries targeting hake in Iberian waters, TAC enforcement is hardly successful and very likely to generate discards. Likewise, any over production generated by high recruitment can not be landed by the fleet, increasing discard practices or under reporting. Under this conditions, management strategies focus on effort management are strongly supported.

A strategy that leads the fishery to F_{max} levels will drive %SPR in 2025 to be between 30% and 40% and increase yield more than 20% with a high probability. Complementary reducing discards will raise mean weight in the landings from the actual 300g to more than 450g in 2015. Both situations combined are expected to lead the fishery to more valuable landings associated with lower exploitation costs, which eventually will provide higher income and drive the fishery to a wealthier situation than today.

In general, discard reduction improves the percentage of virgin biomass, mean weight in the landings and yield for all scenarios. These strategies impose a larger reduction in overall fishing mortality, that can be achieved by closed areas/seasons, changes in mesh size, inclusion of escape devices on the gears or a combination of all.

Besides testing management strategies the analysis focused on testing their robustness to uncertainty on catch information and stock dynamics. All management strategies looked robust to distinct stock-recruitment models, which had a minor influence on the results during the study period 2008-2015. The main impact occurred on the estimation of the parameters of stock-recruitment models, with a large impact on the biological reference points. The differences among F_{msy} estimates were the largest and the management strategies based on this target showed the worst performance in terms of robustness.

The results obtained show that censured catch data in the current assessment, excluding the Gulf of Cadiz and discard, may drive to inappropriate conclusions regarding predictions and probability of recovery. This approach provides an optimistic perspective of the spawning stock biomass in 2015 increasing the risk of failure and compromising the future of the fishery.

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