Estimations of pelagic fish distribution and biomass in the East China Sea using hydroacoustic methods

**(音響調査による東シナ海の浮魚類の分布
および資源量推定に関する研究)**

Doctoral dissertation

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CHAPTER I: GENERAL INTRODUCTION

I.1 Context

The East China Sea (ECS) represents one of the main spawning and nursery areas of small pelagic fishes in the waters off Japanese coasts. It also constitutes an important fisheries ground for commercially valuable pelagic fishes. The pelagic fish stocks have been yearly evaluated using primarily virtual population analysis (VPA) method. Since 1996, acoustic methods have been introduced and the ECS pelagic ecosystem has been monitored annually using acoustic surveys. The deployment of fisheries acoustics has hitherto undergone improvement in terms of duration and coverage of surveys. However, the post-processing of acoustic data has been limited to the calculation of biomass indices.

In this leading work, we tackle the shortcomings in the previous attempts by applying hydroacoustic methods to estimate biomass of commercial pelagic fish species in the ECS. The acoustic data were provided from the fisheries agency (Seikai National Fisheries Research Institute in Nagasaki). The present study is prompted by the need to fulfill the Japanese government desire to improve management of fishery resources in the ESC.

This introductory chapter provides a background to the study. It begins with an overview of hydroacoustic methods role for fish stock assessment, before reviewing its applications and advantages. Finally, the aims and the outlines of the thesis are provided.

I.2 Background

Fish diversity is important for to maintain sustainable productive commercial fisheries. Fisheries that exploit a range of species or a range of populations may have more stable catches than fisheries that exploit a single species (Hilborn *et al.*, 2003). Maintaining such diversity or biological complexity of population structures can only build resilience and

insure a sustainable exploitation of marine resources in the East China Sea (Yachi and Loreau, 1999).

Marine fisheries stock assessment is one of the most important scientific tasks facing the world, due to its role in ensuring the sustainability of marine resources for human consumption. Stock assessment uses various mathematical calculations and statistical techniques to make quantitative predictions of future scenarios of fish population dynamics under alternative management strategies and help managers choose the strategy that would balance harvest with sustainability.

According to several international agreements, countries have to manage their natural resources in ways that conserve both the resource and biodiversity (WSSD, 2002). Achievement of these goals will require holistic assessment and management of fisheries resources and their associated habitat and ecosystems. The stock assessment is a key component of the ecosystem-based fisheries management (EBFM). Consequently accurate fish stock size assessment is crucial for fisheries management.

Earlier studies were typically based on population assessment of commercial or research catch data. These analyses require age-, biomass-, or length-based estimates of abundance (Megrey, 1989; Sparre *et al*., 1989). Historically, net catches are used to obtain abundances, biomass, and length data but costs per sample are high, and samples from any one gear type are representative of a limited bin of the water column. Moreover, results achievement is time consuming. Net-based research surveys can span the geographic range of a stock or species but catches are limited to specific locations in the survey area. So far, in East China Sea waters, the main assessment techniques used to evaluate pelagic fish stocks are based on virtual population analysis (VPA) method. This method makes use of commercial catches which might bias the assessments. Such errors in estimates might generate

overfishing problems (Hansson, 1999; Kuikka *et al.*, 1999). To get rid of these kinds of complications, reliable and fishery independent data are much required.

I.3 Uses and applications of fisheries acoustics

Hydroacoustic methods are one of the few techniques performed in order to provide fisheries independent quantitative estimates of fish stocks. They have undergone a dramatic development in technologies and data management (Simmonds and MacLennan, 2005). Hydroacoustic technology quantifies organism abundance, biomass, and length continuously through the entire water column. Calibrated acoustic instruments are now standard quantitative tools for fishery research and stock assessment. They offer continuous, high resolution observations through the water column, providing a spatial and temporal data (Horne, 2000).

Acoustic surveys using quantitative scientific echosounders commonly employed to determine the abundance and biomass of pelagic fish are becoming increasingly important for the pelagic fisheries management (Koslow, 2009). Owing the common aggregative behavior, small pelagic species appear in echograms as mixture of diverse fish assemblages (Brehmer *et al.*, 2007). First common methods of fish school identification included trawl sampling close to the acoustic targets and expert-based visual interpretation of echograms gained from previous observations of species shoaling patterns. Often, however, these techniques have not enabled unbiased discrimination between co-occurring fish species (Rose and Leggett, 1988). In addition, identifying fish species based on echogram characteristics remains subjective (Cotzee, 2000). Therefore, automated school detection and characterization became more objective and accurate. Measurements of school morphology and internal school features permitted in conjunction with independent evidence to be sure to give reliable echo trace classification and fish school identification

(ICES, 2000). Once fish schools are classified in groups of species having similar acoustic properties, the acoustic estimation of fish abundance remains the ultimate objective. In order to deduce quantitative information about fish targets, such as the number per unit volume, an important requirement is to know the value of target strength appropriate to those fish that have contributed to the received signal.

The addition of correction factors (i.e. TVG, time-varied gain) that compensate for the range dependence of echo amplitudes enabled quantitative estimates of relative abundance. Development of standard calibration procedures (Foote *et al.*, 1987) and studies of relationships between echo amplitude and organism length (Foote, 1987; Furusawa, 1988) facilitated size-based abundance estimates of fish and zooplankton. Echo integration, first described by Dragesund and Olsen (1965), has proved to be reliable technique to estimate the quantity of fish or other scatterers in the acoustic beam, whether or not the received signal contains overlapping echoes (Simmonds and MacLennan, 2005). The determination of the total abundance in the surveyed area needs some assumptions about the density of fish where there are no observations, in zones between the transects which have not been insonified by the acoustic beam. The abundance is calculated independently for each species or category of target for which data have been obtained by partitioning the echo-integrals.

It is common to incorporate target strength (TS) to fish length relationships when estimating fish abundance and when characterizing distribution patterns (Simmonds and MacLennan, 2005). Several equations have been derived to convert horizontal-aspect measurements of acoustic energy into fish length (Love, 1969; Frouzova *et al.*, 2005). When coupled with estimates of fish density, mean fish length estimates can ultimately be converted into a relative index of acoustic fish biomass (Simmonds *et al.*, 1992).

I.4 Aims of the study

In the East China Sea, few attempts to estimate the biomass of pelagic fish populations were undertaken through acoustic surveys. These studies were restricted to subjective fish species classification (Ohshimo, 1996; 2004), whilst, limited to single species in other works for instance Japanese anchovy (Iversen *et al*., 1993; Ohshimo, 1996) and Japanese sardine (Takeshita *et al*., 1988; Ohshimo *et al*., 1998).

The thrust of this study is to examine and to develop a pragmatic stock assessment method based on hydroacoustics which start with identification of target fish species and integrate abiotic factors to understand the distribution of evaluated stock abundance. The ultimate intent is to compare the final results with other assessment methods in order to facilitate the realization of the Japanese government desire to improve management of fishery resources in the East China Sea. The thesis has three main objectives. The first is to examine results of previous attempts of hydroacoustic application in the study area and to classify and to identify acoustically detected fish schools. The second is to address ecological preferences of target species and to investigate relationships between their school properties and environmental factors. The last is to apply post-survey stratification approaches to accurately estimate the density and the biomass.

The thesis begins with a presentation of the study area, survey sampling and acoustic data analysis (chapter 2). The third chapter is primarily concerned with the identification and the classification of detected fish schools. Each school is characterized by a set of descriptors. Two techniques of supervised discrimination are applied and then compared. Their advantages and limitations are discussed with reference to similar studies. On the basis of midwater trawling catch, echo-integrals are partitioned between fish species. Chapter 4 explores and scrutinizes the relationships linking individual fish school

characteristics to environmental factors (temperature and salinity at various depths). Non linear and non-parametric relationships are plotted to better comprehend the effect of environmental factors on school depth, size, abundance and packing density. Chapter 5 describes two approaches of post-survey stratification used to quantitatively assess the coarse pelagic fish stocks in the East China Sea off Japanese coasts. Results presented in this thesis are compared to estimates generated from alternative stock assessment methods. Finally, chapter 6 reviews the application of hydroacoustic method throughout different stages of this study, from post-processing of acoustic data to estimating biomass. Likely sources of uncertainties in biomass estimates are detected and discussed. Helpful suggestions for subsequent works are provided to improve the accuracy of estimations of pelagic fish distribution and biomass in the East China Sea using hydroacoustics.

CHAPTER II: SURVEY SAMPLING AND DATA ACQUISITION

II.1. Survey area

The study area covers off southern western Japanese coasts. It is a part of the East China Sea (ECS) and covers an area of approximately 25 000 nm². It is bounded on the North by the Japan Sea, on the East by the Kyushu Island, on the South by Ryukyu archipelago, and on the West by Korean and Chinese waters. It is connected with the Sea of Japan by the Tsushima strait. The mean water depth of the East China Sea is 370 m, and the continental shelf (<200 m) covers most area of the sea.

The East China Sea off Japanese coasts represents one of the main spawning and nursery areas of small pelagic fishes. It also constitutes an important fisheries ground for commercially valuable pelagic fishes. From 2000 to 2006, the average landing was estimated to roughly 250 000 tons per year and was namely composed of Japanese anchovy *Engraulis japonicus* (Temminck and Schlegel, 1846), round herring *Etrumeus teres* (DeKay, 1842), Japanese jack mackerel *Trachurus japonicus* (Temminck and Schlegel, 1844), chub mackerel *Scomber japonicus* (Houttuyn, 1782), spotted chub mackerel *Scomber australasicus* (Cuvier, 1832) (according to statistics from the Ministry of Agriculture, Forestry and Fisheries, Government of Japan).

II.2 Data collection

2.1 Acoustic data

Echo-integration surveys were conducted annually during late summer from 2002 to 2006 by the Japanese Fisheries Research Agency on board RV Yoko maru. Surveys were carried out along 27 parallel transects spaced by 10 nautical miles (Fig. 2.1). During surveys,

vessel speed was approximately 10 knots and total length of transects ranged from 593 to 828 nautical miles (Table 2.1).

Acoustic data was collected using a hull-mounted SIMRAD EK505 scientific echosounder system operating at 38 kHz. Before every cruise, the performance of the echosounder was monitored using standard target, calibration technique with a copper sphere (Foote *et al*., 1987). Acoustic signals were processed by the EK505 by applying $20\log R+2\alpha R$ time-varying gain (TVG), where R is the range, and 10 dB km^{-1} is the absorption coefficient (α). Operational parameters were chosen as they are used for all five years surveys (Table 2.2). The Elementary Sampling Distance Unit (ESDU) was 1 nmi (1852 m) and data were vertically integrated at 1 m intervals for volume backscattering strength (Sv dB m^{-3}), throughout the water column with the maximum depth of 250 m, which is close to the mean bottom depth of the region. Volume backscattered data were stored on a UNIX workstation in SIMRAD's BI500 data format. Acoustic measurements were logged continuously during all surveys and recorded only during daytime.

Small pelagic fish species may reduce risk of daytime predation by schooling (Connell, 2000). The schooling behavior typically characterizes each fish school in the daytime which is essential for the fish identification. However, during twilight and nighttime, fish schools scatter or overlap, which biases the fish identification in acoustic processing (Brehmer *et al*., 2007; Sassa *et al.*, 2002).

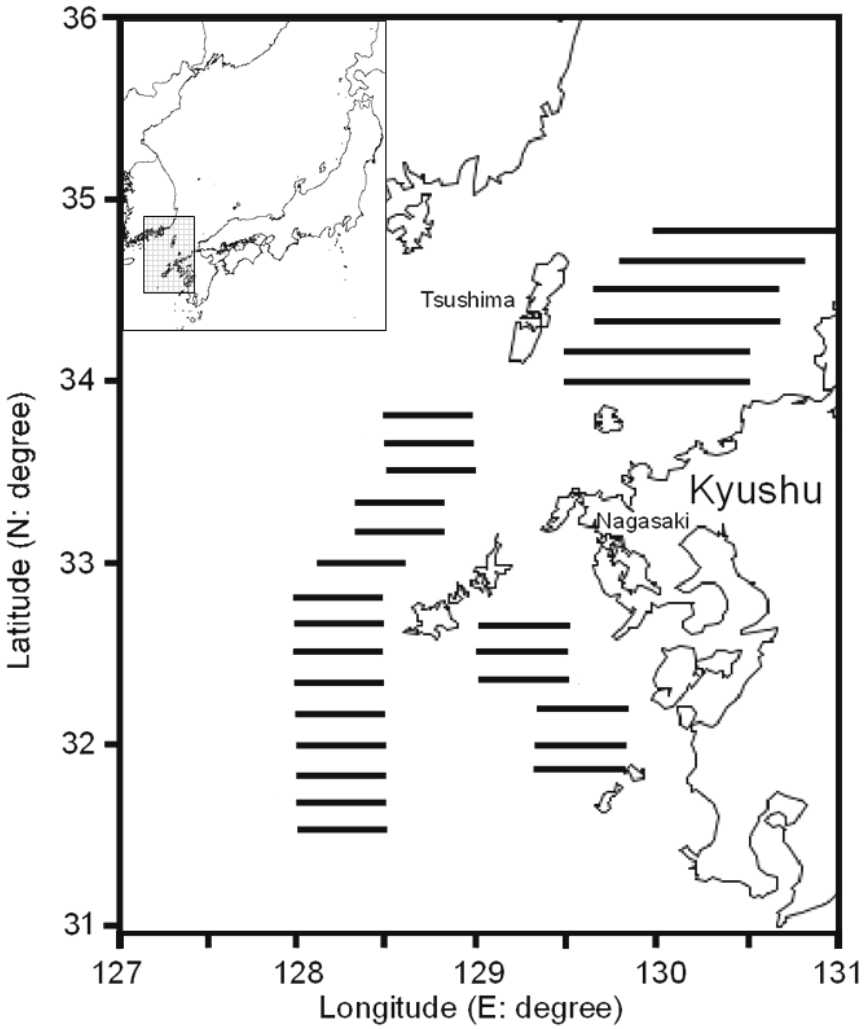


Fig. 2.1 Survey area and acoustic survey scheme.

Table 2.1 Year, begining and end dates, total length of transects, number of detected schools, number of stations of CTD casts and midwater trawls during each acoustic survey.

Year	Begin date	End date	Total length of transects (nautical miles)	N° of detected schools	N° of stations
2002	22 August	24 September	828	221	17
2003	27 August	25 September	828	187	21
2004	24 August	12 September	593	163	12
2005	24 August	10 September	805	168	18
2006	23 August	7 September	791	91	20

Table 2.2 38-kHz settings for the EK505 echosounder used during acoustic surveys.

Parameter	**Unit**
Absorption coefficient	10 dB km^{-1}
Beam angle	12°
Ping rate	0.33 pps
Pulse length	1 ms
TVG gain	- 12 dB
Estimated sound speed	1500 ms^{-1}
Target resolution	0.75 m

2.2 Midwater trawl catch data

The fish composition of midwater trawling catch was used to hence assist partitioning echo-integrals between different fish species. Midwater trawling was only performed at nighttime because of the high net avoidance rate of fish targets in the daytime, which makes it difficult to sample the observed fish schools in acoustic recordings (Suuronen *et al*, 1997). Visual inspection of echograms for several hours permitted the characterization of schooling behavior and swimming depth of target species. The position of the trawl stations was decided based on the expert knowledge and according to the location of peculiar fish concentrations detected during acoustic surveys in the daytime.

A total of 88 midwater trawls were conducted (Table 2.1). Towing speed was approximately 3 knots for a towing time of 30 min. Towing depth was adjusted to fish schools by changing the towing speed and warp length. The mouth of the trawl net was approximately 20 m by 20 m, and the mesh sizes of the cod end and the inner bag were 60 and 20 mm, respectively (Fig. 2.2). The trawl catch was separated by species, and the total weight of each species was determined.

2.3 Other data

Conductivity-temperature-depth (CTD) profiles were taken along the survey tracks at the beginning of each trawling operation yearly from 2002 to 2006 (Fig. 2.3) (Table 2.1). Differential global positioning system (GPS) position and Greenwich Meridian Time (GMT) from the ship's navigation system were appended to each data recording on board before storage. The on-board data recording and entry system, scientific computer system, was used to record series of time, geographic position and the EK 500 vessel log.

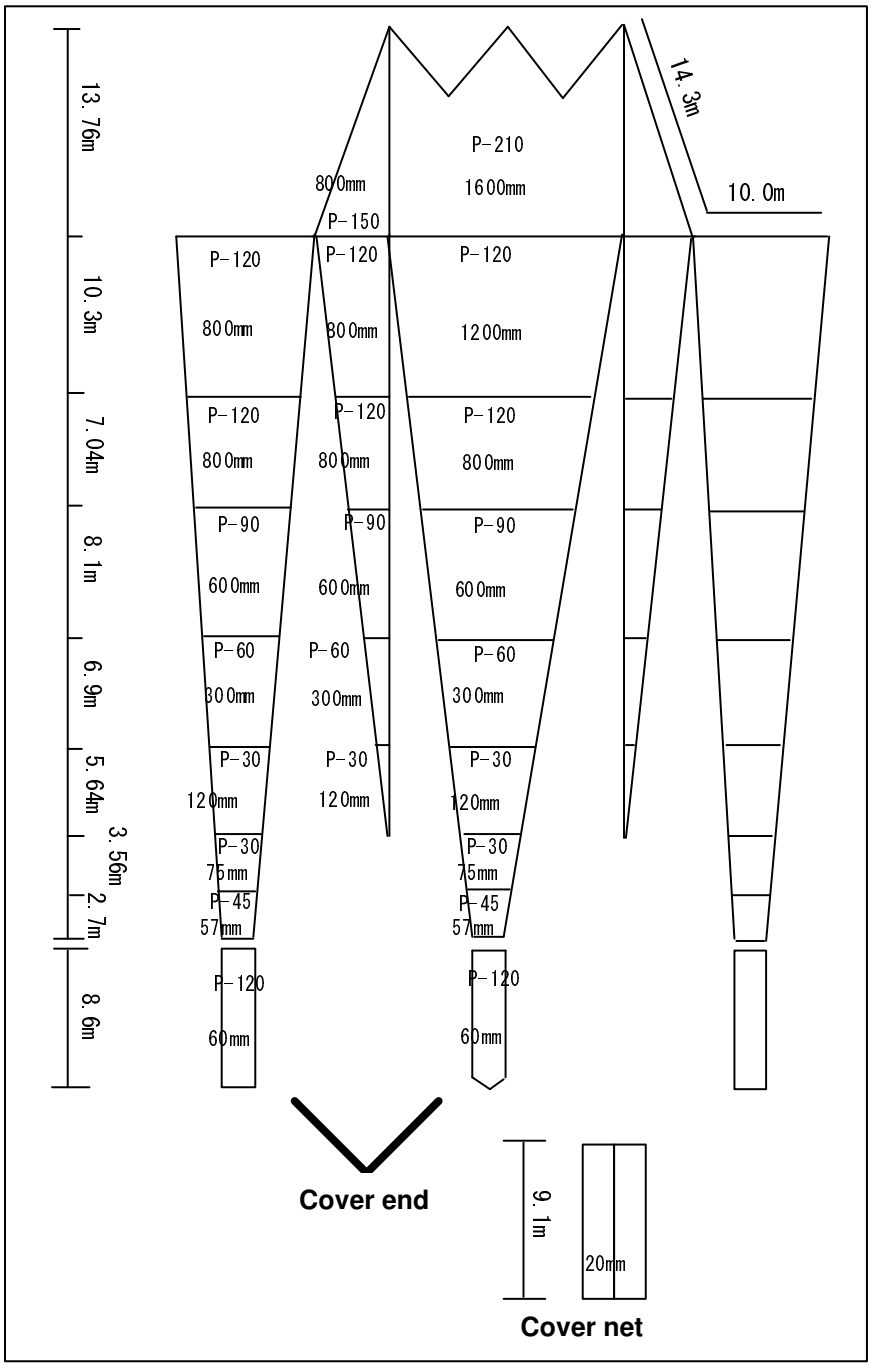


Fig. 2.2 Scheme of the midwater trawl used for fish sampling.

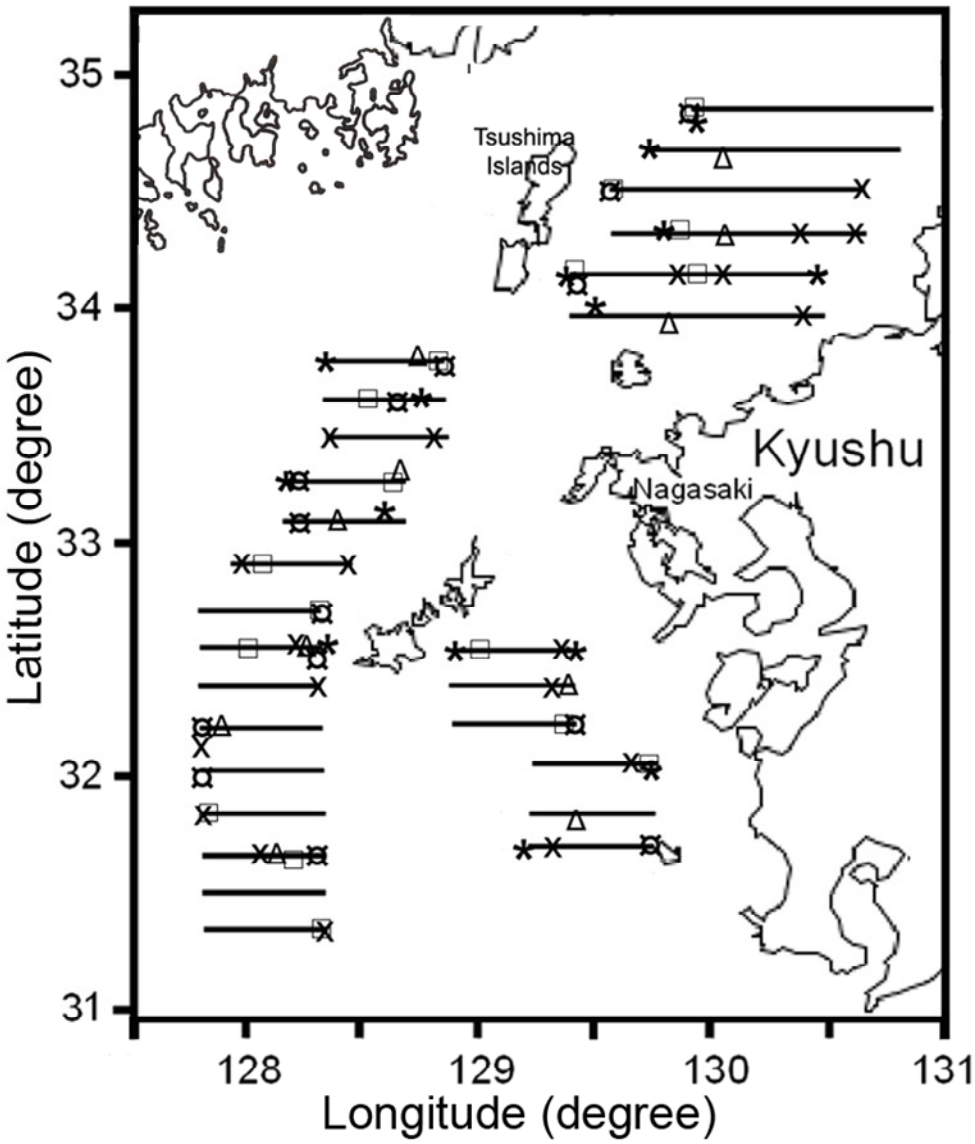


Fig. 2.3 Acoustic survey transects and CTD stations for each year: (Δ) 2002, (X) 2003, (∗) 2004, (□) 2005, (¤) 2006.

II.3 Acoustic data processing

Acoustic data were postprocessed using Echoview Software version 4.50 (Myriax, 2007). The software was utilized to identify ping numbers, ranges, volume backscattering strength (*Sv*) values and water depth. Volume backscattering coefficients (s_v) with 1 m resolution (cells) were digitized using Echoview to generate two-dimensional images.

The volume backscattering coefficient (s_v) is defined as:

$$s_v = \sum \sigma_{bs} / V_0$$

where the sum is taken over all the targets contributing to echoes in the backscattering cross-section σ_{bs} from the sampled volume V_0. The equivalent logarithmic measure is the volume backscattering strength expressed by: $Sv = 10\log_{10} s_v$ (dB m^{-1}). In our data *Sv* is averaged over a volume much larger than V_0, covering a larger range interval and several pings, the logarithmic equivalent is called the mean volume backscattering strength (MVBS) (Simmonds and MacLennan, 2005).

The seafloor was automatically detected using the ‘‘maximum *Sv* backstep’’ algorithm, where the backstep was set at 1 m. Data deeper than 1 m above the selected bottom line were removed due to the false bottom detection. Data shallower than a depth of 10 m were also removed from analyses to eliminate the transmit pulse and reduce backscatter by surface bubbles.

A background threshold of -67 dB was applied equivalently to all echograms. The threshold was determined by analyzing a subset of data collected from each year and allowed accurate detection of all possible aggregations of target fishes. Fish aggregations were detected and characterized using the ‘‘Schools detection’’ module implemented in Echoview. Input parameters were set according to schools’ features observed in acoustic records. The algorithm pattern required schools to be at least 8 m long and 4 m high.

Adjacent aggregations were linked to shape one school if the maximum horizontal linking distance was 15 m and the maximum vertical connection distance 5 m.

Then echograms were visually inspected, and doubtful and 'false' detections (scattering layer, acoustic interference) were removed. Connected aggregations with dimensions smaller than the minimum school length and height parameters were discarded.

For each detected acoustic target, a set of five school descriptors was calculated and extracted, and they fell into three categories (Table 2.3) (Fig. 2.4):

(1) morphological: school length, height and height mean;

(2) energetic: mean volume backscattering strength (*Sv*);

(3) positional: mean school altitude (Depth).

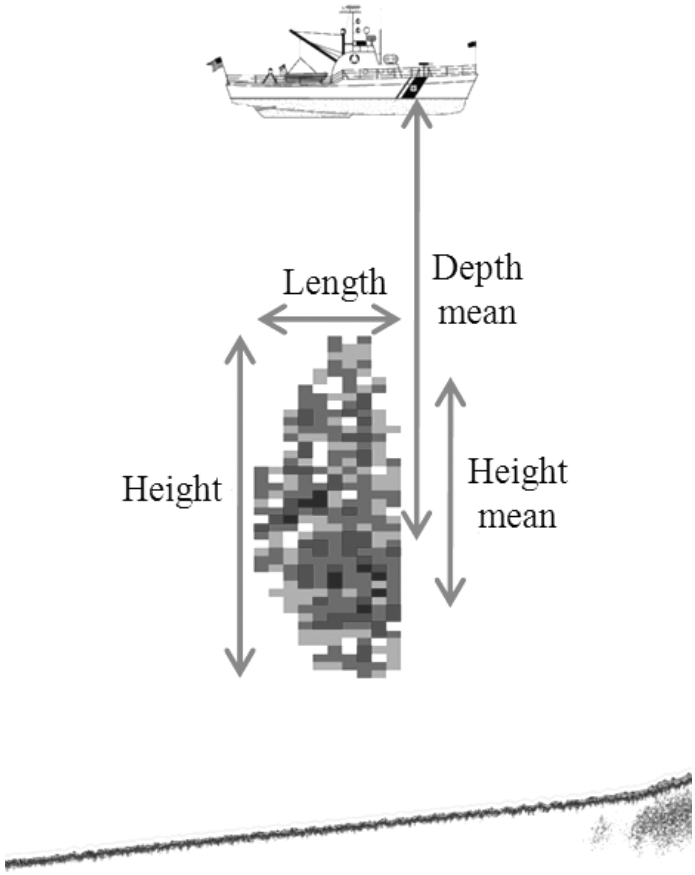


Fig. 2.4 Morphological and positional descriptors measured for one typical school during data processing.

Table 2.3 Definitions and units of school descriptors used in both analysis methods.

Descriptor	Units	Definition
Morphological		
Length	m	The horizontal distance along transect from the first to the last ping crossing the school
Height	m	The vertical distance separating the maximum and minimum depths of the rectangle bounding the school
Height mean	m	The mean distance from the upper to the lower limit along each ping crossing the fish school
Energetic		
Mean volume backscattering strength (*Sv*)	dB m^{-3}	The mean volume backscattering strength which gives an indication of the mean density of the school
Positional		
Mean school depth (Depth)	m	The distance from the sea surface to the geometric center of the fish school

II.4 Fish group classification

The identified target fishes were classified into three types of fish groups according to their schooling characteristics and ethological properties. The verification of this typology also involved the results of the midwater trawl catch amount and composition.

The classification was partially based on the previous findings of Ohshimo (2004) from acoustics surveys conducted following a similar survey scheme on the same study area.

The first type (G1) consisted of compactly aggregated schools, assumed to be Japanese anchovy and round herring, within the upper layer of the water column. The second group (G2) appeared in the midwater layers, mostly above the bottom rise structure, and it was thought to be composed of jack mackerel and chub mackerel. The last group (G3), assumed to consist of lantern fish and pearlside, occurred in demersal layers mainly along slopes and formed horizontally elongated schools in contact with the seabed (Fig. 2.5). Some detected fish schools that did not fall within this typology were neglected.

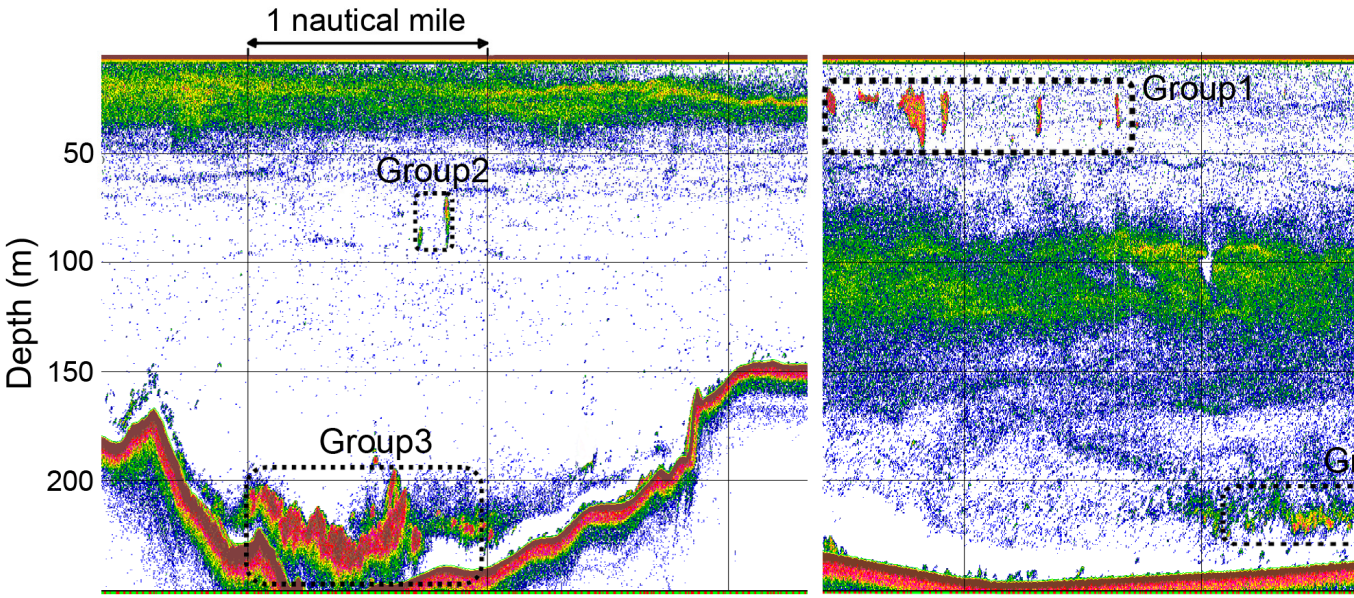


Fig. 2.5 Acoustic recordings showing typical schools of three different fish groups.

CHAPTER III: CLASSIFICATION AND IDENTIFICATION OF FISH SCHOOLS

III.1 Introduction

Development of hydroacoustic technology to remotely detect aquatic organisms is less than a century old, and continues to evolve rapidly. The first biological application of acoustics was to detect the presence of fish in a tank (Kimura, 1929). Following World War II, the utility of echosounders at sea was demonstrated by researchers and fishermen (Sund, 1935; Balls, 1948) who showed that sound could be used to locate and qualitatively visualize distributions, abundances, and behaviors of fish. Experienced commercial fishers were soon combining their knowledge of fishing grounds with the intensity, location, and size of marks on paper echograms to identify fish and shrimp species. Improved resolution and digital sampling of reflected sound has further enhanced the potential for computerized species identification of acoustic targets (Simmonds and MacLennan, 2005). The distinction between fish targets is highly needed to deal with each target fish echoes separately. Although a lot of progress has been made, the classification and subsequent identification of acoustic targets to taxa or species are still the Achilles heel of fisheries acoustics (MacLennan and Holliday, 1996; ICES, 2000).

Fish species identification has been limited by the difficulty in objectively allocating backscattered energy of echo-traces to species (Mackinson *et al*, 2004; Lundgren and Nielsen, 2008). Echo-trace classification defined as the detection and description of aggregations in acoustic data can be used to study behavioral and ecological processes in aquatic environments (ICES, 2000). It is generally agreed that besides integration of target species' biomass, useful information, such as features from digitized echograms, can be extracted from the acoustic data (Horne, 2000).

The early attempts at fish identification introduced basically subjective and time-consuming methods and were followed by several empirical studies that applied simple signal processing techniques to fisheries acoustic data (Rose and Leggett, 1988; Souid, 1988). The availability of inexpensive and high speed, small computers in the late 1980s smoothed the progress of allocation of fish echoes to species. Attempts to use the information from single pings gave way to image processing techniques capable of scrutinizing complete images (Reid and Simmonds, 1993; Richards *et al*., 1991; Lu and Lee, 1994), or as many records independently (Lee *et al*., 1990). The use of wide-band acoustics for classification showed considerable promise in experimental studies (Simmonds *et al*., 1996a; Zakharia *et al*., 1996). A liability to their application is that they are complex to implement and demand equipment which, for now, is well out of the reach of most fisheries research organizations.

Multifrequency acoustic systems were routinely used to separate organisms with markedly different size and swimbladder characteristics, based on their different reflectance at low and high frequencies. Examples of the types of organism successfully discriminated in this way include fish with swimbladders (e.g., hake or pollock) distinguished from euphausiids (Cochrane *et al*., 1991; Kang *et al*., 2002) layers of large copepods, euphausiids, and small fish distinguished on a whale feeding ground (Macaulay *et al*., 1995); and three classes of fish: small fish, large fish with swimbladders (e.g. myctophids vs. macrourids and morids) and large fish without swimbladders (orange roughy) (Kloser *et al*., 2002). In ecosystems where the differences among fish species are less well-defined, various techniques of discriminant analysis between the echo-traces themselves were used, with varying degrees of success (Scalabrin *et al*., 1996; Woodd-Walker *et al*, 2003). Habitat associations have also been used to improve classification (Richards *et al*., 1991).

Several attempts of these methods involved expert scrutiny of echograms combined with concurrent trawling data. Visual scrutiny of acoustic data depends on human experience and is then subject of biases, difficult to be quantified. Objective methods are more efficient, timely, less/or not dependent on subjective interpretation and are controlled by evaluating their accuracy (Jech and Michaels, 2006). These automated methods require data processing and detection of acoustic features from echograms in a first step, and secondly, description of selected schools characteristics with a set of descriptors (Reid *et al*, 2000). They aim to train an algorithm on a set of identified, single species schools. Then the algorithm is adopted to identify other schools (Simmonds *et al*, 1996a; Haralabous and Georgakarakos, 1996). Success of objective methods relies primarily on suitable choice of acoustic descriptors in number and efficiency. Although it may be possible to identify only a small proportion of echo-traces from the acoustic records alone, it is worthwhile to perform a separate analysis of the identified records which will thus not be subject to errors in the interpretation of fishing samples. However, this must not be taken as an excuse to avoid physical verification. The collection of biological samples remains an essential part of the survey procedure. In the case of ecosystems with high fish diversity, such as the East China Sea, where small schools are numerous, species classification highly depends on verification via trawl data.

This first chapter focuses on the identification of pelagic fish community based on acoustic descriptors characteristics. Two objective tools of supervised echo-trace classification are applied: discriminant function analysis (DFA) and artificial neural network (ANN). The DFA options are selected and the architecture of the network is established in order to implement the analysis. The performance of both methods in objectively classifying pelagic fish schools is described and evaluated.

III.2 Material and Methods

III.2.1 Data collection and analyses

The acoustic data acquisition and post-processing are detailed in chapter II (c.f. II.2.1). 830 fish schools were detected from five years data. Each school was characterized by five acoustic descriptors.

88 midwater trawling tows were conducted to obtain biological samples of observed fish schools. Trawls catches provided information on species composition in catch amount, start and end times of the haul (Table 2.1). This information was required to aid the process for fish species identification.

III.2.2 Statistical analysis

Discriminant function analysis (DFA) is a well-known statistical procedure used to predict group membership based on a combination of the interval variable (Duda *et al*, 2001). DFA allows discrimination among fish schools into three groups by resulting in discriminant functions. These functions are generated from schools with known group membership. The functions can then be applied to other schools of unknown group membership given that extracted descriptors values are available.

The five school descriptors constituted the predictor variables for this discrimination analysis, whereas, the dependent variable was fish group (G1, G2, G3) defined a priori on the basis of visual expert scrutiny and direct sampling results.

DFA was performed using SPSS (version 6.0) based on Mahalanobis distances (D). Mahalanobis distance is the distance between a case and the centroid for each fish group (of the dependent variable) in attribute space. Using this procedure, each school is allocated to the fish group for which D has the smallest value (McLachlan, 2004).

Classification accuracy was estimated with leave-one-out cross-validation in which the discriminant function is first derived from only n-1 schools and then used to classify the other school left out. The procedure is repeated n times, each time omitting a different observation (Landau and Everitt, 2004). DFA was applied for overall years data pooled together.

III.2.3 Artificial neural networks

Artificial neural networks (ANN) were also used as a method of species classification and identification of fish schools from acoustic data. They imitate human neuron functioning and solve problems by applying knowledge gained from past experience to new situations (Arbib, 2003). The descriptor values extracted from a certain fish school define a vector pattern that represents this school. So a neural network learns from descriptor patterns of previously identified fish schools and therefore, develops the ability to correctly classify new patterns of further acoustic data.

A multiple layer perceptrons (MLPs) neural network was constructed and computed using Matlab 6.0 (Mathworks, 2008). MLPs are the most commonly and the simplest network type used primarily due to their speed and versatility (Basheer and Hajmeer, 2000). They consist of three feed-forward layers: input, hidden and output (Fig. 3.1). In a neural network model, the weights between neurons are the links between the inputs and the outputs, in effect the links between the problem and its solution. The weights contain all the information about the network. These weight adjustments occur backwards, layer by layer in a looping pattern, starting with the output layer and ending with the input layer.

The iteration step can be summarized by:

$$w_{st}^{new} = w_{st}^{old} + \Delta w_{st} = w_{st}^{old} + \eta \frac{\partial \mathrm{E}}{\partial w_{st}}$$

where E is the error, Δw_{st} is the weight change between neuron *s* to neuron *t* in the next layer and η is the learning rate. The learning rate is chosen to balance the speed and the convergence of the iteration process. Specifically, the smaller η is, the more training iterations will occur and the minimization process will tend to converge.

The input layer was composed of five variables. The number of nodes in the hidden layer was determined by testing the performance of the model using a range of node numbers. The dependent variable fish groups represented the output layer. The data set was split into a training set and validation set consisting of 70 and 30% of the identified schools, respectively, with the same proportion of each fish group. Based on supervised learning, the neural network was trained by means of a backpropagation learning algorithm (BP) in order to develop the ability to correctly classify new fish schools from further acoustic data (Rumelhart *et al*., 1986).

The fish school classification based on their relative descriptors occurred in two major phases. First, during the learning phase, internal parameters within the network were adjusted iteratively. The performance of the network, equivalent to classifying schools into fish groups accurately, was maximized. This stage continued until there was no further increase in network performance or classification success. Although the aim of the training is to reduce the error as much as possible. However, decreasing the error too much leads to the network learning the noise rather than underlying relationships. Precautions were taken to avoid over-fitting (over-training) of the network's model. Finally, during the validation phase, which is the second phase, the optimal network was applied to test sets, along with cross-validation.

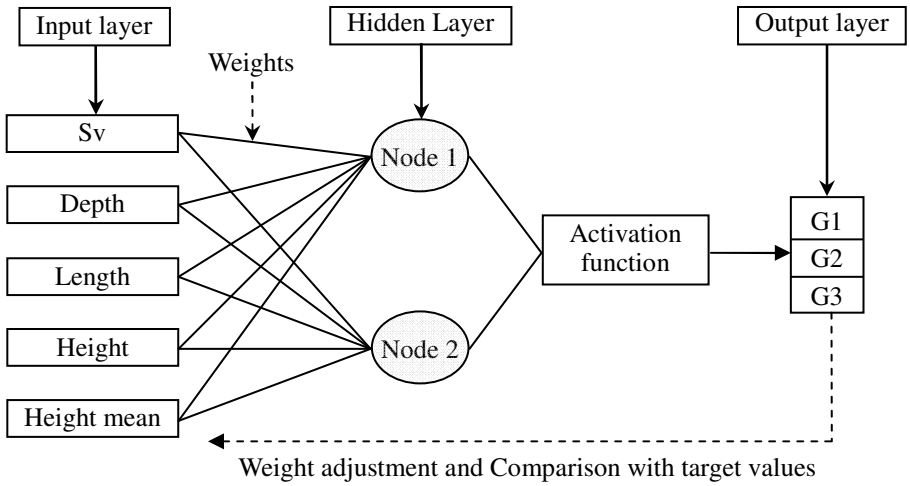


Fig. 3.1 Network architecture for the model used for ANN application.

III.3 Results

III.3.1 Classification using discriminant function analysis

Discriminant function analysis was computed using 830 detected schools and five acoustic descriptors (Tables 2.1 and 2.3). Since the dependent variable, fish school, has three groups, two canonical discriminant functions were determined. Both functions were significant, but nearly all of the variance in the model was captured by the first discriminant function (Table 3.1). The small Wilk's lambda coefficients indicated that only the first function was reliable. The eigen values confirmed the significant difference between both discriminant functions. The standardized discriminant function coefficients were used to compare descriptors measured on different scales. Coefficients with large absolute value correspond to variables with greater discriminating ability. This implies that within the first function, for instance, depth contributed the most. Thus, descriptors in rank order of efficacy in discriminating fish schools are depth, height, height mean and length, while mean volume backscattering strength *Sv* comes last.

The confusion matrix showed the results of the DFA using five acoustic descriptors for discriminating fish schools (Table 3.2). Emboldened values on the main diagonal of each confusion matrix represent the number of schools that were correctly identified within every fish group. The overall correct classification was evaluated at 85.1%. The correct recognition rates per group showed high scores for G1 schools. Almost 95% were well assigned and distinguished from other groups. G2 schools represent 57% of the total number of schools and were the least correctly classified with a relatively low rate of 80.3%. The proportion of G3 schools is small, with only 13.2%, and had a correct classification score of 81.8%.

Table 3.1 Results of discriminant analysis using five descriptors for overall year data

Analyzed school group discriminant function	Wilk's λ	% of Variance	Eigen value	Standardized canonical discriminant function coefficient					Significance Level
				Depth	Height	Height mean	Length	*Sv*	
First function	0.269	94.6	2.291	0.971	0.305	-0.304	0.158	0.043	0.000
Second function	0.885	5.4	0.130	-0.296	0.537	-0.424	0.835	-0.093	0.000

Table 3.2 Confusion matrix of DFA analysis.

		Predicted groups				
		G1	G2	G3	Total	% Correct
Observed groups	G1	**234**	10	0	244	95.9
	G2	62	**382**	32	476	80.3
	G3	5	15	**90**	110	81.8
	Overall	301	407	122	830	85.1

Number of schools from each group (true classification) distributed over predicted groups. Emboldened values denote correctly classified schools.

III.3.2 Classification using an artificial neural network

Application of the trained network to five years of pooled acoustic data resulted in predicted species composition that corresponded well to those observed with an overall correct classification evaluated at 87.6% for the validation data set (Table 3.3). The model performed well for classifying G1 schools with a correct classification rate of 95.9%, but less for G3 and G2 schools, with 84.8 and 83.9%, respectively.

The contribution factor of a variable is the sum of the absolute values of the weights generated from this particular variable. It reveals the importance of input variables, descriptors, to classify fish schools. The analysis showed similar ordering of descriptor categories to DFA results and indicated that the heaviest impact in classifying was assigned to positional, morphological and then energetic properties of a school. However, the ascending order within the morphological descriptors category differs slightly though depth was the most efficient descriptor (Fig. 3.2).

Table 3.3 Results of ANN classification from the two data sets.

		Predicted groups				
		G1	**G2**	**G3**	**Total**	**% Correct**
Observed groups	Training data set					
	G1	**169**	3	1	173	97.7
	G2	21	**297**	13	331	89.7
	G3	1	6	**69**	76	90.8
	Overall	191	306	83	580	92.2
	Validation data set					
	G1	**71**	3	0	74	95.9
	G2	15	**120**	8	143	83.9
	G3	1	4	**28**	33	84.8
	Overall	87	127	36	250	87.6

Emboldened values represent correct assignment.

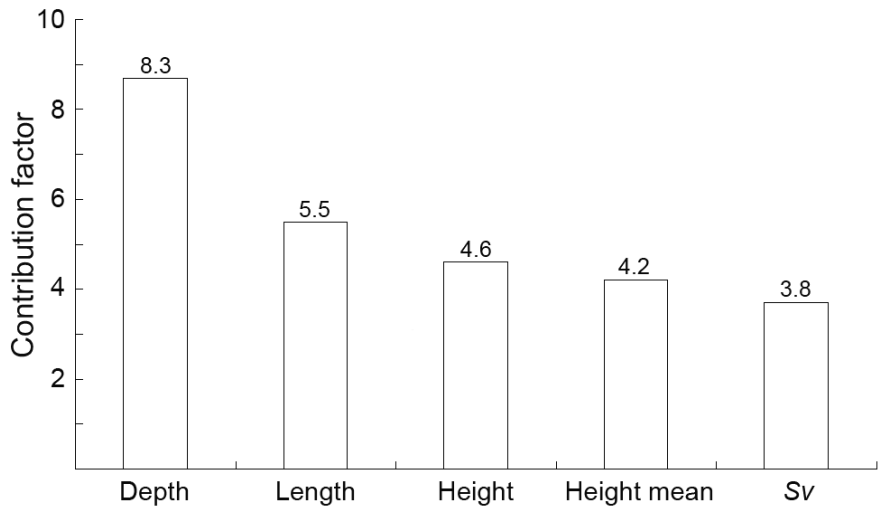


Fig. 3.2 Proportion of the contribution factor of each descriptor used as input into the artificial neural network.

III.3.3 Validation with catch data

Midwater trawling catch assisted in fish identification concurrently with expert-based scrutiny of echograms. Examination of catch data over all 88 tows showed that the dominant target species was jack mackerel, which contributed 22% by weight of the total catch, followed by Japanese anchovy (18.4%) and lantern fishes (16%) (Table 3.4). Round herring was an exception in 2002 and was the most abundant species, reaching 20% by weight of the total catch in the same year. The non-target species that did not fall in the three identified categories of major species were clustered into one group as ‘‘others’’ and represented around 28% of the total catch amount (Table 3.4). Catch composition was also valuable to verify the classification of target species into three groups of fish schools. Table 3.5 shows catch composition data from selected trawls hauled near the locations where schools of G1, G2 or G3 were observed in the daytime. Each group of species was assigned according to the most dominant species comprised in each trawl catch.

A summary of trawl hauls with fish schools matching with acoustically detected schools is shown in Table 3.6. The catch composition according to the amount and number of trawl hauls is summarized in Tables 3.5 and 3.6. Throughout the overall data, the number of detected schools evenly matched with the pooled total catch amount of target species. The correspondence between detected and caught G1 schools was estimated to be 44% by weight of the catch from 11 hauls, mainly made up of Japanese anchovy as it is the most abundant species in G1. The mismatch is primarily due to the high amount of catch of the G2 and G3 species. Around 34% of the detected G2 schools were validated by catch data from 11 hauls. Other co-occurring species, mainly represented by puffer fishes and squids, made up 43% of the total catch amount and were fairly abundant in 15 hauls; some of them were small catches (less than 2 kg). In the case of G3 schools, nearly 41% by weight of

identified schools were validated by catch results. Bycatch species that were caught during the same trawl hauls represented 33% of the total catch but belonged to one trawl haul.

Table 3.4 Catch amount (kg) of abundant species assumed to compose fish groups.

Fish group	Species		2002	2003	2004	2005	2006	Total
	Scientific name	Common name						
Group 1	*Engraulis japonicus* (Temminck & Schlegel, 1846)	Japanese anchovy	44.2 (13.4)	7.2 (1.8)	55.4 (42.0)	36.9 (9.3)	139.7 (49.1)	283.4 (18.4)
	Etrumeus teres (DeKay, 1842)	Round herring	67.7 (20.5)	10.8 (2.7)	0.9 (0.7)	5.5 (1.4)	23.0 (1.8)	107.8 (7.0)
	Sardinops melanostictus (Temminck & Schlegel, 1846)	Japanese sardine	0	0.1 (0.03)	0.1 (0.1)	0.1 (0.03)	0.7 (0.2)	1.0 (0.1)
Group 2	*Decapterus macrosoma* (Bleeker, 1851)	Shortfin scad	7.3 (2.2)	6.4 (1.6)	3.4 (2.6)	0.9 (0.2)	3.0 (1.1)	21.0 (1.4)
	Decapterus maruadsi (Temminck & Schlegel, 1843)	Round scad	0	0.2 (0.1)	0	28.1 (7.1)	0.3 (0.1)	28.6 (1.9)
	Scomber japonicus (Houttuyn,1782)	Chub mackerel	2.1 (0.6)	0.5 (0.1)	0.6 (0.5)	8.4 (2.1)	0	11.6 (0.8)
	Scomber australasicus (Cuvier, 1832)	Spotted chub mackerel	0	0	2.8 (2.1)	8.4 (2.1)	5.6 (2.0)	16.8 (1.1)
	Trachurus japonicus (Temminck & Schlegel, 1844)	Japanese jack mackerel	38.6 (11.7)	215.1 (54.2)	35.0 (26.5)	37.6 (9.5)	15.1 (5.3)	341.4 (22.2)
Group 3	*Diaphus* spp (Eigenmann& Eigenmann, 1890)	Lantern fishes	0	43.3 (10.9)	3.8 (2.9)	191.7 (48.5)	7.3 (2.6)	246.1 (16.0)
	Maurolicus japonicus (Ishikawa, 1915)	Pearlside	0.8 (0.2)	0.1 (0.03)	0.1 (0.1)	50.2 (12.7)	0.1 (0.4)	51.3 (3.3)
Others	*Arothron* spp (Müller, 1841)	Puffer fishes	113.8 (34.4)	60.6 (15.3)	8.6 (6.5)	0.8 (0.2)	0.6 (0.2)	184.3 (12.0)
	Auxis rochei (Risso, 1810)	Bullet tuna	6.3 (1.9)	0	0	1.9 (0.5)	3.9 (1.4)	12.1 (0.8)
	Diodon hystrix (Linnaeus, 1758)	Porcupinefish	0.9 (0.3)	0.2 (0.1)	0	0	32.0 (11.2)	33.1 (2.2)
	Loglio edulis (Hoyle, 1885	Swordtip squid	5.9 (1.8)	8.7 (2.2)	8.3 (6.3)	16.6 (4.2)	14.4 (5.1)	53.8 (3.5)
	Psenopsis anomala (Temminck & Schlegel, 1844)	Melon seed	0.2 (0.1)	1.7 (0.4)	0	5.9 (1.5)	4.7 (1.7)	12.4 (0.8)
	Todarodes pacificus (Steenstrup, 1880)	Japanese common squid	6.7 (2.0)	2.6 (0.7)	0.7 (0.5)	2.0 (0.5)	1.6 (0.6)	13.5 (0.9)
	Others		36.4 (11.0)	39.3 (9.9)	12.4 (9.4)	0.8 (0.2)	32.7 (11.5)	121.5 (7.9)
Total catch of all species			330.9	396.8	131.9	395.4	284.5	1539.5

Values between brackets in lower line represent percentage (%)

Table 3.5 Comparison of acoustically detected schools with trawl catch composition.

			Caught species								
			G1			G2			G3		
	Fish group	Number of hauls	Japanese anchovy	Round herring	Japanese sardine	Jack mackerel	*Scomber spp*	*Decapterus spp*	Lantern fishes	Pearlside	Others
Detected schools	G1	11	**184.6 (40.7%)**	**16.5 (3.6%)**	**0.5 (0.1%)**	142.2 (31.3%)	1.2 (0.3%)	2 (0.4%)	92.4 (20.4%)	0.1 (0.02%)	30.35 (6.7%)
	G2	28	58.6 (11.9%)	28.3 (7.3%)	0.05 (0.01%)	**138.7 (28.1%)**	**11.7 (2.4%)**	**20.2 (4.1%)**	22.8 (4.6%)	0.1 (0.02%)	213.42 (43.2%)
	G3	7	10.4 (5%)	41 (19.7%)	0	0	0.2 (0.1%)	2.1 (1%)	**34.2 (16.4%)**	**51 (24.5%)**	**69.45 (33.3%)**

Upper line of each row represents catch amount by kg. Lower line indicates percentage of catch amount

Table 3.6 Summary of acoustically detected schools with most abundant caught specie in number of trawl hauls.

		Caught species				
		G1	G2	G3	Others	Total
Detected schools	G1	6	1	2	2	11
	G2	4	11	1	15*	28
	G3	3	0	3	1	7

* 5 hauls scored less than 2 kg of total catch per haul

III.4 Discussion

III.4.1 Comparison of classification methods

In this study, ANN and DFA models were optimized in order to classify fish schools. Both techniques showed nearly similar recognition performance. The overall classification rate was higher for ANN than DFA, but was only slightly higher. As for the three fish groups' relative classification, there were minor differences in classification success based on the two specified methods. In particular, differences were trivial for G2 schools, whereas the successes of discrimination of G1 and G3 schools were significantly more important with ANN than DFA (Tables 3.3 and 3.2). The particularly effective power of ANN to classify fish schools is attributed to its ability to handle non-linear relationships between descriptors and dependent variables, through the presence of many intervening information processing units, which each uses the binary logistic activation function (Basheer and Hajmeer, 2000). ANN established functional relationships of the data by learning from the input training data set (Chen and Ware, 1999; Cabreira *et al*., 2009). A further advantage of ANN is the small impact of extreme values on discrimination success and the absence of any specific assumptions on the distribution of the data. On the other hand, despite these advantages, a liability of its application is that it needed much more computing time than discriminant analysis, especially during optimization procedures.

Similar performances of ANN and DFA in identifying fish schools corroborate our findings that ANN is more effective than DFA (Simmonds *et al*., 1996a; Haralabous and Georgakarakos, 1996; Woodd-Walker *et al*., 2003). Moreover, they reported better, sometimes far better, overall classification rates. These mentioned case studies inferred that an increasing number of descriptors should lead to an improvement in

discrimination efficiency. However, Scalabrin *et al* (1996) found a lower rate when classifying only three species using nine school parameters. Theoretically, the greater the number of parameters that can be included in the model, the more likely the analysis will assign a school image to the correct group (Haralabous and Georgakarakos, 1996). However, in our practical analysis, for both classification methods we were limited to five acoustic descriptors as input variables.

III.4.2 Factors controlling fish-group classification

The fish schools classification is defined as the discrimination of acoustic backscatters to the species, genus or group level, depending on the richness of fish diversity (Jech and Michaels, 2006). In the present work, the classification of fish echo-traces into three fish groups was reliable due to the high fish diversity in the East China Sea. The acoustic responses of numerous target species were categorized based solely on their schooling characteristics.

The feasibility of this approach is justified by the existence of acoustic populations. Groups of echo traces show a consistent pattern in space and time at a regional scale (Petitgas *et al*., 2003). In tropical waters, Gerlotto (1993) succeeded to divide highly multispecific fish communities into four fish acoustic populations. However, for some marine systems at high latitudes, such as the North Atlantic Ocean, species richness is relatively poor. The low number of target fishes and the occurrence of monospecific schools permitted a lower level of discrimination and yielded a higher successful classification rate (Scalabrin *et al*., 1996).

The vertical distribution of fish schools in the water column gave evidence of the typology applied in this study. G1 schools existed predominantly in the upper layer of

the water column above the thermocline detected at approximately 50 m depth (Fig. 3.3a). The G2 schools were observed within a deeper layer below the thermocline.

G3 schools were distributed in the bottom half of the water column below a depth of 150 m until the closest layer to the sea bottom. The vertical distribution of G3 species is in agreement with the vertical range (160-200 m) reported by Fujino *et al.* (2005) in the case of pearlsides and below a depth of 200 m in the case of mesopelagic lantern fishes (Watanabe *et al*., 1999).

The vertical distribution of fish schools exhibited a noticeable pattern that corresponds to the overlap of G1-G2 schools and G2-G3 schools in water layers at 60-80 m and 160-180 m, respectively. Fish schools co-occurring within these depths could not be discriminated properly on the basis of the positional descriptor. Both methods (DFA and ANN) resulted in relatively weaker performance within these overlap layers; the correct classification rate did not exceed 88%.

Notwithstanding the fair limitation of fish-group classification within 'overlap' layers, the results of DFA and ANN revealed that the school's depth was the most effective acoustic descriptor in successfully discriminating schools into the three groups. On the other hand, morphological acoustic descriptors and backscattered volume *Sv* contributed to distinguishing among species. In fact, the G3 species pearlsides and lantern fishes formed generally large elongated aggregations that were fairly dense and characterized by relatively low *Sv* values. The G2 species jack mackerel, spotted mackerel and chub mackerel aggregated in relatively smaller schools marked by higher *Sv* values (Fig. 3.3 b, c, d).

Although the vertical distribution of the target fishes cannot be addressed in detail within the scope of this work, it provided valuable information about the environmental

and physiological properties of identified target species. The occurrence of Japanese anchovy, Japanese sardine and round herring above the thermocline was most likely related to temperature gradient patterns. Temperature at the sea surface varied between surveys from 26.5 to 28.8°C, and the thermocline is found to occur at 50-60 m depth, (Fig. 3.4). The thermocline might have played the role of a barrier that restricted the migration of these species to deeper layers. Thus, the thermal barrier implicitly facilitated the identification of species confined to the upper layers (Ohshimo, 1996).

The availability of food as well as avoidance of predation could also be plausible key factors concerning the vertical distribution patterns (Zwolinski *et al*., 2007). Small fish may have migrated to a depth level with a lower concentration of larger fish to avoid predation (Watanabe *et al*., 1999). Myctophids and pearlsides fishes feed on zooplankton (Chen, 1994). They ascend from the sea bottom at night following food and prey patterns and are thought to compete for food with pelagic fish within the upper layer (Ohshimo, 1996; 2004).

III.4.3 For a better fish identification

Several works have been using multiple frequency echosounding to allocate fish echoes to species by using the frequency difference in mean volume backscattering strength (MVBS) and target strength differencing (Anderson *et al*., 2007; Gauthier and Horne, 2004). These methods showed a considerable promise and provided high rates of correct classification in restricted ecological situations, that is, none have provided a classifier which can be applied over broad ranges of time and space (LeFeuvre *et al.,* 2000). In the East China Sea particularly, owing to the high fish diversity, the use of an extended number of narrowband acoustic frequencies may ameliorate the fish species

identification. More precisely, low frequencies might be the best to increase species discrimination, for instance, midwater layers of mesopelagic fish appear much stronger on 12 kHz than on 38 kHz (Barr, 2000; O'Driscoll, 2003).

Simultaneously, with more accurate acoustic surveys, additional trawl data should facilitate the discrimination between fish species within each group. In parallel, the increase in the amount of collected data enhances ANN training and thus its efficacy.

Taking the advantage of its fast performance and the speed of processing using modern computers, the application of ANNs in real-time classification would be advantageous in fisheries stock assessments.

In the same order of magnitude, further statistical analysis should be performed to evaluate the consistency between acoustic data and trawl data. Ideally, the fish schools detected during daytime acoustic surveys will be caught using the midwater trawling conducted only at night time. The horizontal migration of fish may bias the verification of identified fish schools using trawl data. However, in this present work, the time lag was neglected since the same fish schools observed on echograms were meticulously chosen to be caught. Quantification of uncertainty of the match between both data sets may lead to improve the objectivity of fish identification and classification.

III.5 Conclusion

The study has demonstrated that neural network can perform reasonably well in classifying fish schools, and slightly better than discriminant function analysis. The survey provided a learning sample by combining synchronous "ground truth" (biological) data from trawl catches with two techniques of recognition and

classification. One significant finding of this analysis is the considerable fish-group discrimination provided by the use of a set of five descriptors including positional, energetic and morphologic school criteria. The choice was made to cover many school features while avoiding parameters likely to generate redundant information. For both methods, it was concluding that adding other acoustic parameters (such as skewness and school elongation) during model optimization led to a decrease in the overall classification rate. In some studies, more complex criteria were implemented to parameterize the shape and intrinsic structure complexity of the school (Haralabous and Georgakarakos, 1996; LeFeuvre *et al*., 2000). These authors recognized that using such descriptors are satisfactory for classification purpose of large schools but likely to become not valuable to some extent with smaller schools.

In this first step of the thesis, I succeeded to improve potentially the objectivity of the identification and discrimination of fish species, illustrated by high correct classification rates accounted for both tools of analysis. The work on these approaches continues with an expanded acoustic data set of all three group species.

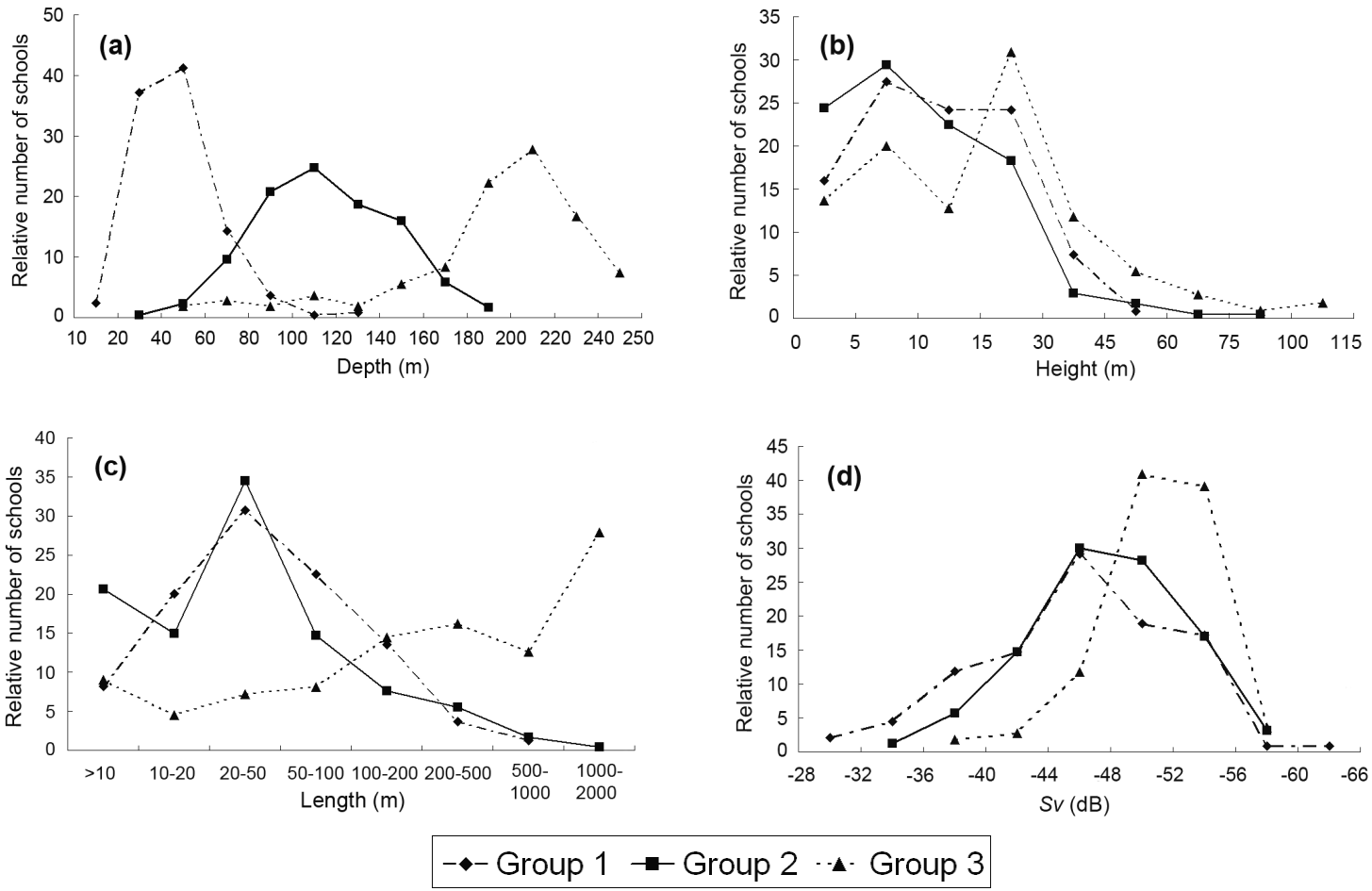
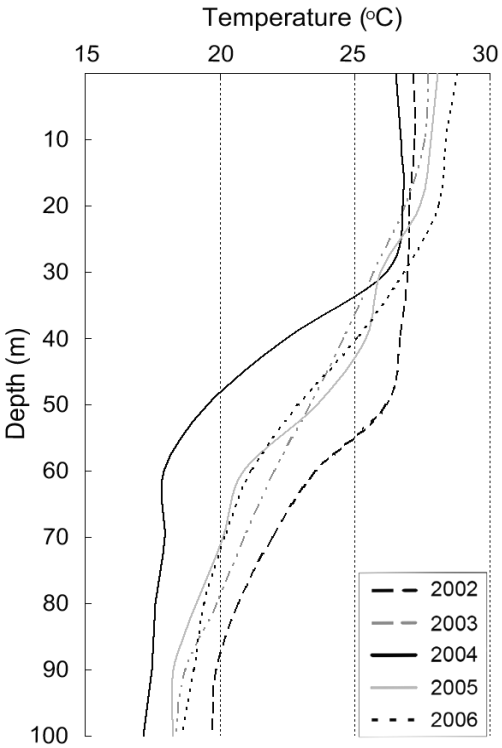


Fig. 3.3 Distribution of detected schools in relation with depth (a), height (b), length (d) and *Sv* (c).

Fig. 3.4 Vertical profiles of temperature during surveys.



CHAPTER IV: RELATIONSHIPS BETWEEN ENVIRONMENTAL FACTORS AND FISH SCHOOL CHARACTERISTICS

IV.1 Introduction

For more than half a century, acoustics has been a leading tool in fishery stock assessment. Today, ecosystem-based fishery management emerges as new strategy to establish fisheries management scenarios and poses new challenges for fishery scientists. EBFM depends on the assessment ecological relationships of exploited species with their environment. Understanding the impact of environmental factors on marine ecosystems is a key component to implement EBFM of marine resources (Frid *et al*., 2006). Acoustic methods are among the most promising tool to meet these scientific challenges, if it is properly combined with other tools involving ecology and oceanography, as well as fisheries (Koslow, 2009). The simultaneous collection of a wide range of ancillary variables, i.e., hydrographic (e.g., water depth) or biotic (e.g., zooplankton), during acoustic surveys offers a platform of opportunity for studying the effect of environmental factors on spatial and vertical distribution patterns of fish schools.

Acoustic surveys are able to give quasi-synoptic data on the distribution of fish biomass over a wide area and are not dependent on commercial catch statistics (MacLennan and Simmonds, 2005).

Studying habitat selection and migrations of fishes are crucial in understanding fish distribution and ecology at individual, species and community levels (Fréon and Misund, 1999). Fish, especially pelagic species, live in a three-dimensional environment, which represent a heterogeneous ecosystem. Generally, the most important abiotic factors believed to determine pelagic species distributions are temperature, oxygen, salinity, currents, bottom depth and nature of the seabed. Among corresponding biotic factors are

food availability, presence of predators and differences in the physiological requirements of different life stages. It is thus relevant to study fish habitat selection and preferences in both horizontal and vertical perspectives. Some factors may influence both horizontal and vertical distributions, while other factors are relevant mainly for the distribution along one spatial dimension.

Fish are generally ectotherms, but they are able to thermoregulate by selecting areas of favorable water temperature (Batty, 1994). Most pelagic fish can detect temperature variations smaller than 0.1ºC, which allows them to orientate towards areas favorable to their metabolism (Fréon and Misund, 1999). The thermocline may act as a limiting factor (barrier) for vertical habitat selection (Swartzman *et al*., 1994a; 1995). However, the significance of the thermocline may vary depending on other environmental factors, such as absolute temperature, prey density, distance to the bottom, etc. (Swartzman *et al*., 2002).

In the past, most of the marine resources-habitat correlations that have been demonstrated involved a single environmental parameter (e.g., temperature) and had often ignored the nonlinear and non-monotonic nature of such a relationship (Mann, 1993). However, relationships would be expected to be non linear and non-parametric, although general features of the relationship might hold true from year to year. Therefore, traditional linear models are often inadequate for detecting and quantifying any environmental effects and their complex interaction with fish ecological characteristics (Maravelias, 1999). The current analysis was conducted using a non-parametric regression technique, called the generalized additive models (GAMs), that offer an attractive possibility for overcoming statistical problems linked to the normality and linearity assumptions of GLMs (Hastie and Tibshirani, 1990). GAMs offer advantages over conventional regressive methods because it is not dependent on specific functional relationships (e.g., linearity) and it is flexible in

its assumptions regarding the statistical distribution of the data (Swartzman *et al*., 1995). GAMs extend the power of any conventional regression technique by fitting smoothed non-parametric functions to estimate relationships between the response and the predictors. The underlying probability distribution for the data can be any distribution from the exponential family, including the Normal, Poisson, and Binomial distributions (Swartzman *et al*., 1992).

There are numerous applications of GAM to marine ecology and fisheries spatial data. Guisan *et al.* (2002) reviewed several key examples of the use of GAMs in ecological modeling efforts. These include, but are not limited to, distribution study of eggs (Fox *et al*., 2000; Wood and Augustin, 2002; Ciannelli *et al*., 2007), tuna (Zagaglia *et al*., 2004), seatrout (Kupschus, 2003), squids (Denis *et al*., 2002), flatfish (Swartzman *et al*., 1992; Simpson and Walsh, 2004), herring (Maravelias *et al*., 2000a), and demersal fish (Katsanevakis and Maravelias, 2009).

GAMs have been widely applied to acoustic datasets to elucidate the effects of environmental factors on the vertical distribution of many fish species (Swartzman, 1997; Swartzman *et al*., 1999; Taylor and Rand, 2003; Winter *et al*., 2007). GAMs have also been used to describe relationships between environmental factors and horizontal distributions of herring in the Northeastern Atlantic (Maravelias and Reid, 1997; Bailey *et al*., 1998; Maravelias *et al*., 2000a; 2000b), and walleye pollock in the Bering Sea (Swartzman *et al*., 1994b; 1995).

In this present chapter, we have designed our analyses to investigate the effects of environmental factors on the individual school characteristics of pelagic fish schools. We focused on school size, vertical distribution patterns, the packing density and abundance of previously identified fish species group. GAMs were applied to estimate and quantify the

intrinsic relationships between fish school properties and environmental factors (surface and bottom temperature, surface and bottom salinity, and depth), and to study the different functional responses between the fish species and the co-located environmental variables.

IV.2 Material and Methods

IV.2.1 Fish school characteristics

Acoustic data collection and analysis were detailed in the third chapter III (c.f. chapter III). The significance of the six acoustic descriptors used in the analysis are explained in Table 4.1.

Fish schools were identified and objectively classified into two groups based on their acoustic descriptors. The first group (G1) consisted of compactly aggregated schools of three small pelagic fishes occurring within the upper layer of the water column: Japanese anchovy (*Engraulis japonicus*), Japanese sardine (*Sardinops melanostictus*), and round herring (*Etrumeus teres*). The second group (G2) appeared on the midwater layers and was composed of chub mackerel (*Scomber japonicus*), spotted mackerel (*Scomber austratasicus*), jack mackerel (*Trachurus japonicus*), and two species of the same genus *Decapterus maruadsi* and *Decapterus macrosoma*.

IV.2.2 Environmental factors

A suite of environmental factors that may have a potentially important influence on bathymetric distribution of fish aggregations were investigated. The environmental variables included in the analyses get into three headings, characterizing bottom topography, water temperature and water salinity, respectively (Table 4.2). Temperature and salinity measurements were collected throughout 88 stations using a CTD profiler

(Niel Brown Mark III B) (Fig. 4.1). Bottom depth was derived from echograms and corresponded to the vertical distance from the water surface to the bottom crossing each identified school.

Table 4.1 Significance of acoustic descriptors.

Descriptors	Units	Significance
Morphological		
Length	m	The size of the fish school
Height	m	The size of the fish school
Energetic		
Volume backscattering strength (*Sv*)	dB/m^3	The packing density of the fish school
Area backscattering coefficient (*Sa*)	m^2/nm^2	The fish school abundance per 1 nautical mile
Positional		
School depth (S_depth)	m	The position of the fish school in the water column

Table 4.2 Summary of environmental factors (covariates).

Covariates	Indication	Unit
Bottom depth	B_depth	m
Sea surface temperature	SST	℃
Temperature at 30 m depth	T_30	℃
Temperature at 100 m depth	T_100	℃
Temperature near the bottom	T_bottom	℃
Sea surface salinity	SSS	psu
Salinity at 30 m depth	S_30	psu
Salinity at 100 m depth	S_100	psu
Salinity near the bottom	S_bottom	psu

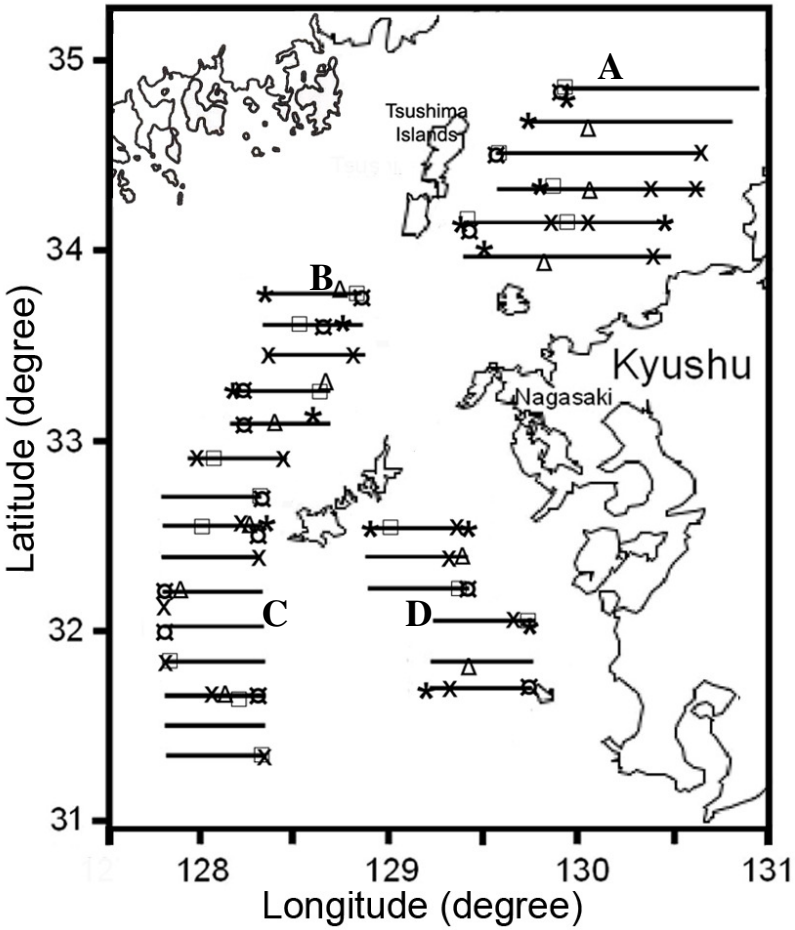


Fig 4.1 Acoustic survey transects and CTD stations for each year: (Δ) 2002; (x) 2003, (*) 2004, (□) 2005, (¤) 2006. Virtual transects (A, B, C and D) used to draw vertical profiles.

IV.2.3 Data analysis

2.3.1 Generalized additive model analyses

GAMs are non-parametric extensions of generalized linear models (GLMs) (Hastie and Tibshirani, 1990). Essential and sufficient assumptions to apply GAMs are the functions' additive characteristic as well as the smoothness of the components (Hastie and Tibshirani, 1990; Wood and Augustin, 2002). GAMs, like the GLM, use a link function to establish a relationship between the mean response of the variable and a smoothed function of the explanatory variable "covariate". The major particularity is that GAMs are more flexible, generating both linear and complex additive response shapes, as well as a combination of the two within the same model, whereas GLMs fit functions linear in their parameters, allowing for linear and polynomial response shapes (Wood and Augustin, 2002).

Given a response variable y and a set of forcing variables x (covariates), the relationship between the two is established by (Hastie and Tibshirani, 1990):

$$y = \beta_0 + \sum_k S_k(x_k)$$

where y is the response to a random environmental variable, β_0 is an intercept term, x_k is the value of the kth covariate and $S_k(\ )$ represents smooth functions of kth covariate.

The extension of GAM to two-dimensional data is accomplished with thin-plate regression splines (Wood, 2003). The dependent variable is assumed to be the sum of unspecified functions of the covariates and their interactions.

The GAM-based analysis used the "mgcv" package (version 2.8.0) of the statistical software R (R Development Core Team, 2008). The analysis permitted to calculate adjusted r^2 and deviance explained (analogous to variance in a linear regression). The GAMs were applied using an identity link function and a Gaussian error distribution.

Smoothness parameters, representing the number of degrees of freedom for each smooth,

were estimated via generalized cross-validation scores "GCV scores", where mgcv-optimization selected automatically the effective explanatory variables and their relative degrees of freedom. Wood (2001) suggested that, in case of contrived outputs, selection and removal variables were decided upon subjective judgment. Following the guidelines of Wood (2001), variables were removed if three criteria were fulfilled: (i) the estimated degrees of freedom were close to 1; (ii) the confidence interval was zero everywhere; and (iii) the deletion of a variable results in decrease of the GCV score. Functions with the lowest GCV scores were selected. Covariates were deleted until approximate significance levels of all smoother terms were $p < 0.01$. This criterion value for variable exclusion was chosen because of the relatively small sample size of fish schools (McBride *et al*., 1993). The data collected overall the five years, school acoustic descriptors and environmental covariates were pooled. The relationships were calculated for each fish-group separately. The shapes of the functional forms for the selected covariates were plotted.

2.3.2 Environmental factor analysis

The acoustic data consisted of continuous recordings while cruise tracking, while CTD data were only available from the sampling stations. A horizontal grid of 5 nm was employed to cover the sampling area. Within each grid, temperature and salinity were estimated at different depth levels using five years data pooled and averaged. For grids not including sampling stations, linear interpolation and extrapolation were applied to calculate temperature and salinity from the nearest location to the acoustic sample (detected fish school).

IV.3 Results

IV.3.1 Environmental factors

Sea water temperature and salinity did not display large variation between the five years surveys. An illustration of vertical profiles of salinity and temperature along four transects (Fig. 4.1) drew from CTD measurements recorded in 2005 (Fig. 4.3).

Thermocline depth was defined as the depth at which temperature had declined by 80% of its value at the surface. After observing vertical profiles for each year (e.g., in 2005 Fig. 4.3), on most casts, the thermocline occurred at depths around 50 m. The thermocline depth was estimated from averaged values in the sampling stations along each transect. This definition of the thermocline is consistent with the hydrography of the surveyed area (Senjyu *el al*., 2008) and has been used in similar studies (Ohshimo, 2004).

The distribution of sea water temperature and salinity values at different depth levels was illustrated in Figure 4.4. The box plot analysis was useful to highlight the variance of the input data used in the GAMs analysis.

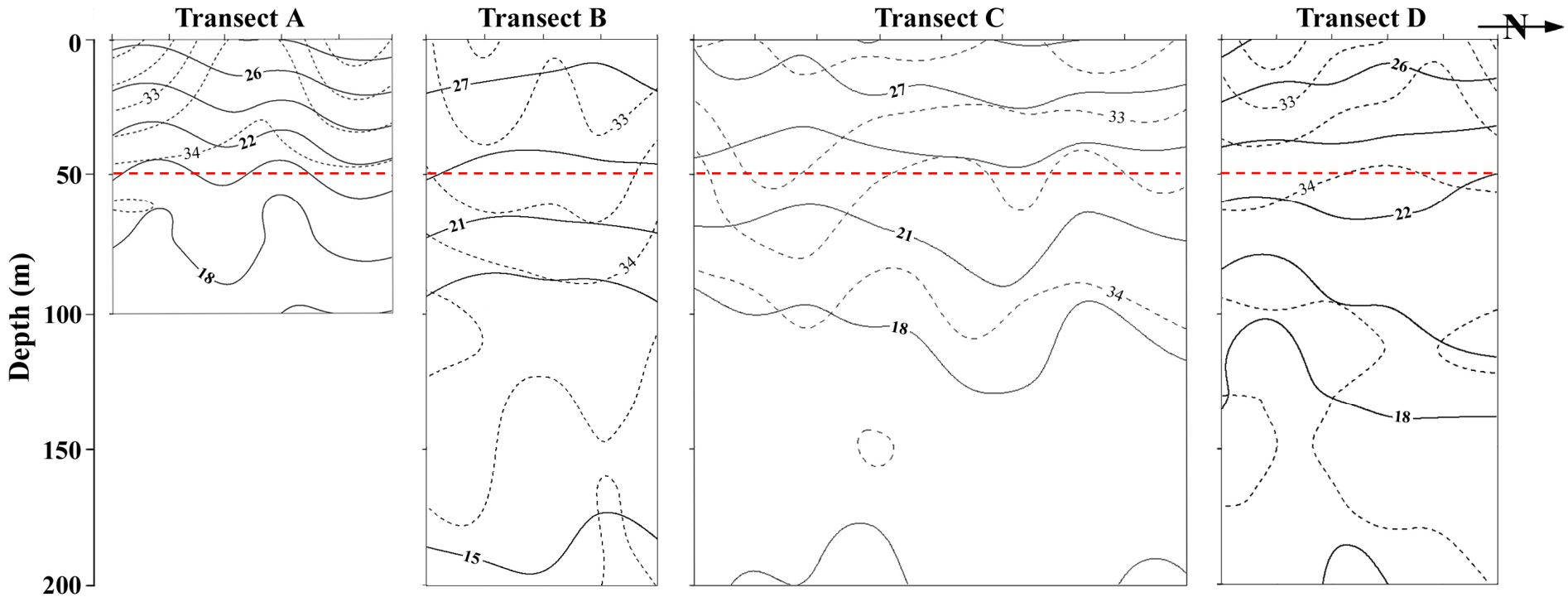


Fig. 4.3 Vertical profiles of temperature (bold line) and salinity (broken line) in 2005, along transects represented in Fig. 4.1.

The horizontal dashed line in red indicates of thermocline estimated to occur at 50 m depth.

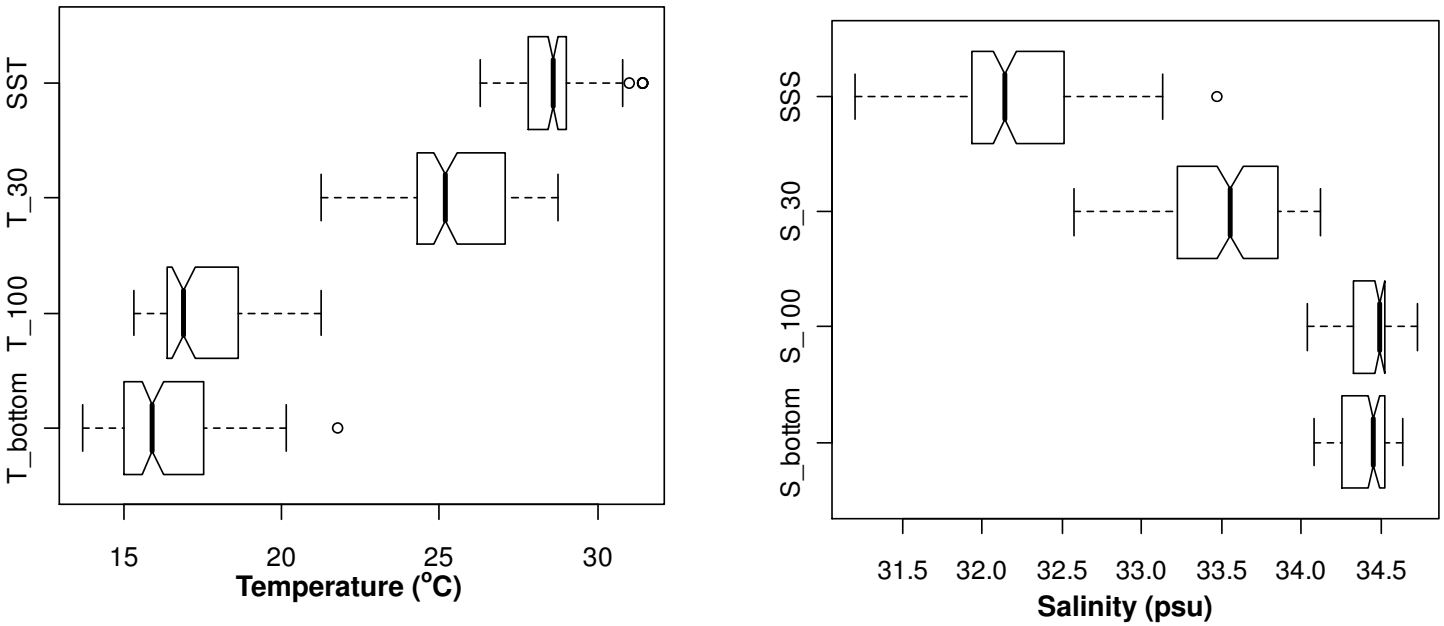


Fig. 4.4 Boxplot analysis for distribution of measurements among temperature and salinity.
The boxplot analysis shows the interquartile range of each examined temperature (box), the median (line inside the box), minimum and maximum values (whiskers); circles represent values 1.5–3 times outside the interquartile range; squares represent values more than 3 times outside the interquartile range.

IV.3.2 Generalized additive models

The GAMs analysis aims to examine the effects of environmental variables on the acoustic characteristics of fish schools. Results of selected environmental covariates are summarized in Table 4.3 and Table 4.4, corresponding to fish group 1 and 2 respectively. Selected covariates differed among the two fish-groups and according to various school parameters.

For both fish groups, all selected covariates were found to be significant ($p < 0.01$) and in some cases (e.g., bottom depth, S_100, S_bottom) were highly significant ($p < 0.001$). The significance values (p levels) of GAM covariates for all descriptors included in the analysis are given in Table 4.3 and Table 4.4.

The analyses highlight differences in the effectiveness of selected covariates set for each model. In the case of fish G1, the best covariates set was recorded for the model controlling the *Sv* density, followed by the school depth model, accounting for 48.3% and 43.1% of the explained deviance, respectively (Table 4.3). For the school height, only bottom depth was selected, but the deviance was 19.5%. School abundance *Sa* is controlled solely by the temperature at 30 m depth and explains 21.7% of the deviance. On the other hand, school length is not influenced by any environmental covariate.

Within the fish group G2, the school depth model selected the bulkiest variables' set including four covariates. Bottom depth, T_100, S_100 and S_bottom captured the largest amount of deviance (88.3%) for the school position in the water column (Table 4.4). The temperature and salinity at a depth of 100 m had the absolute effect on the school abundance with 25% of the explained deviance. The length model is exclusively associated to the bottom depth which explained 17.4 % of the variation (Table 4.4).

The individual relationships between school parameters and each selected variables are plotted to better comprehend the effect of each of selected environmental factors analyzed in the GAMs. Plots show the fitted curves and the location of observations on the individual covariate (Figures 4.5 to 4.13). The 95% confidence intervals, represented by grey shading, are plotted around the best fitting smooths for the variable effects. The *x*-axis for each covariate plots includes tick marks, termed the rug, on which show the location of observations along the variable range. The *y*-axis reflects the relative importance of relationship between school parameter with covariate.

Table 4.3 The contribution of selected environmental variables in the characteristics of G1 fish schools based on GAMs.

	Fish school abundance (*Sa*)		School packing density (*Sv*)		School depth		School length		School height	
Parameters										
GCV score	39081		24.933		406.46		-		163.79	
Deviance explained (%)	21.7		48.3		43.1		-		19.5	
Adjusted r^2	0.101		0.319		0.228		-		0.08	
	d.f	p-value	d.f	p-value	d.f	p-value	d.f	p-value	d.f	p-value
Covariates										
Bottom depth	-	-	1.676	<0.01	3.8	<0.001	-	-	2.412	<0.01
Sea surface temperature	-	-	-	-	-	-	-	-	-	-
Temperature at 30 m	2.652	<0.001	1.759	<0.001	-	-	-	-	-	-
Temperature at 100 m	-	-	-	-	-	-	-	-	-	-
Temp near the bottom	-	-	-	-	-	-	-	-	-	-
Sea surface salinity	-	-	-	-	7.892	<0.001	-	-	-	-
Salinity at 30 m	-	-	5.721	<0.001	8.166	<0.001	-	-	-	-
Salinity at 100 m	-	-	-	-	-	-	-	-	-	-
Salinity near the bottom	-	-	-	-	-	-	-	-	-	-

d.f. refers to the degrees of freedom for the spline smoother in the final model. P-value refers to the statistical significance

Table 4.4 The contribution of selected environmental variables in the characteristics of G2 fish schools based on GAMs.

	Fish school abundance (*Sa*)		School packing density (*Sv*)		School depth		School length		School height	
Parameters										
GCV score	6807		18.68		325.55		7712.8		111.59	
Deviance explained (%)	25		46		88.3		17.4		38.8	
Adjusted r^2	0.103		0.26		0.742		0.059		0.217	
	d.f	p-value	d.f	p-value	d.f	p-value	d.f	p-value	d.f	p-value
Covariates										
Bottom depth	-	-	2.832	<0.01	6.239	<0.001	3.375	<0.01	-	-
Sea surface temperature	-	-	-	-	-	-	-	-	-	-
Temperature at 30 m	-	-	-	-	-	-	-	-	-	-
Temperature at 100 m	6.819	<0.01	8.313	<0.01	7.745	<0.001	-	-	8.781	<0.001
Temp near the bottom	-	-	5.114	<0.01	-	-	-	-	8.415	<0.001
Sea surface salinity	-	-	-	-	-	-	-	-	-	-
Salinity at 30 m	-	-	-	-	-	-	-	-	-	-
Salinity at 100 m	2.093	<0.01	8.938	<0.001	8.956	<0.001	-	-	-	-
Salinity near the bottom	-	-	-	-	3.381	<0.001	-	-	-	-

d.f. refers to the degrees of freedom for the spline smoother in the final model. P-value refers to the statistical significance

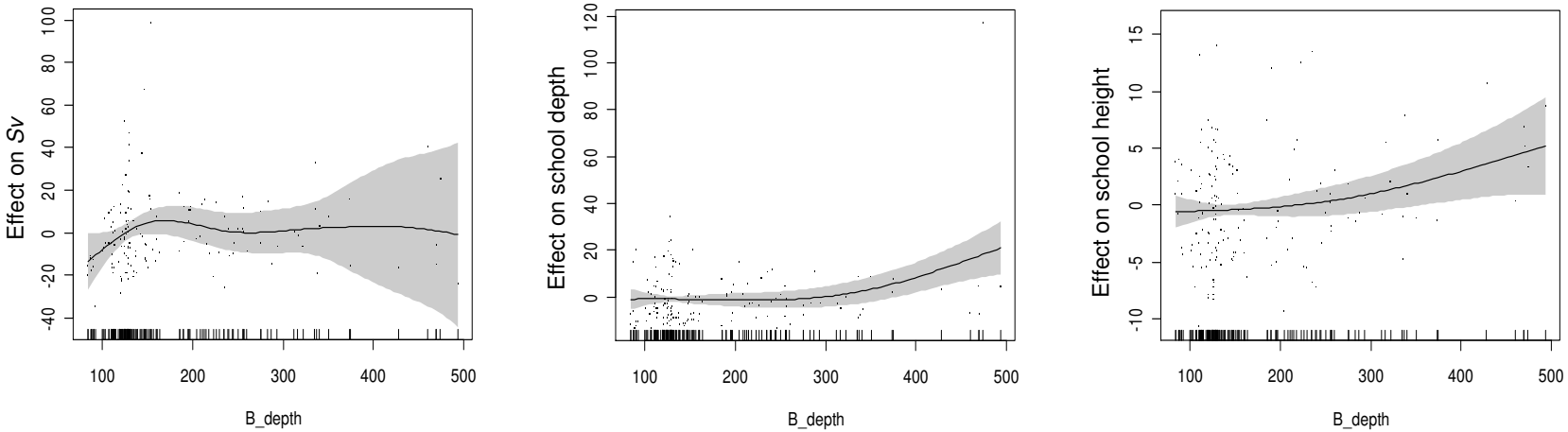


Fig. 4.5 Responses shapes of bottom depth effect on school characteristics of **Group1** fish species.

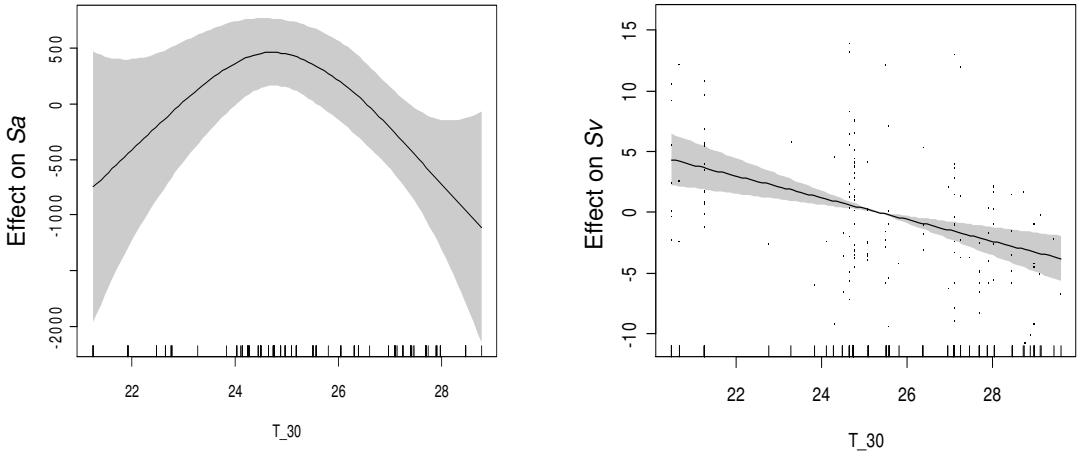


Fig. 4.6 Responses shapes of temperature at 30 m depth effect on school characteristics of **Group1** fish species.

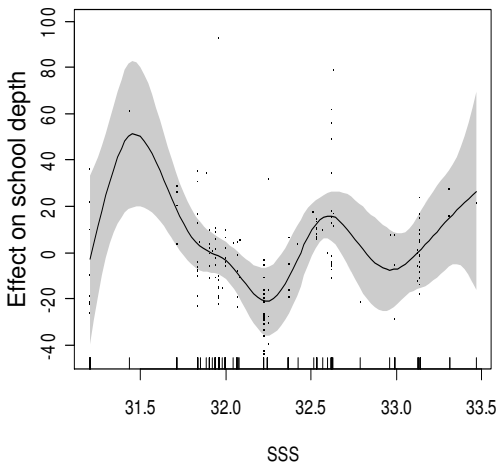


Fig. 4.7 Response shape of sea surface salinity effect on school characteristics of **Group1** fish species.

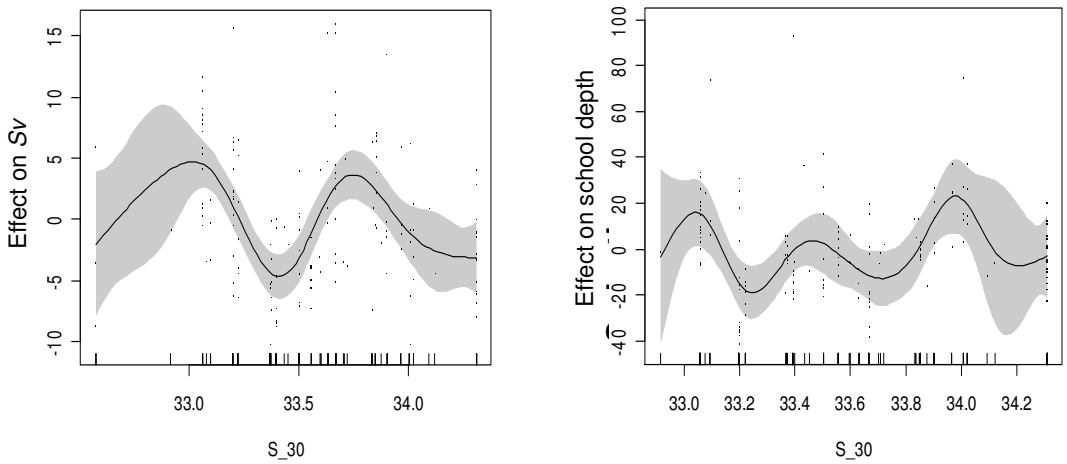


Fig. 4.8 Responses shapes of salinity at 30 m depth effect on school characteristics of **Group1** fish species.

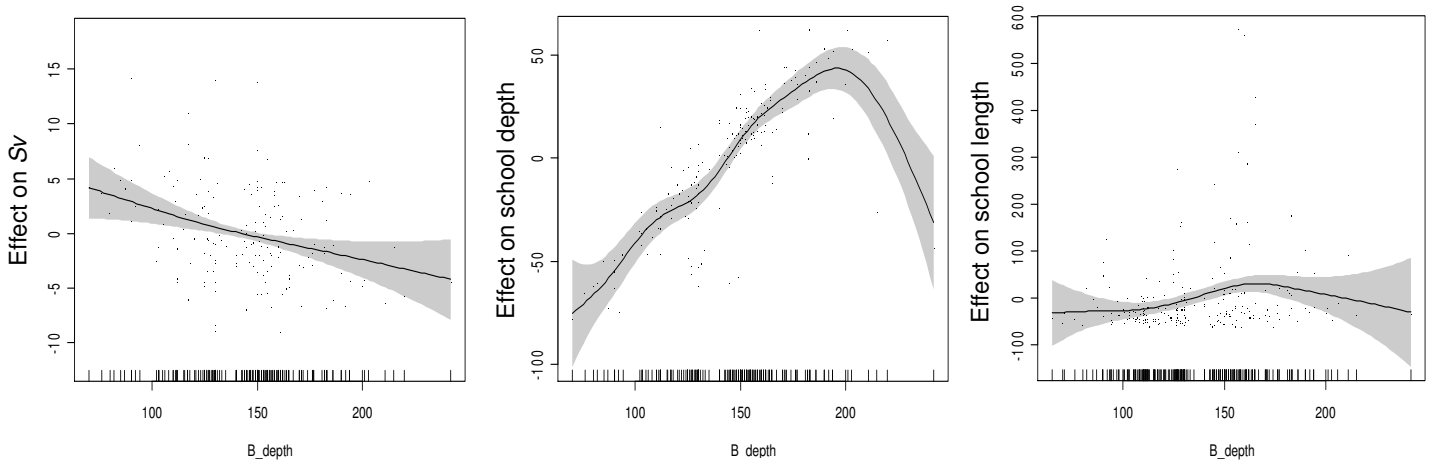


Fig. 4.9 Responses shapes of bottom depth effect on school characteristics of **Group2** fish species.

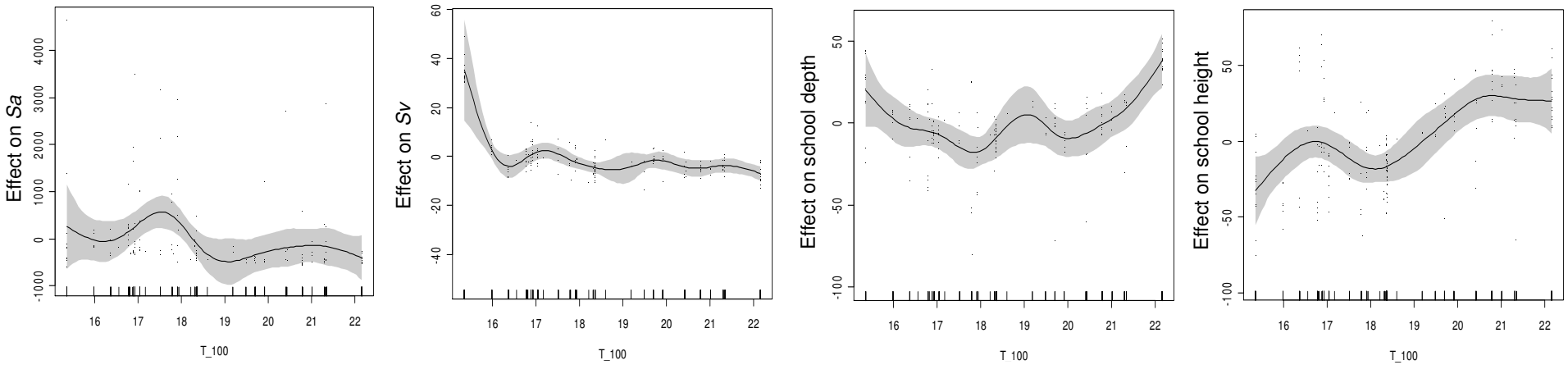


Fig. 4.10 Responses shapes of temperature at 100 m depth effect on school characteristics of **Group2** fish species.

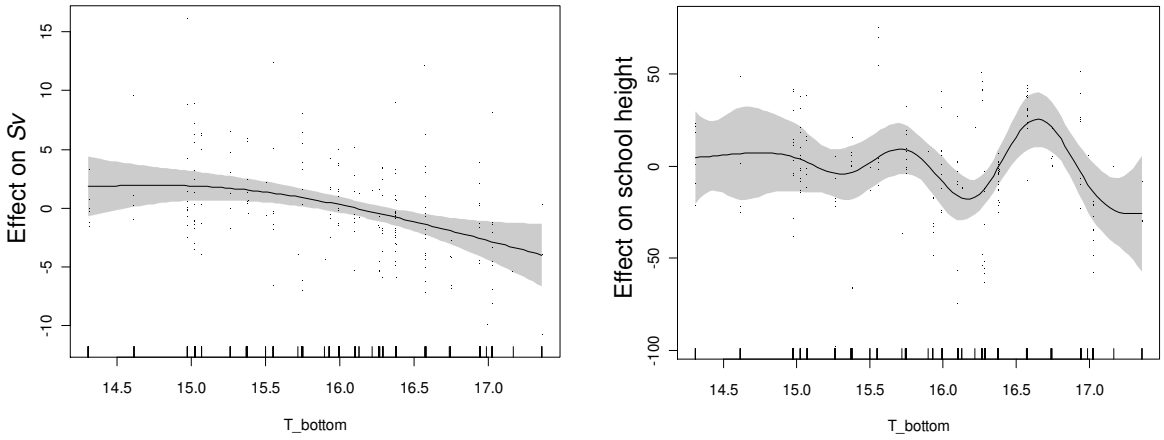


Fig. 4.11 Responses shapes of temperature near the bottom effect on school characteristics of **Group2** fish species.

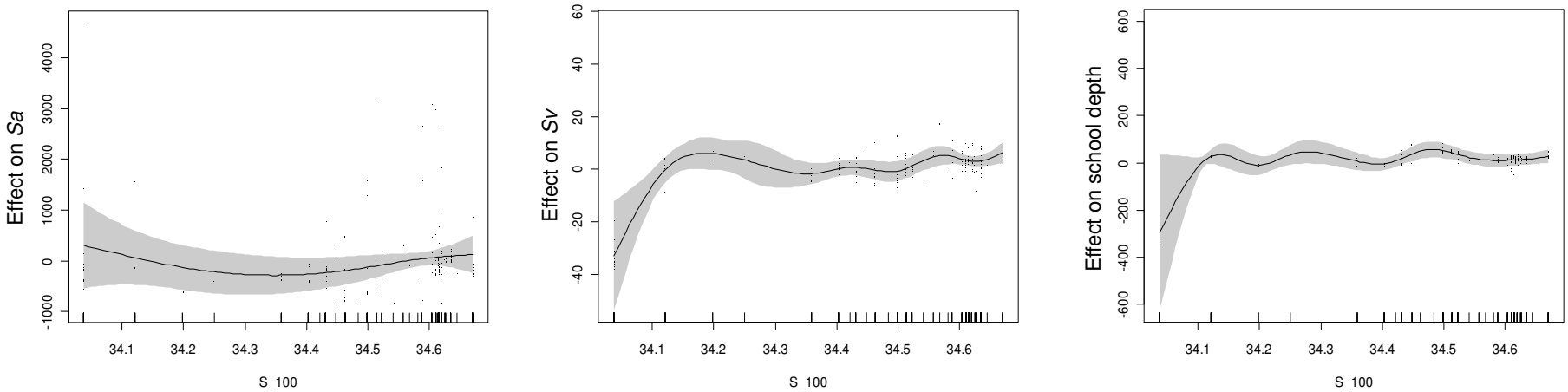


Fig. 4.12 Responses shapes of salinity at 100 m depth effect on school characteristics of **Group2** fish species.

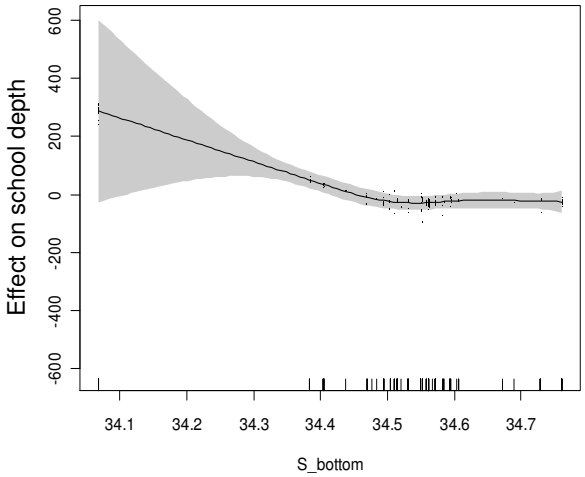


Fig. 4.13 Response shape of salinity near the bottom effect on school depth of **Group 2** fish species.

IV.3.2 Effects on individual school characteristics

Looking at the functional forms plotted from GAMs results, the bottom topography correlates positively to the acoustic parameters. The group G1 schools were detected at the bottoms of 80m depth to 490 m corresponding to the deepest point detected in the survey area. The observed data point on *x*-axis reveals a concentration of schools in relatively shallow areas, between 100 and 170 m (Fig. 4.5). The school height increased with bottom depth starting from 260 m depth and remains unchanging in shallower waters (< 200m) (Fig. 4.5).

The fish packing density of G1 fish schools was negatively related to the water temperature at 30 m depth, which ranged from 20.5 to 29.6℃ (Fig. 4.6). This indicates that the decrease in temperature favors the occurrence of schools with high density. On the contrary, the school size was not related to the sea water temperature.

There are highly significant relationships between the water salinity, the density and the depth of fish schools for both fish-groups. Interestingly, these two acoustic parameters are strongly related to the temperature at 100 m depth and temperature near the sea bed, but G1 schools, by contrast, are under the only effect of temperature at 30m depth.

The G2 schools occurred at bottoms ranging from depths of 65 to 270 m (Fig. 4.9). The concave functional form showed a peak at 170 m depth, corresponding to the optimum depth for the occurrence of long fish schools. The bottom depth influenced also the density and the position of fish school length (Fig. 4.9). The latter reached the optimum at nearly 180 m depth.

The shapes of the functional forms indicated the significant influenced of the water temperature at 100 m depth on acoustic descriptors, explicitly *Sa*, *Sv*, depth and height of fish schools (Figure 4.10)

IV.4 Discussion

IV.4.1 Environmental effects on fish schools

Results demonstrate that GAMs can be a useful tool to describe the relationships between schools' characteristics and environmental factors using smooth functions. The addition of more covariates in the GAM models (e.g., temperature and salinity at different depths) yielded to non significant changes and did not appear to affect the estimated correlations substantially. The covariates' selections together with the adjustment of the exclusion criterion are valuable for the best model fittings represented by interpretable and plausible relationships. These analyses would not have been possible with traditional regression approaches, which do not provide separate measures of the variable explained independently or jointly by two or more groups of covariates.

Overall, the above results indicate a rather high independent contribution of bottom topography and water temperature and somewhat lower independent contributions of water salinity. However, the highest amount of variation in the fish density and the school position in the water column is related to the joint effect of all three groups of variables (Tables 4.3 and 4.4). Other studies have also indicated that similar influences of environmental variables. Maravelias (1999) found that herring exhibited preferences for areas with specific bathymetric and substratum conditions. Also, Maravelias *et al*. (2000a) observed that bottom depth has both a direct main effect and an interactive effect together with zooplankton biomass on herring abundance in the North Sea.

The GAMs analyses supported our partition of fish schools into two fish groups. In general, it could be concluded that responses of school properties to environmental factors for the

detected G1 schools differed markedly from those classified as G2. Although all the schools detected were analyzed without differentiating between species within each group, the midwater trawling performed during these surveys gave an indication of the species composition (c.f. III.3.3).

Looking at GAMs results related to G1 species, it is concluded that there is a strong effect of bottom depth on *Sv*, school height and position in the water column. These species preferred relatively high temperature above the thermocline occurring at around 50m depth (Fig. 4.3). Therefore, the thermocline might play as an effective thermal barrier in limiting sardine, anchovy and round herring within the upper water column layer. In the same order of idea, Takasuka *et al*. (2007) found a strong linkage between anchovy and sardine growth and water temperature. These authors suggested a hypothesis in which both species necessitate optimal temperatures for growth rates during the early life stages.

The response shape of the school abundance *Sa* against T_30 illustrated a concave form. This reveals that 24.7^{o}C represent the optimal temperature favorable for the occurrence of the maximum of abundance (Fig. 4.6).

Interestingly, for G2 species, only five factors bottom depth, temperature and salinity at 100 m depth controlled all the characteristics of fish schools (*Sa*, *Sv*, S_depth and size) (Table 4.4). That is, G2 species tended to occur at lower temperature below the thermocline and in relatively shallower bottoms. Their corresponding schools' depth increased positively with bottom depth. They tended to form large schools at 150 m depth. Schools with high density have a preference to shallow bottom depths (<180 m) (Fig. 4.9). Other studies reported a tight relationship between water temperature and fish density of chub mackerel and spotted mackerel (Hiyama *et al*., 2002; Yukami *et al*., 2009).

IV.4.2 Significance of environmental factors

Over the course of these five years, results reveal that the thermocline represent a significant thermal obstruction led to concentrate sardine, anchovy and round herring within the upper water column layer. Other species occur in deeper waters below the thermocline and prefer lower temperature. Senjyu *el al*. (2008) reported that in the East China Sea, a strong water stratification occur in summer time (from June to October) and a clear thermocline and halocline appear in the upper 50 m; they start to develop in June, mature in August, and weaken and deepen in October. These findings corroborate the steadiness of temperature and salinity measurements throughout the five years.

Salinity was not very significant in controlling the vertical distribution. In shallow waters, species are mixed together. Senjyu *et al*. (2008) indicated that the salinity is affected by the atmospheric and oceanographic conditions in the study area. The relatively low water salinity appears persistent annually from summer to autumn.

In the marine ecosystem, the bottom topography of an area is closely related to its hydrography. The East China Sea off Japanese coasts (west of Kyushu coasts) is a hydrographically dynamic region. It is commonly believed that the main feature is the transport of the Kuroshio Branch Current west of Kyushu which bifurcates from the eastward path of the Kuroshio main stream and originates the Tsushima Warm current flowing through the Tsushima strait (Ichikawa and Beardsley, 2002; Lie *et al.*, 1998). Hence, the surface current entering the East China Sea from the Taiwan Strait is considered also as a key factor responsible for the salinity condition in the East China Sea (Senjyu *et al*., 2009).

The work of Takikawa *et al*. (2008) gave a comprehensive description of the current system and revealed another hydrographic structure feature which is the counterclockwise cyclonic eddy located in the eastern channel of the Tsushima Straits. The counterclockwise eddy advects northeastward to the Japan Sea by the Tsushima Warm Current. Further works should include biological parameters (e.g., primary production) to be examined. According to Takikawa *et al*. (2008), nutrient concentrations under the surface mixed layer were high. The inflow brings by turbulence a significant input of nutrient-rich water to the surface, which may play a significant role in primary production in the Tsushima Straits and the Japan Sea (Onitsuka *et al*., 2007). In such context, more observational research is needed to evaluate the effect of biological factors on the ecological preferences of pelagic fishes through distribution and schooling patterns.

IV.5 Conclusion

The present work has shown that the vertical distribution patterns and school size of pelagic fish species result from a combination of variety of environmental factors. The study findings are essential for better understanding of fish-ecosystem interactions and will provide leading indicators to more efficient fish stock monitoring. It should be remembered that the relationships demonstrated here are likely to be occurring in summer season. Additional data sets throughout the whole year would be useful in further testing the stability and continuity of the suggested relationships during other seasons. However, unlike other physical factors that may change over time, bottom topography does not change significantly and should be considered consistent. Focusing studies on additional environmental parameters effects using GAM analyses should be conducted for a better comprehension of properties of small pelagic fish populations.

CHAPTER V: ESTIMATIONS OF DISTRIBUTION AND BIOMASS

V.1 Introduction

Accurate measurements of fish biomass are crucial to the management of marine ecosystems and their associated fisheries (MacLennan and Simmonds, 2005). Surveys to estimate fish biomass are expensive and time-consuming. Constraints on survey cost and time compel managers to use efficient sampling methods and to optimize the survey design so as to maximize the precision of the resulting estimates (Simmonds and Fryer 1996b, Fablet *et al*., 2009).

Combined acoustic and midwater trawl surveys have proved to be an efficient sampling method of pelagic fish. Acoustic measurements provide insight on patterns of vertical fish distribution because fish are sampled throughout the water column, while midwater trawls provide catch composition and other biological information (Godø *et al*., 1998). The two methods are typically implemented in a single survey design in two stages. First, transects along which fish density is acoustically estimated are selected. Acoustic transects are evenly distributed across the entire sample space by using a systematic or a random design that strives for uniform coverage. Second, layers of the water column along each transect are targeted for sampling with the midwater trawl. Midwater trawls are deployed to capture acoustically detected fish schools, but trawling positions are decided based on the choice of the expert conducting the survey.

To improve the efficiency of a survey, sampling effort is optimally allocated among strata that partition the sample space (Jolly and Hampton, 1990; Smith and Gavaris, 1993). Sampling effort should be optimally allocated within each stage of the survey design. Stratification at the geographic scale should be used to optimize allocation of acoustic

transects in different regions for estimation of fish biomass.

Stock assessment of small pelagic fish in our surveyed area has been limited to the results of Ohshimo (2006). This first attempt succeeded to estimate the acoustic abundance index based on the partitioning of echo-integrals into fish-groups.

In the present work, we tackle the biomass assessment of small pelagic fish by utilizing two approaches of combined acoustic and midwater trawl surveys through stratification. The echo-integrals of fish groups (G1 and G2) identified in the third chapter, were in turn used here for conversion into fish density, and ultimately fish biomass. Biomass estimates and their uncertainties, generated from both stratification approaches, were detailed and discussed.

V.2 Material and methods

V.2.1 Horizontal fish distribution

The acoustic data were collected from parallel transects spaced by 10 nautical miles (Fig. 2.1) and then were postprocessed using Echoview Software (c.f. to II.2.2). The basic acoustic measurements derived from fish echoes were the volume backscattering coefficient (s_v) and the area backscattering coefficient (s_a). The latter is the measure of the energy returned from a layer between two depths in the water column. It is defined as the integral of s_v with respect to depth through the layer:

$$s_a = \int_{z_1}^{z_2} s_v \, dz \tag{5.1}$$

where z_i is the depth. In the present study, z_1 and z_2 were 10 and 250 m depth, respectively. Elementary distance sampling units (EDSUs), defined as the distance over which acoustic data are integrated from a single sample, was set at 1 nautical mile (1852 m).

Using the conversion formula, the nautical area backscattering coefficient Sa (m^2 nm^{-2}) is as follows:

$$Sa = 4\pi \, (1852)^2 \, s_a \tag{5.2}$$

While the echo-integration is in progress, there is a simple relationship between the fish density per unit volume and the backscattered energy, which is the echo-integrator equation (Simmonds and MacLennan, 2005). The theory depends on a major assumption about the distribution of targets within the transducer beam, known as the linearity principle (Foote, 1983). The abundance of the target species is the total volume occupied by schools multiplied by the mean packing density of the fish. Consequently, in the present study, the fish abundance was assumed to be proportional to the area backscattering strength.

The spatial distribution of fish abundance assumed to be expressed by *Sa* was mapped using ArcGIS v9.3.1 GIS software (ESRI Inc., Redlands, CA, USA). The *Sa* values of each fish-group collected in each year were visualized together with sea surface temperature SST. The horizontal distribution of the nautical area backscattering strength *Sa* permitted to highlight regions of high fish concentrations and assisted the partition of the surveyed area into three strata (blocks). Hence, the mapping supported the post-survey stratification needed for further biomass estimates.

V.2.2 Density estimation

2.2.1 Target strength – fish length relationship

It is common for fisheries acoustic researchers to incorporate target strength (TS) to fish length relationships when estimating fish abundance and biomass (Simmonds and MacLennan, 2005). Echo intensities of detected fish schools are integrated and converted using target-strength (TS) dependencies on fish length, called TS-L relationships, into fish density (fish m^{-3}) for calculation of fish biomass (MacLennan *et al*., 2002). Several equations have been developed to convert horizontal-aspect measurements of acoustic energy into fish length (Love, 1969; Furusawa, 1988; Frouzova *et al*., 2005).

TS-L relationships of target species around Japanese waters were collected from published experimental results. The relationships used to relate acoustic target strength to fish length are detailed in Table 5.1.

The TS-length regression equation incorporates acoustic target strength (TS, in dB) against fish length (L, in cm) in the following form:

$$TS\ (dB) = a_n + b_n \log (L) \qquad (5.3)$$

where a_n and b_n are constants for a given species, assumed to be known from published

experimental evidence. In all the equations used and for all the target species b was set to 20 (Table 5.1).

The equivalent formula for the backscattering cross-section is:

$$\sigma_{bs} = 10^{0.1\ TS} = 10^{(a+b\ \log(L)\ /\ 10)} \tag{5.4}$$

$$\sigma_{bs} = 10^{0.1}\ TS$$

Owing the same size and features, target species of the same genus are generally not acoustically distinguishable. As no literature relative to target strength estimates is currently available for Japanese round scad *Decapterus maruadsi* and shortfin scad *Decapterus macrosoma*, it was assumed for the purposes of the biomass estimates that TS of both species are similar to that obtained by Abe *et al*. (2009) for Jack mackerel *Trachurus japonicus*. It was also assumed that both species belonging to genus *Scomber*, *Scomber japonicus* and *Scomber australasicus* have the same TS-length relationship.

Since an EDSU included more than one species of fish, it was necessary to divide the echo-intensity between species, taking into account the weight of each species in the sample and their differential length-based TS regressions. Echo-integrated energy per EDSU was allocated to different species based on the composition and catch amount from midwater trawl samples taken in the immediate vicinity. The surveyed area was partitioned in blocks and trawl catch amount was averaged for each block (Table 5.2). Details of stratification in blocks are provided below (c.f. V.2.3.1).

Table 5.1 Parameters of target strength-length relationships by species.

	Species	a_n	b_n	Reference
Group 1	**Japanese anchovy** *Engraulis japonicus*	-64	20	Amakasu *et al*. (2010)
	Japanese sardine *Sardinops melanostictus*	-67	20	Miyanohana *et al*. (1990)
	Round herring *Etrumeus teres*	-66.6	20	Ohshimo *et al*. (pers.com)
Group 2	**Japanese jack mackerel** *Trachurus japonicus*	-67	20	Abe *et al*. (2009)
	Chub mackerel *Scomber japonicus*	-65	20	Miyanohana *et al*. (1990)
	Spotted chub mackerel *Scomber australasicus*	-65	20	Miyanohana *et al*. (1990)
	Japanese round scad *Decapterus maruadsi*	-67	20	Abe *et al*. (2009)
	Shortfin scad *Decapterus macrosoma*	-67	20	Abe *et al*. (2009)

Table 5.2 Midwater trawl catch composition (in kg) by species for each block (B1, B2 and B3).

		2002				2003				2004				2005				2006			
		B 1	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**
Group1	Japanese anchovy	0.1	0.0	44.1	44.2	0.3	0.0	6.9	7.2	0.7	4.0	50.8	55.4	20.0	0.1	16.8	36.9	24.5	0.0	115.2	139.7
	Round herring	22.2	6.5	39.0	67.7	1.3	1.5	8.0	10.8	0.0	0.6	0.3	0.9	0.1	0.5	4.9	5.5	13.0	0.6	9.4	23.0
	Japanese sardine	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.1	0.1	0	0.0	0.1	0.1	0.1	0.0	0.7	0.7
Group2	Jack mackerel	0.5	33.3	4.8	38.6	146.2	22.6	46.3	215.1	8.1	11.2	15.8	35.0	0.1	13.0	24.5	37.6	1.1	11.5	2.6	15.1
	Scomber spp	0.4	1.3	0.4	2.1	0.0	0.3	0.2	0.5	0.0	2.8	0.6	3.4	0.2	6.5	10.2	16.8	1.1	4.1	0.4	5.6
	Decapterus spp	4.1	0.4	2.8	7.3	0.3	4.7	1.6	6.6	0.0	0.4	3.0	3.4	0.1	3.0	25.9	29.0	0.2	2.0	1.1	3.3

2.2.2 Weight-length relationship

The fish density is required as a weight while the TS-L equation is given for individual fish. The length of fish estaimated from the TS-L equation must be converted to compatible units (kg). This may be done by reference to the weight-length relationship for each target species.

For a fish of length L, the weight W is variable but the mean relationship is given by an equation of the form:

$$\mathrm{W} = a_f \mathrm{L}^{bf} \tag{5.5}$$

where a_f and b_f are constants for one species determined from fish sample of midwater catch.

2.2.3 Weight-based target strength

As the target strength of one fish was defined in equation (5.3), the corresponding weight-normalized target strength TS_w has an analogous form with different constants:

$$TS_w = a_w + b_w \log(\mathrm{L}) \tag{5.6}$$

Since the number of individuals per unit weight of fish is (1/W), the constant coefficients are related by the formulas (Simmonds *et al.*, 1992):

$$a_w = a_n - 10 \log(a_f) \tag{5.7}$$

$$b_w = b_n - 10\, b_f \tag{5.8}$$

The fish density was uniformly estimated for transect by combining the conversion factors: the weight-length relationships, the target strength-length relationships, and the weight-based length-target strength relationships. The results are detailed in Table 5.3. Consequently, the density (fish weight nm^{-2}) was computed for each target species.

Table 5.3 Measurements by year and by species of mean length, target strength (TS) weight-length relationships (a_f and b_f), and weight-based target strength (a_w, b_w and TS_w).

	Species	Mean length (cm)	TS	a_f	b_f	a_w	b_w	TS_w
2002	Japanese anchovy	8.65	-45.26	6.0E-06	3.18	-11.75	-11.7	-37.15
	Japanese sardine	13.2	-41.59	1.9E-05	2.94	-19.74	-9.4	-44
	Round herring	14.76	-40.62	1.4E-05	2.97	-18.11	-9.67	-44.14
	Jack mackerel	18	-38.89	8.5E-06	3.1	-16.29	-11	-48.09
	Scomber spp	22	-37.15	1.1E-05	3.03	-17.4	-10.3	-49.24
	Decapterus spp	16	-39.92	4.1E-05	2.93	-21.17	-9.34	-47.07
2003	Japanese anchovy	9	-44.92	1.1E-05	2.97	-14.47	-9.67	-35.72
	Japanese sardine	14	-41.08	1.9E-05	2.94	-19.79	-9.4	-44.59
	Round herring	14.8	-40.57	1.5E-05	2.98	-18.33	-9.77	-44.68
	Jack mackerel	12.2	-42.29	3.1E-06	3.59	-11.88	-15.93	-51.71
	Scomber spp	21	-37.56	1.1E-05	3.01	-17.4	-10.1	-48.15
	Decapterus spp	15	-40.48	4.1E-05	2.9	-21.17	-9	-45.54
2004	Japanese anchovy	10	-44	1.5E-05	2.8	-15.66	-8	-34.08
	Japanese sardine	13	-41.72	1.9E-05	2.86	-16.75	-8.6	-38.8
	Round herring	14.2	-40.95	1.2E-05	3.03	-14.95	-10.3	-42.28
	Jack mackerel	12.7	-41.92	6.9E-06	3.24	-15.41	-12.4	-46.93
	Scomber spp	20.4	-37.8	1.1E-06	3.03	-15.4	-10.3	-56.56
	Decapterus spp	15	-40.48	4.1E-05	2.9	-21.17	-9	-45.54
2005	Japanese anchovy	10.4	-43.67	1.23E-05	2.93	-14.75	-9.3	-36.57
	Japanese sardine	13.1	-41.66	1.89E-05	2.86	-18.25	-8.6	-40.37
	Round herring	13.55	-41.37	1.23E-05	3.03	-16.25	-10.3	-43.09
	Jack mackerel	13.35	-41.50	4.60E-05	3.17	-15.85	-11.7	-46.13
	Scomber spp	20.7	-37.68	6.05E-06	3.03	-15.40	-10.3	-51.66
	Decapterus spp	15.25	-40.34	4.12E-05	2.93	-21.17	-9.3	-46.51
2006	Japanese anchovy	10.8	-43.33	9.62E-06	3.06	-13.83	-10.6	-39.05
	Japanese sardine	13.2	-41.59	1.88E-05	2.86	-19.75	-8.6	-41.94
	Round herring	12.9	-41.79	1.25E-05	3.03	-17.55	-10.3	-43.89
	Jack mackerel	14	-41.08	8.5E-05	3.1	-16.29	-11	-45.32
	Scomber spp	21	-37.56	1.1E-05	3.03	-15.39	-10.3	-46.76
	Decapterus spp	15.5	-40.19	4.14E-05	2.96	-21.17	-9.6	-47.48

2.2.4 Area density calculation

For species *i*, the area density (kg nm^{-2}) is given as follows:

$$\overline{\rho}_i = \frac{W_i \; Sa}{4\pi \sum_i W_i \; \overline{\sigma}_{bs_i}} \tag{5.9}$$

where *Wi* is the weight of species *i* in the trawl sample, *Sa* is the total nautical area scattering coefficient in equation (5.2) attributed to all species present in the EDSU. $\overline{\sigma}_{bs\,i}$ is the mean backscattering cross-section for one kg of fish of species *i* derived from equations (5.4) and (5.6). The equations were applied to each survey year. The mean density observed along the whole length of a transect is considered as one sample. The density calculations were used to generate estimates of biomass and variance.

V.2.3 Biomass estimation

So far the analysis has produced an estimate of the mean density of the insonified fish from each transect and for each target species. The next step is to determine the total density and biomass in the survey area. A post-stratification of the surveyed area was carried to estimate the total density of the stock. Two methods of strata delimitation were performed: stratification in blocks and stratification in transects.

2.3.1 Stratification in blocks

The surveyed area was partitioned into three blocks chosen on the basis of the following criteria:

* The horizontal distribution of acoustic backscattering strength coefficient during five years.
* The peculiar hydrographic conditions that govern each strata (B1 in coastal area, B2 in offshore area and B3 in the Tsushima straight) (Fig. 5.1).
* The expert knowledge of the ecological properties of the ecosystem.

The characteristics of each block were detailed in Table 5.4. Degree of coverage (DOC) defined measure the sampling intensity of an echo sounder survey (Aglen, 1989), was estimated for each block. It is calculated as follows: $\mathrm{DOC} = \frac{L}{\sqrt{A}}$

where L is the total length of the nautical miles and A is the coverage of the survey area. The results presented by Aglen (1989) pointed out that surveys made with DOC above 6 are considered as sufficient to cover the total fish distribution. However, the priority in this study was given to spacious area coverage instead of DOC.

For each species, in the *k*th block, meanfdensity $\overline{\rho}_k$ was estimated by taking the weighted mean of density for each transect (5.9) by total number of EDSU in the transect (Jolly and Hampton, 1990):

$$\overline{\rho}_k = \frac{\sum_{i=1}^{N_k} \overline{\rho}_{k\,i} n_{k_i}}{\sum_{i=1}^{N_k} n_{k_i}} \tag{5.10}$$

The estimated variance of the stratified mean density is also weighted:

$$Var(\overline{\rho}_k) = \frac{N_k}{N_k - 1} \frac{\sum_{i=1}^{N_k} (\overline{\rho}_{k\,i} - \overline{\rho}_k)^2 \; n_{k_i}^2}{(\sum_{i=1}^{N_k} n_{k_i})^2} \tag{5.11}$$

where $\overline{\rho}_{k_i}$ is mean density in the *i*th transect in *k*th block, N_k is the number of transects in *k*th block, and n_{k_i} is the number of EDSUs (equivalent to 1 nautical mile) in the *i*th transect.

The biomass in the *k*th block is estimated by multiplying mean density in block (5.10) by its coverage:

$$\mathrm{B_k} = \mathrm{A}_k \overline{\rho}_k \tag{5.12}$$

where A_k is area of *k*th block

The variance of biomass in *k*th block is calculated using the following equation:

$$\mathrm{var}(B_k) = A_k^2 \, \mathrm{var}(\overline{\rho}_k) \tag{5.13}$$

The coefficient of variation biomass in *k*th block is calculated as follows:

$$\mathrm{CV}(B_k) = \frac{\sqrt{\mathrm{var}(B_k)}}{B_k} \tag{5.14}$$

Considering the total stratified population, the total biomass B_0 in the surveyed area is the sum of biomass in each block:

$$B_0 = \sum_{k=1}^{N} B_k \tag{5.15}$$

In a similar manner, the variance estimate is defined as:

$$\mathrm{var}(B_0) = \sum_{k=1}^{N} \mathrm{var}\, B_k \tag{5.16}$$

where *N* is number of blocks.

At last, the coefficient of variation is derived from equations (5.15) and (5.16):

$$\mathrm{CV}(B_0) = \frac{\sqrt{\mathrm{var}(B_0)}}{B_0} \tag{5.17}$$

2.3.2 Stratification in transects

The total surveyed area covers the fishing grounds of target species. The surveys are intentionally designed to sample the full range of these species, knowing that each species has ecological preferences which delimit its horizontal distribution. Therefore, many

transects are beyond a fish–group ground and represent a large number of EDSU with zero density counts, thus inflating the variance of the density count data set.

To reduce the impact of these zero-count transects, the total survey area is post-stratified into two strata depending on the occurrence or absence of acoustic backscatter in each transect. Strata 0 contains transects with "vacant" samples where mean density is zero, whereas strata 1 consist of transects including samples with positive values. In this latter case, positive strata, the density count by transect is weighted by the sum of the sampling unit (EDSU which is equal to 1 nautical mile in this study). The weighting in the zero strata is unnecessary since density counts are zero.

The stratified estimate of density, $\overline{D}$ (kg nm^{-2}), is defined as:

$$\overline{D} = \frac{A_0}{A}\overline{D}_0 + \frac{A_1}{A}\overline{D}_1 \tag{5.18}$$

Where $\overline{D}_0$ and $\overline{D}_1$ represent the mean density of strata 0 and strata 1, respectively. $\overline{D}_0$ is zero by definition. A_1 and A_0 are the relative area of the two strata. A_1 is the geographic area of strata 1. A is the total coverage of the survey area ($A = A_1 + A_0$).

The variance of estimated density, adjusted for post-stratification (Jessen, 1978) is determined as:

$$\mathrm{Var}(\overline{\mathrm{D}}) = \frac{\mathrm{A}_0^2\ \mathrm{Var}(\overline{\mathrm{D}}_0)}{\mathrm{A}^2} + \frac{\mathrm{A}_1^2\ \mathrm{Var}(\overline{\mathrm{D}}_1)}{\mathrm{A}^2} \tag{5.19}$$

where n is the number of nautical miles, $\overline{D}_1$ and $Var(D_1)$ are estimated by:

$$\overline{D}_1 = \frac{\sum_{i=1}^{N} D_{1_i}\ n_i}{\sum_{i=1}^{N} n_i}$$

$$\mathrm{Var}(\overline{D}_1) = \frac{\sum_{i=1}^{N} (D_{1i} - \overline{D}_1)^2}{(\sum_{i=1}^{N} n_i)^2} \tag{5.20}$$

Therefore the biomass estimated and its variance can be deduced as follows:

$$\text{Biomass} = \overline{D}_1 \; A \tag{5.21}$$

$$\mathrm{var}(B) = Var(\overline{D}_1) \quad A^2 \tag{5.22}$$

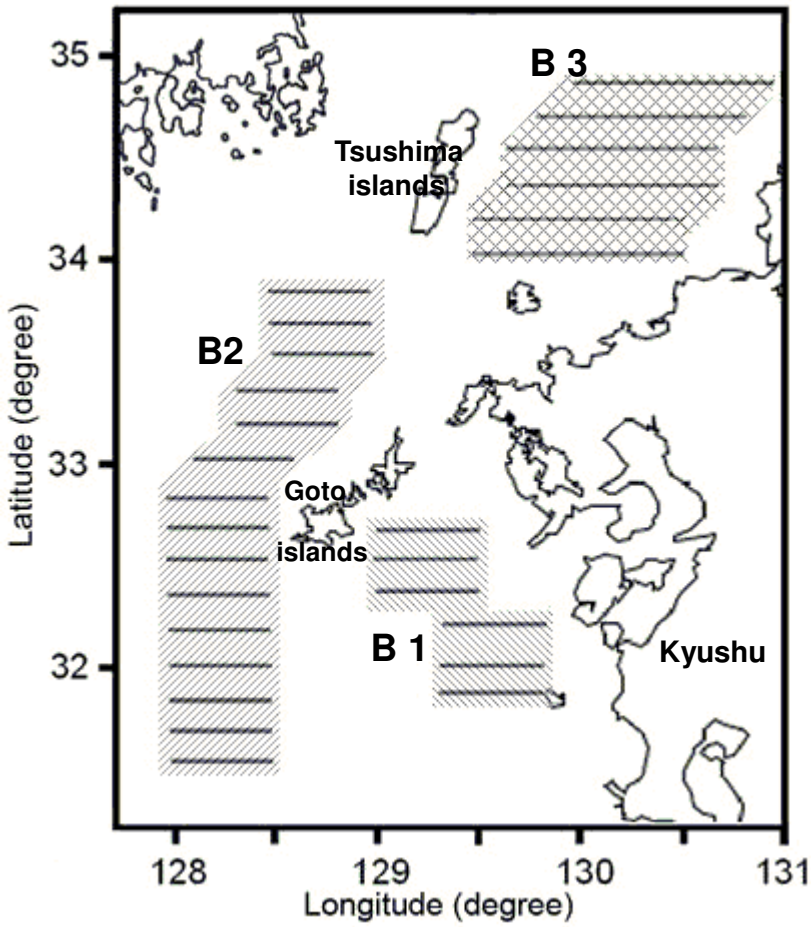


Fig. 5.1 Stratification by blocks (B1, B2 and B3).

V.3 Results

V.3.1 Horizontal fish distribution

The horizontal distribution of fish density expressed by the area backscattering strength for group 1 and group 2 for each year were illustrated in Figures 5.2 to 5.6.

G1 fish species showed a more or less homogenous spatial distribution throughout years. They occurred mainly in the western coastal area off Kyushu and in the Tsushima straight, except in 2002 where they appeared in high densities in the waters west of Goto island. In the same year, 75% of the total trawl catch consisted of G1 species (Table 5.2). In 2004, the catch amount of Japanese anchovy represented nearly the whole bulk of G1 catch. This species was not found in the western part of the survey area and was spatially limited to the coastal regions and to the eastern waters of Tsushima Island. The spatial distribution of G1 species corroborates with the findings of previous studies conducted in the East China Sea and Japan Sea (Ohshimo, 2006; Ohshimo *et al*., 2009).

Over all the five years, G2 species showed relatively low fish densities and scarce distribution in the offshore western region of the survey area and in the Tsushima straight. The fish density was relatively lower and sporadically distributed in the coastal region of the surveyed area. In 2003, nearly 97% of the total catch of G2 consisted of Japanese jack mackerel. However, this species was not detected in the eastern part off Kyushu coasts.

Table 5.4 Characteristics of block size: transect length, area and degree of coverage (DOC).

	2002				2003				2004				2005				2006			
	B 1	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**	**B 1**	**B 2**	**B 3**	**Total**
Transect length (nm)	137	249	330	716	150	376	283	809	150	168	254	572	151	358	280	789	155	335	283	773
Area (nm^2)	1500	5000	3000	9500	1500	5000	3500	10000	1200	2300	3500	7000	1500	5000	3500	10000	1500	4600	3500	9600
DOC	3.5	3.5	6	7.3	3.9	5.3	4.8	8.09	4.3	3.5	4.3	6.8	3.9	5.1	4.7	7.89	4	4.9	4.8	7.89

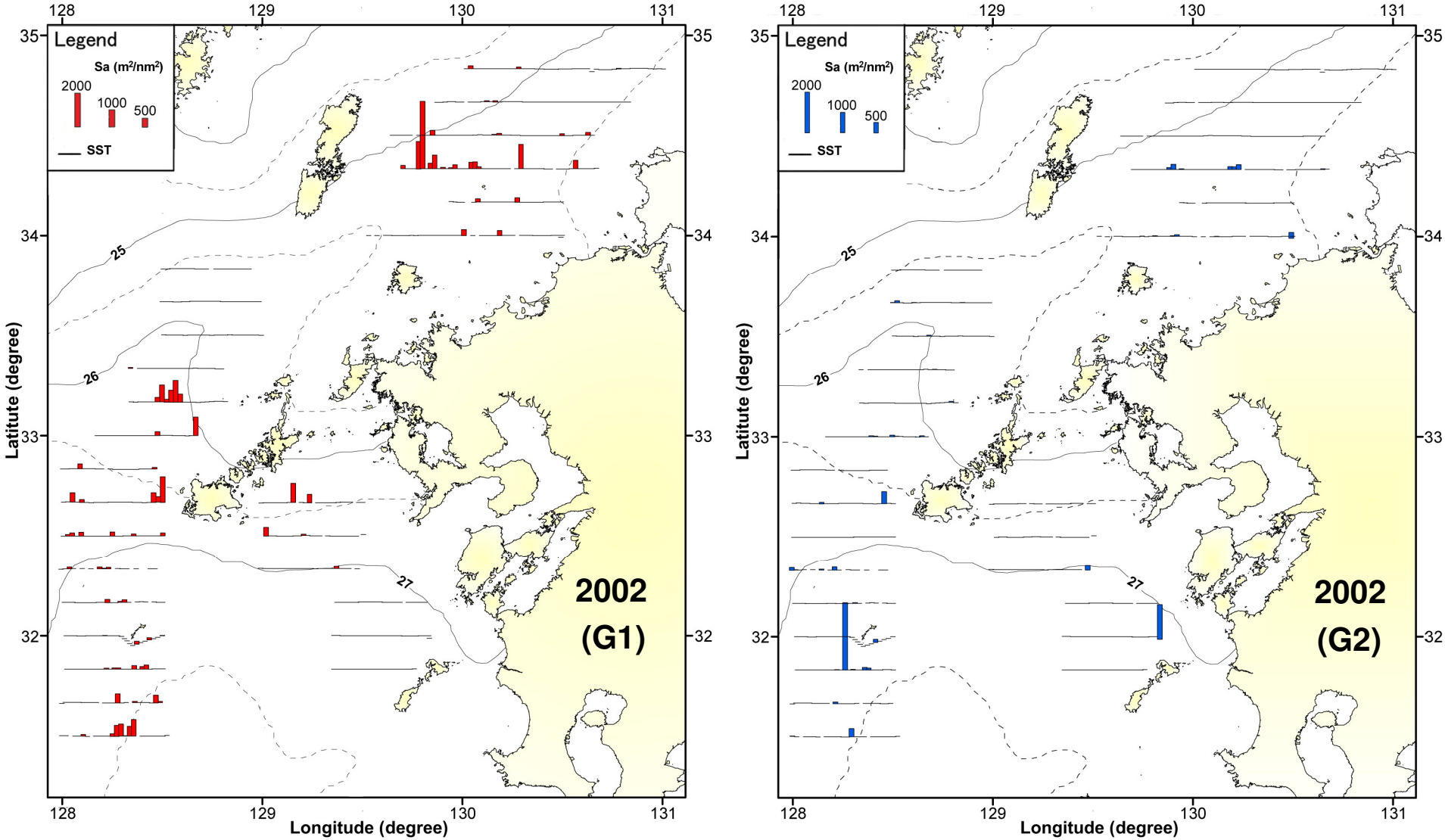


Fig. 5.2 Distribution of fish density (*Sa*) of Group 1 (left) and Group 2 (right) species together with the sea surface temperature in 2002.

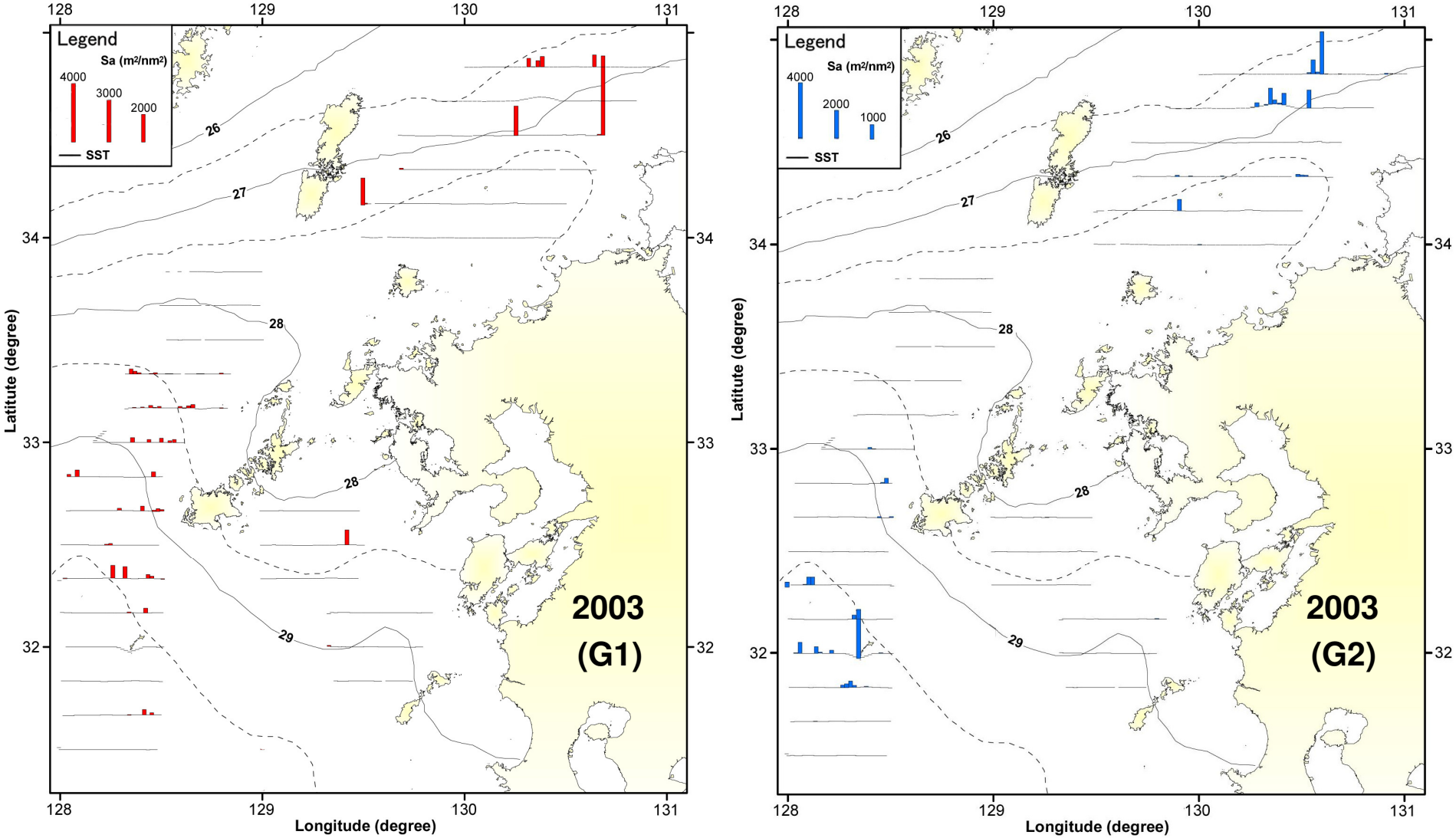


Fig. 5.3 Distribution of fish density (*Sa*) of Group 1 (left) and Group 2 (right) species together with the sea surface temperature in 2003.

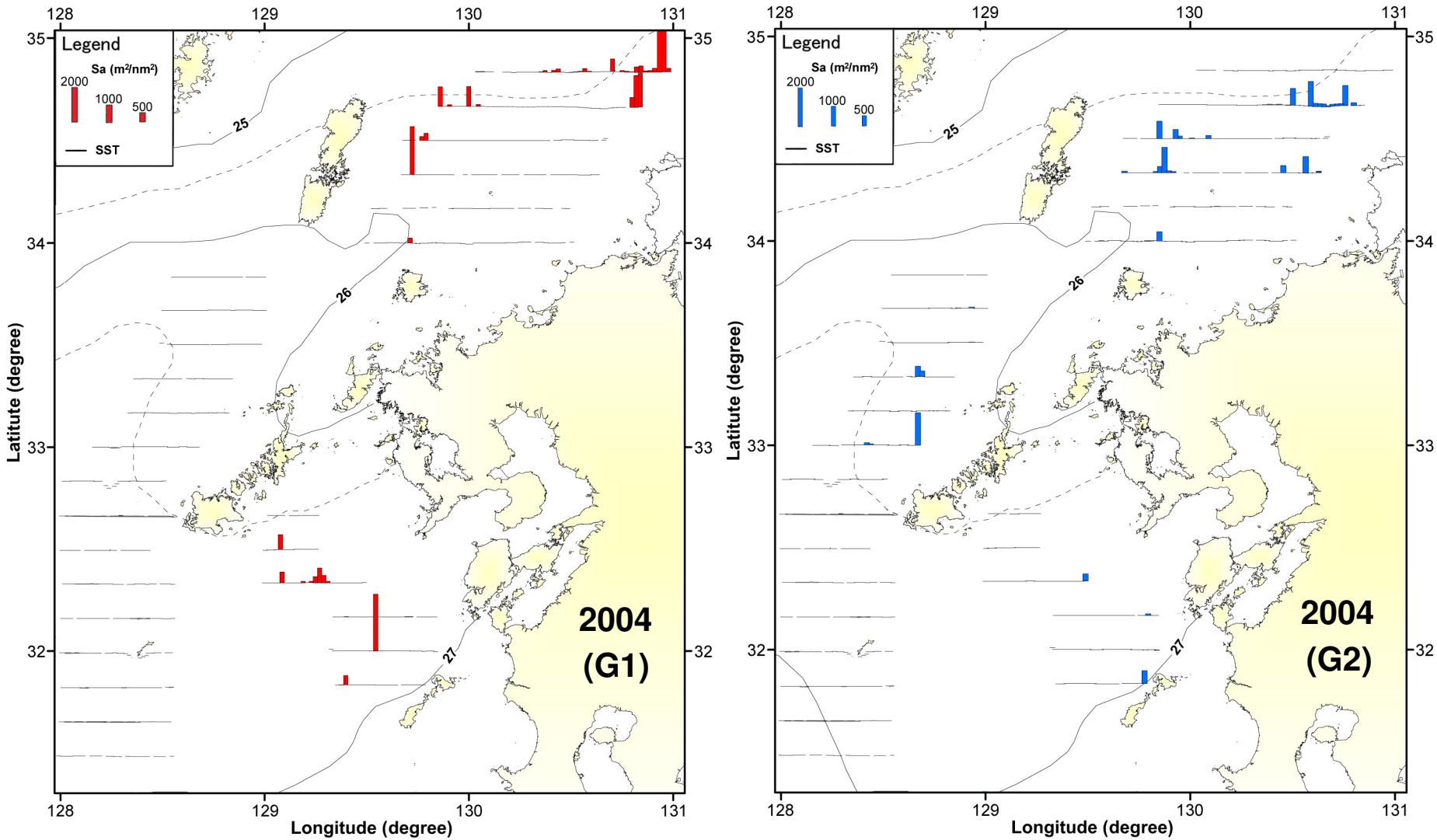


Fig. 5.4 Distribution of fish density (*Sa*) of Group 1 (left) and Group 2 (right) species together with the sea surface temperature in 2004.

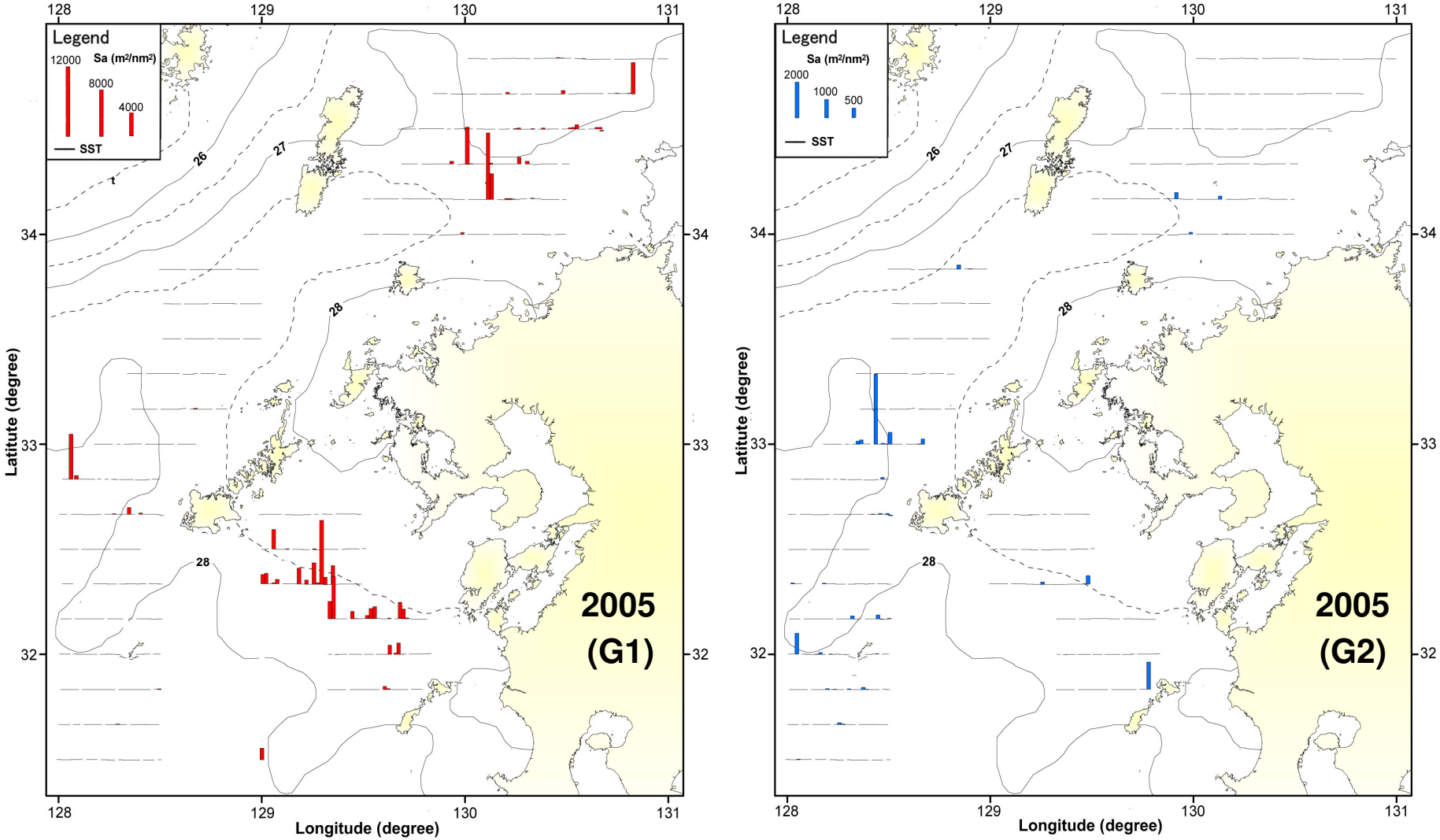


Fig. 5.5 Distribution of fish density (*Sa*) of Group 1 (left) and Group 2 (right) species together with the sea surface temperature in 2005.

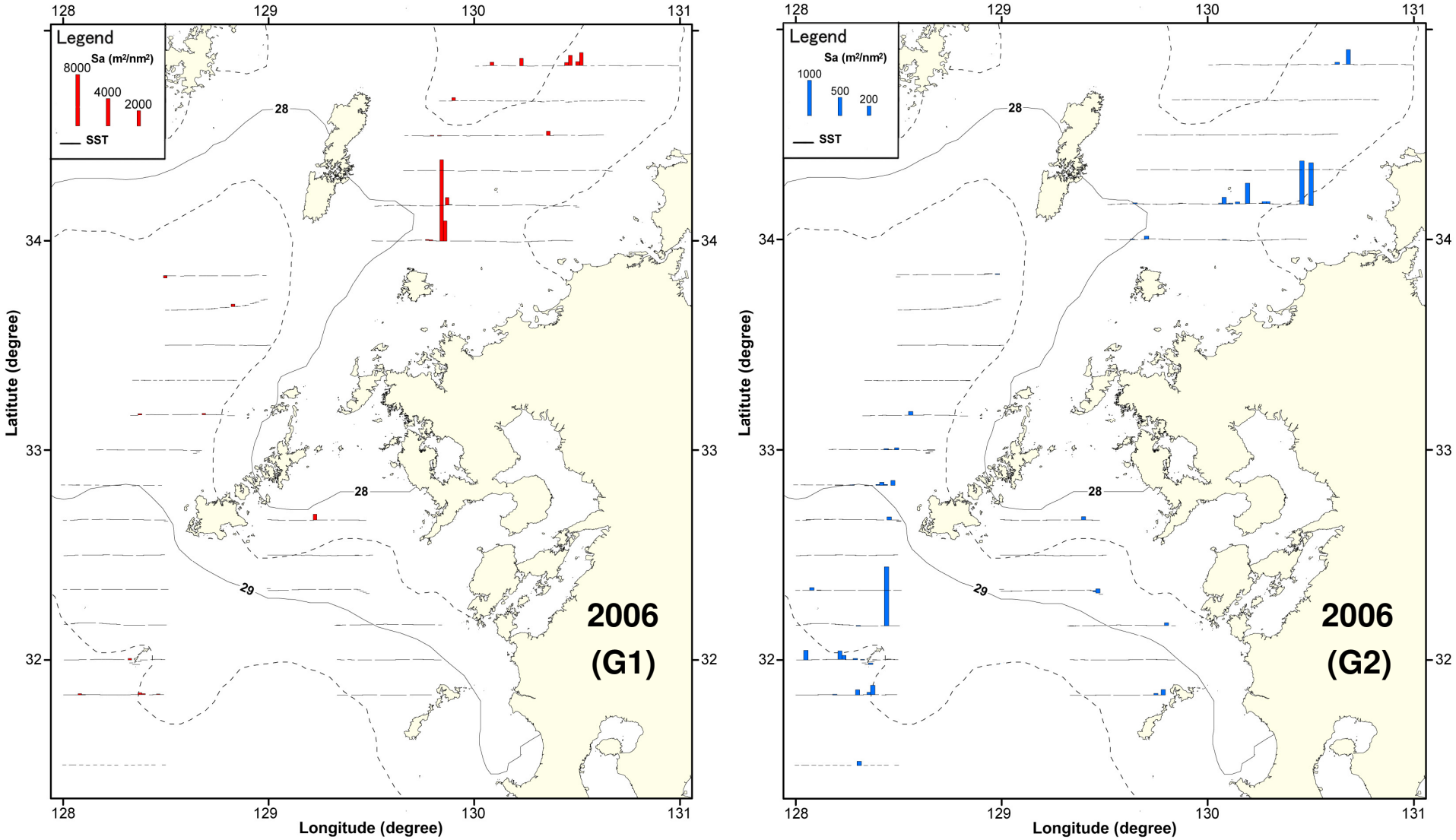


Fig. 5.6 Distribution of fish density (*Sa*) of Group 1 (left) and Group 2 (right) species together with the sea surface temperature in 2006.

V.3.2 Biomass estimates

V.3.2.1 Stratification in blocks

Estimates of biomasses and variances are shown in Table 5.5. The biomass ranged between 360 and 1.3 million tons. The degree of coverage estimated for each block was less than 6, which was recommended by Table 5.4. The block 3 in 2004 made the exception and the DOC was equal to 6.

The contributions of each block for the total biomass estimated by year are illustrated in the figures 5.7 to 5.11. G1 species was composed mainly of Japanese anchovy and round herring. Over all the five years, the estimated biomass of Japanese sardine did not exceed 1500 tons. The distribution of this biomass was always limited to block 3, whereas it was totally absent from block 1 and 2, except in 2005 with a little amount of nearly 16 tons (Fig. 5.10). Over the five years, Japanese anchovy was not present in block 2, except in 2005 with a relatively little biomass (25 260 tons). Round herring showed also a sparse occurrence in block 2, it was missing in 2004 (Fig 5.9).

The distribution of the biomass of G1 species might be explained by their ecological preferences and their habitual ground, limited to the coastal waters off Kyushu and the Tsushima straight connecting with the Japan Sea. The highlighted biomass distribution agree with the results of Ohshimo *et al*. (2009) revising the long-term biomass distribution of the Japanese sardine.

Both species of *Scomber* were not detected in block 1 in 2003 and 2004 and barely existed during other years with a tiny biomass accounting for less than 9000 tons. However, the exception was in 2005 with approximately 42 500 tons. The largest amount of biomass was accounted for Jack mackerel and was identified in block 3 in 2004.

The estimated coefficients of variation (CVs) for estimates of total biomass from each

survey ranged from 27 to 76% (Table 5.5). The high CVs, as identified in 2002, were mostly due to the patchy distribution of Japanese anchovy and *Decapterus*, resulting in high dispersion between the weighted mean density estimates within the same block. Thus, the proximate very high and zero measurements within transects generated high uncertainty of estimates, illustrated by high CVs.

The inconsistent fish distribution could be explained the aggregated distribution pattern caused by the peculiar oceanographic conditions in the surveyed area. Another source of error in the estimate could be the inadequate DOC as defined by Løland *et al*. (2007), the most biasing factor of the total uncertainty in the biomass estimates. The DOC was inferior to 6 in almost of all blocks. That is, the skewed distribution of fish density was combined with the small spatial coverage of acoustic surveys.

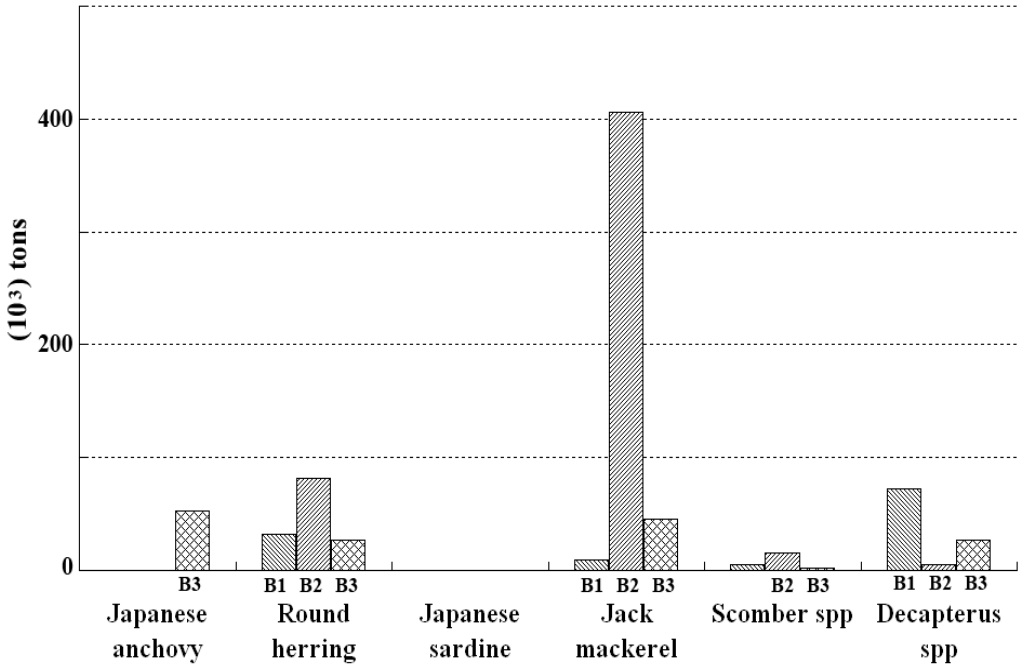


Fig. 5.7 Contributions of blocks to the total biomass estimated in 2002 based on stratification in blocks.

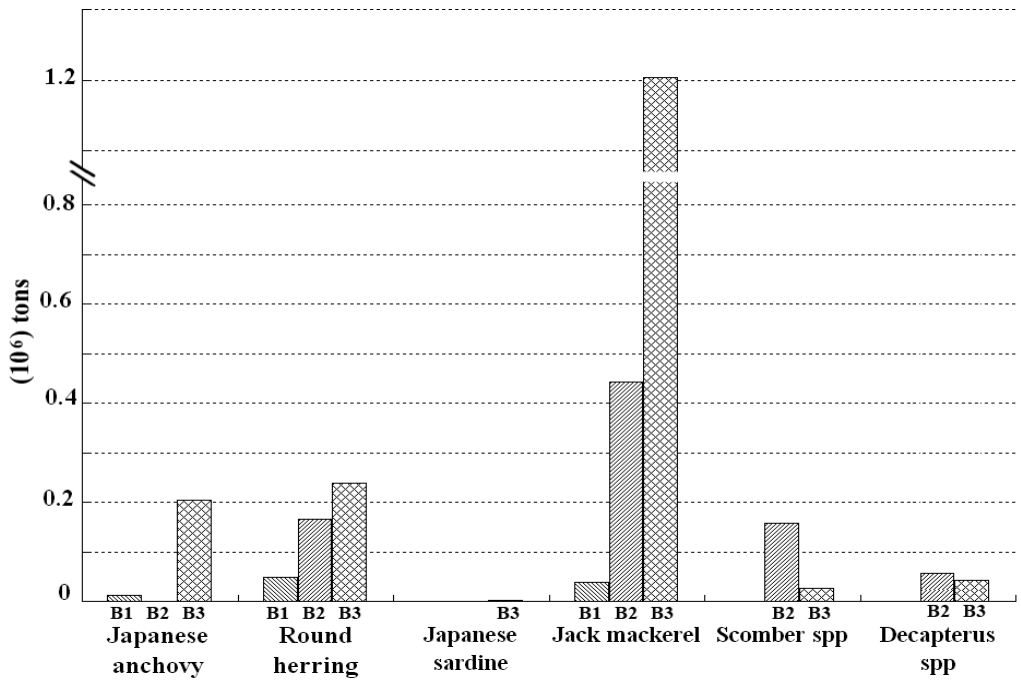


Fig. 5.8 Contributions of blocks to the total biomass estimated in 2003 based on stratification in blocks.

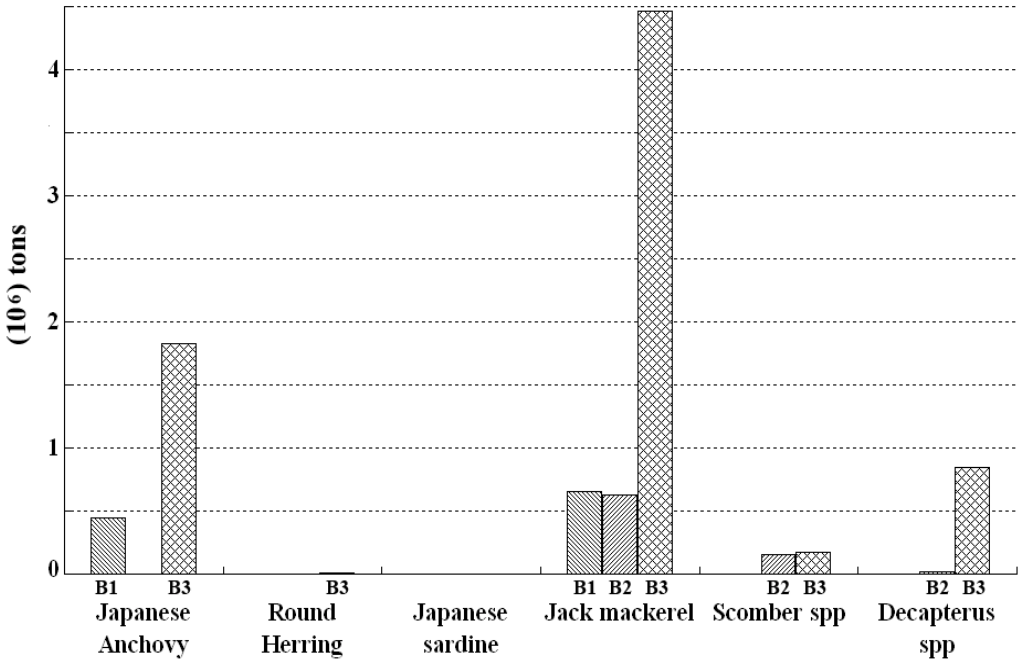


Fig. 5.9 Contributions of blocks to the total biomass estimated in 2004 based on stratification in blocks.

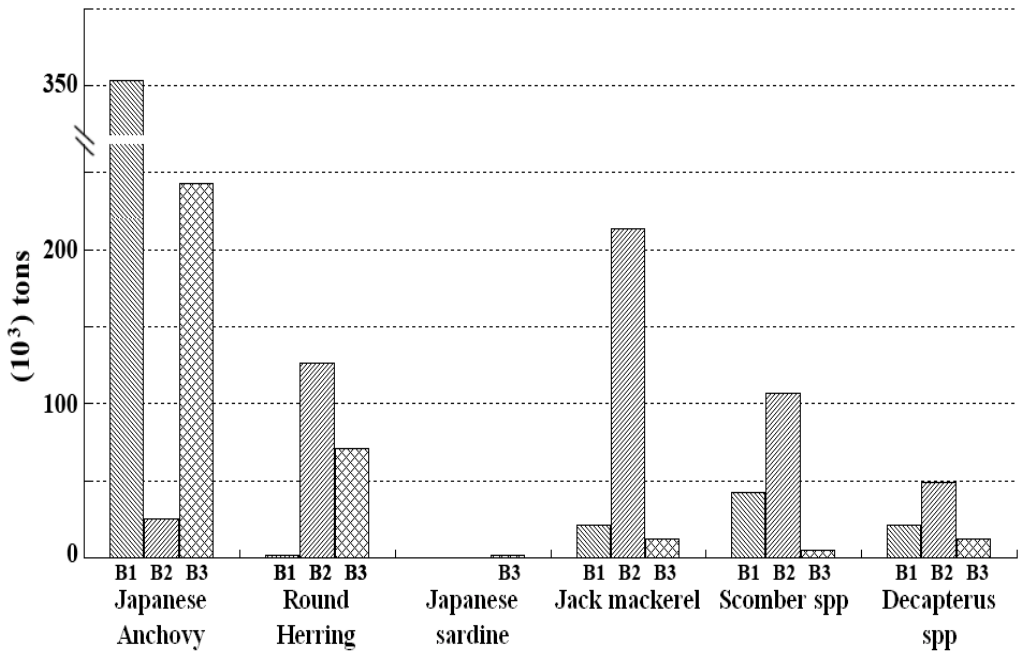


Fig. 5.10 Contributions of blocks to the total biomass estimated in 2005 based on stratification in blocks.

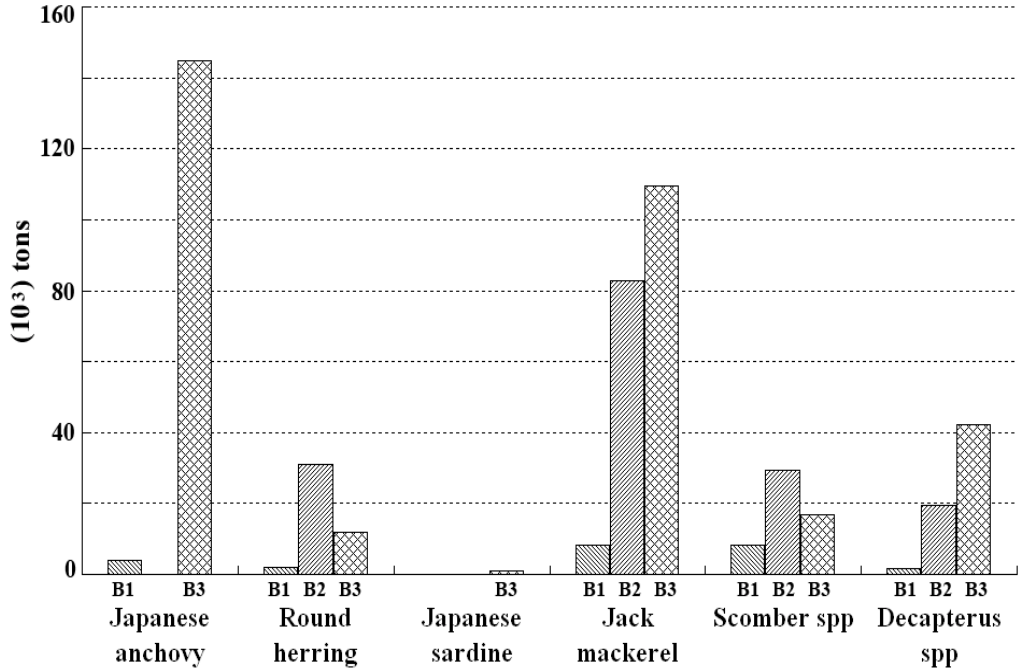


Fig. 5.11 Contributions of blocks to the total biomass estimated in 2006 based on stratification in blocks.

3.2.2 Stratification in transects

The gregarious behavior of pelagic fish forming aggregations tends to generate acoustic data with a high proportion of zeroes and right-skewed distribution of positive values (Gimona and Fernandes, 2003; Walline, 2007). Under these conditions, the stratification in transects was applied owing the recurrent low number and spatially sparse positive values occurring along survey transects.

The estimated biomass ranged between 348 and 1.22 millions tons (Table 5.6). Similarly to the results of the based-blocks stratification approach, 99% of the biomass of G1 species was made up of Japanese anchovy and round herring. In the G2, jack mackerel was always the most abundant species and its biomass accounted for 49 to 96% of the total biomass of G2 in 2003 and 2004 respectively (Fig. 5.8, 5.9).

The CVs ranged between 10 and 73%. The high CVs resulted from the wide discrepancy of weighted mean density between positive transects. The mean density calculated from one transect was in some cases four figures larger than from the adjacent transect. The jack mackerel accounted for the highest biomass in 2004 and was distributed quite consistently between 13 transects, resulting hence in a remarkable low variance of biomass. The small variance of *Scomber* spp biomass in 2003 was also the result of the uniform distribution along 14 transects, despite the small biomass amount, accounting for less than 0.5% of the total biomass of G2 species.

Table 5.5 Biomass (in tons), variance and coefficient of variance (CV) estimates for each year based on stratification in blocks.

		2002			2003			2004			2005			2006		
		Biomass	Variance	C V	Biomass	Variance	CV	Biomass	Variance	CV	Biomass	Variance	CV	Biomass	Variance	CV
Group1	Japanese anchovy	52897	1.6E+09	0.76	43183	6.4E+08	0.59	227362	7.4E+09	0.38	622363	3.7E+10	0.31	148643	6.4E+09	0.54
	Round herring	140315	2.7E+10	0.27	90386	1.1E+09	0.36	1080	2.5E+05	0.46	199191	1.1E+10	0.52	44901	1.6E+08	0.29
	Japanese sardine	0	0	0	598	1.3E+05	0.61	360	2.7E+04	0.46	1447	3.1E+05	0.39	895	2.3E+05	0.54
Group2	Jack mackerel	460852	4.8E+10	0.42	1304112	2.9E+11	0.38	575602	3.5E+10	0.37	246764	1.8E+10	0.47	200440	3.2E+09	0.33
	Scomber spp	23165	9.4E+07	0.48	36799	1.9E+08	0.41	32717	1.4E+08	0.33	154219	5.3E+09	0.55	54616	7.8E+09	0.44
	Decapterus spp	103681	4.1E+09	0.62	109465	7.1E+09	0.44	87069	1.2E+09	0.39	82329	1.2E+09	0.43	63047	1.0E+09	0.51

Table 5.6 Biomass (in tons), variance and coefficient of variance (CV) estimates for each year based on stratification in transects.

		2002			2003			2004			2005			2006		
		Biomass	Variance	C V	Biomass	Variance	CV	Biomass	Variance	CV	Biomass	Variance	CV	Biomass	Variance	CV
Group1	Japanese anchovy	58197	1.7E+09	0.71	41036	5.1E+08	0.55	225784	5.8E+09	0.34	684067	6.3E+10	0.37	146481	1.1E+10	0.73
	Round herring	171317	6.2E+09	0.46	114479	1.8E+09	0.37	1043	2.1E+05	0.44	178065	8.1E+09	0.51	52318	2.8E+08	0.32
	Japanese sardine	0	0	0	583	1.1E+05	0.58	348	2.3E+04	0.44	1442	3.0E+05	0.38	909	4.5E+05	0.74
Group2	Jack mackerel	488052	1.7E+10	0.27	1221701	3.6E+11	0.49	578004	2.2E+07	0.10	233267	1.5E+10	0.52	193476	5.4E+09	0.38
	Scomber spp	12538	2.8E+07	0.42	34959	2.8E+07	0.25	34387	1.9E+07	0.23	156311	4.8E+09	0.45	55518	2.0E+08	0.26
	Decapterus spp	120862	5.5E+09	0.62	118926	4.3E+08	0.45	85935	6.4E+08	0.29	83957	1.1E+09	0.39	59280	1.1E+09	0.56

V.4. Discussion

4.1 Evaluation of stratification approaches

The estimated biomass on the basis of the stratification in transects was slightly more precise than from stratified blocks for many species. For instance, throughout the five years, the variance of the biomass estimates of the two species of *Scomber* were tighter and markedly smaller from 2002 to 2004 (Fig. 5.16). The error uncertainty in biomass estimates of jack mackerel showed also a significant decrease in 2004 (Fig. 5.15). The reduction of the variance intervals was not massive though for the remaining species.

The inaccuracy in estimates can be explained by the spatial correlation of the positive samples in few EDSU with high density. On the contrary, if acoustic data was uniformly distributed in the surveyed area, relatively tiny fish densities would be widely distributed along survey transects. Hence, the variance of biomass estimate would markedly decrease.

Minor dissimilarity between both approaches in estimating biomass and variance are considered as intrinsic analyses errors and could be explained by the trivial inaccuracy of blocks and strata delimitation.

According to the results illustrated in the previous chapter, the fish biomass distribution might be correlated to the vertical stratification of the water temperature and salinity. On the other hand, the overlay of sea surface temperature map with fish density did not provide noticeable correlations. This result was not unexpected because of the consistency of SST values throughout the East China Sea during the survey time, corresponding to the late summer season (c.f. chapter IV).

Notwithstanding the trivial dissimilarity in biomass estimates between both approaches, the stratification was beneficial to accurately investigate the pelagic fish stocks in the East China Sea. The choice of stratification approach was crucial to meet the objectives of this

study. Cochran (1977) stated, ‘‘If intelligently used, stratification nearly always results in a smaller variance for the estimated mean or total than is given by a comparable simple random sample’’.

An alternative methodology is to use uninformative stratification, in which the surveyed space is arbitrarily divided into many small strata. For instance, Simmonds and Fryer (1996) found that accuracy of the mean abundance of Atlantic herring *Clupea harengus* in the North Sea increased with increasing stratification. Godø *et al.* (1998) reported that a few larger strata were beneficial in expanding catch composition to acoustic densities because they better reflected the variability in catchability and reduced the influence of individual trawl samples. Smith and Gavaris (1993) pointed out that the greatest gain in estimates accuracy is achieved not through stratification alone but through optimal allocation to the strata. The stratification scheme should consist of a few large strata instead of many small strata.

4.2 Comparison with other methods

The biomass estimates on the basis of both approaches of stratification are illustrated in Figures 5.12 to 5.17. The Japanese anchovy shows an upward trend in 2004 to reach a peak in 2005 which corresponds to the highest amount of landings. The estimates are biased for *Scomber* spp, when landings were larger than the estimated biomass in 2002, 2003, 2004 and 2006. The biased results are most likely due to the limited duration of surveys, whereas, the landings were estimated from catches taken all over the year.

Compared to VPA estimates, provided by the Fisheries Research Agency, our results illustrated large discrepancy for some species. The stock was underestimated by 90% for Japanese sardine and *Scomber* spp. However, for the latter species, both assessment

methods showed similar trend of biomass stock. The acoustic estimates differed by 10% in 2006 for Japanese sardine and round herring. The catch per unit effort (CPUE), obtained from Fisheries Research Agency, has similar trend to acoustic estimates for *Decapterus* spp.

The errors in acoustic estimates might have regrettable consequences for the fishery management in the East China Sea. However, if management measures are to be based on uncertain biomass estimates, it is advisable to be too low than too high. Furthermore, it is inadvisable to change the standard methodology of acoustic survey. It should be more cautious to revise the sources of estimates errors. Typical systematic sampling design, as used in the present study, can provide the most precise estimate of the mean biomass over the surveyed area (Table 5.6). Nevertheless, this survey design can not provide sampling variances using traditional formulas based on random sampling theory (Jolly and Hampton, 1990). Therefore the requirement for stationarity in the mean and variance was met by the post-stratification of the survey area.

Notwithstanding the approach of stratification in transects did not yield clear reduction of the estimate variance, it has to be concluded that in general the heteroscedastic data from acoustic survey represent a challenge facing both post-stratification methods for biomass estimation. In such conditions, an adaptive survey approach could be implemented to reduce the total uncertainty in the biomass estimates. The adaptive design has been widely applied in acoustic surveying (Thompson and Seber, 1996 and Harbitz *et al*, 2009). It is a procedure where the sampling intensity depends on the values observed during the survey. More explicitly, this approach defines a stratum for each observation and how to take additional observations in that stratum when the acoustic density exceeds a predetermined threshold (Conners and Schwager, 2002). Hence, the overall estimate accuracy could be

increased by adaptively including additional transects between the original transects in regions of high abundance (approximately in the region of the Block 1 and Block 3).

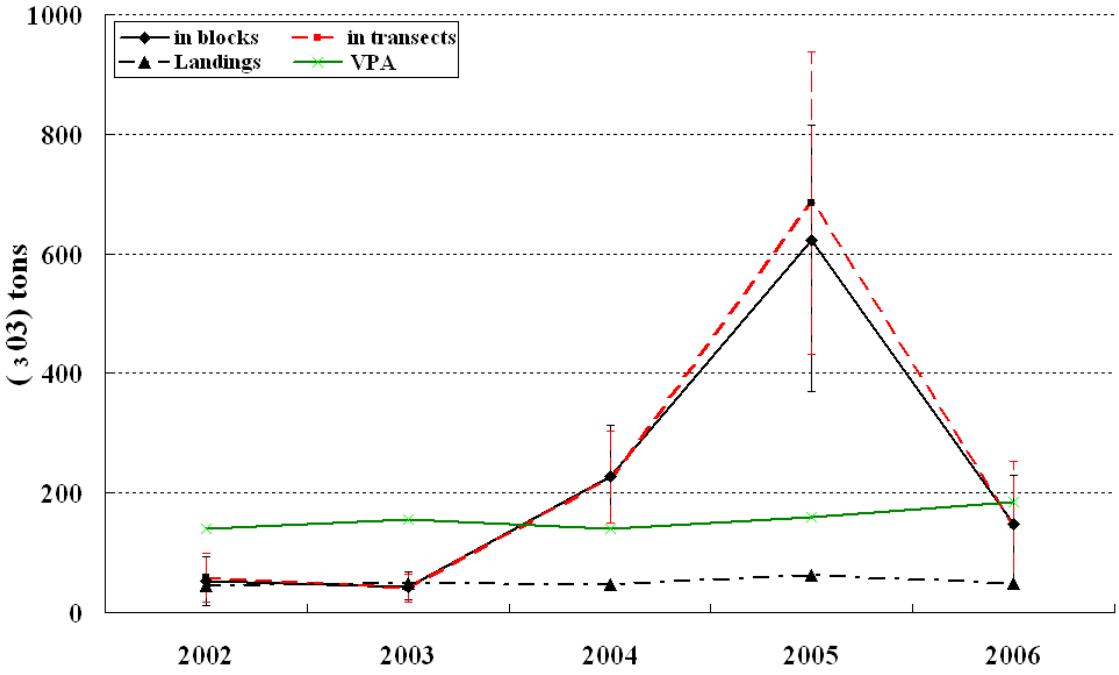


Fig. 5.12 Biomass estimates of Japanese anchovy resulted from stratification in blocks (bold line) and in transects (red dashed line) in comparison with VPA results (green line) and landings (dashed line). Vertical bars represent standard error.

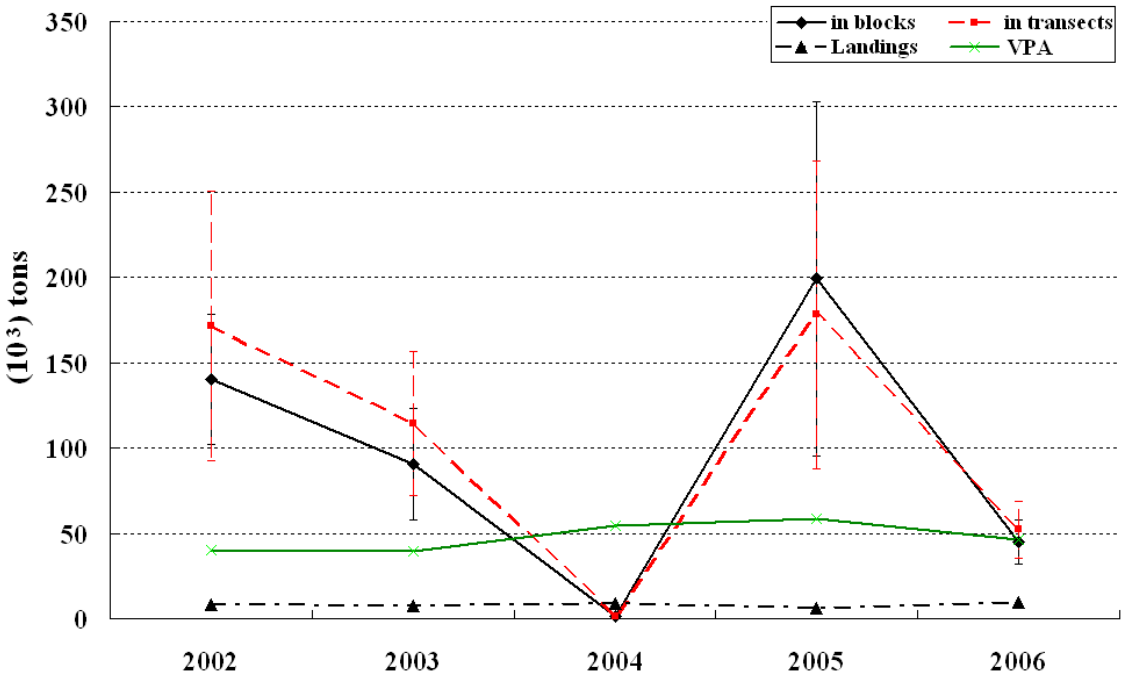


Fig. 5.13 Biomass estimates of round herring resulted from stratification in blocks (bold line), in transects (red dashed line) and in comparison with VPA results (green line) and landings (dashed line). Vertical bars represent standard error.

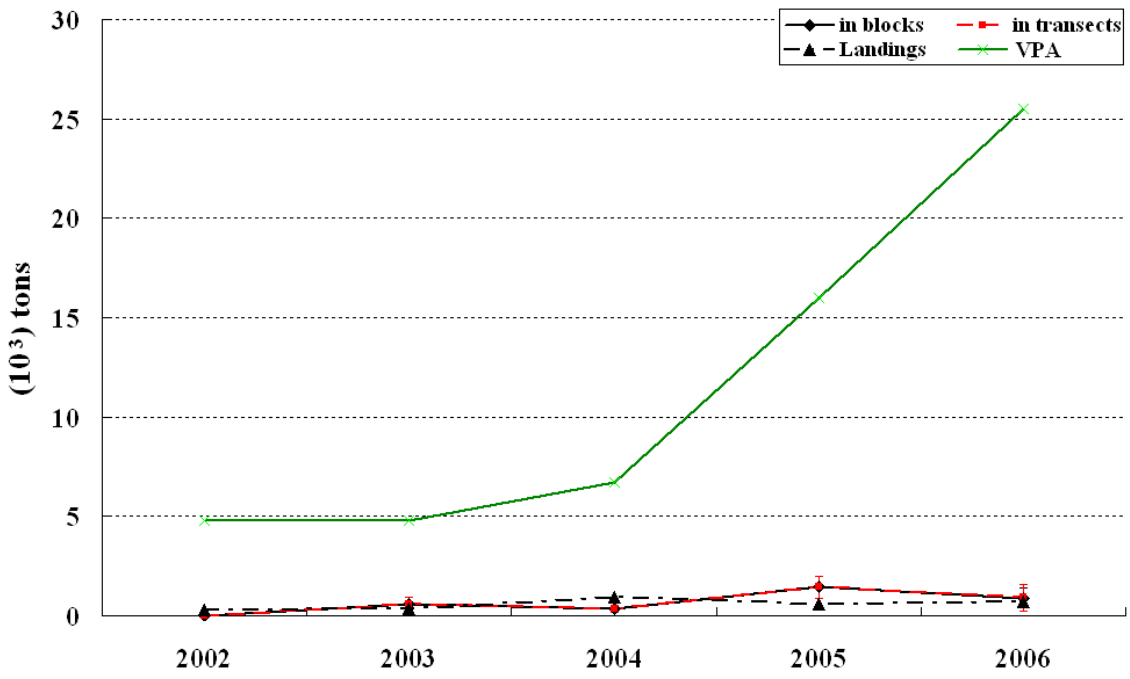


Fig. 5.14 Biomass estimates of Japanese sardine resulted from stratification in blocks (bold line), in transects (red dashed line) and in comparison with VPA results (green line) and landings (dashed line). Vertical bars represent standard error.

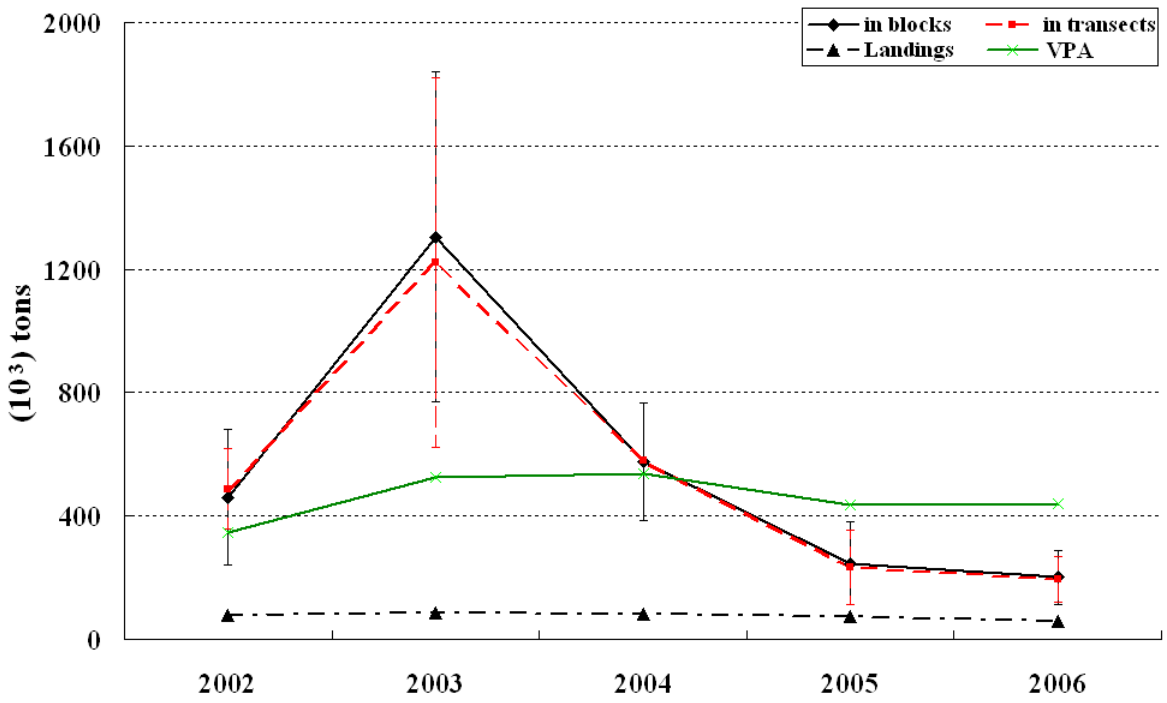


Fig. 5.15 Biomass estimates of Jack mackerel resulted from stratification in blocks (bold line), in transects (red dashed line) in comparison with VPA results (green line) and landings (dashed line). Vertical bars represent standard error.

Fig. 5.16 Biomass estimates of *Scomber* spp resulted from stratification in blocks (bold line), in transects (red dashed line) and in comparison with VPA results (green line) and landings (dashed line). Vertical bars represent standard error.

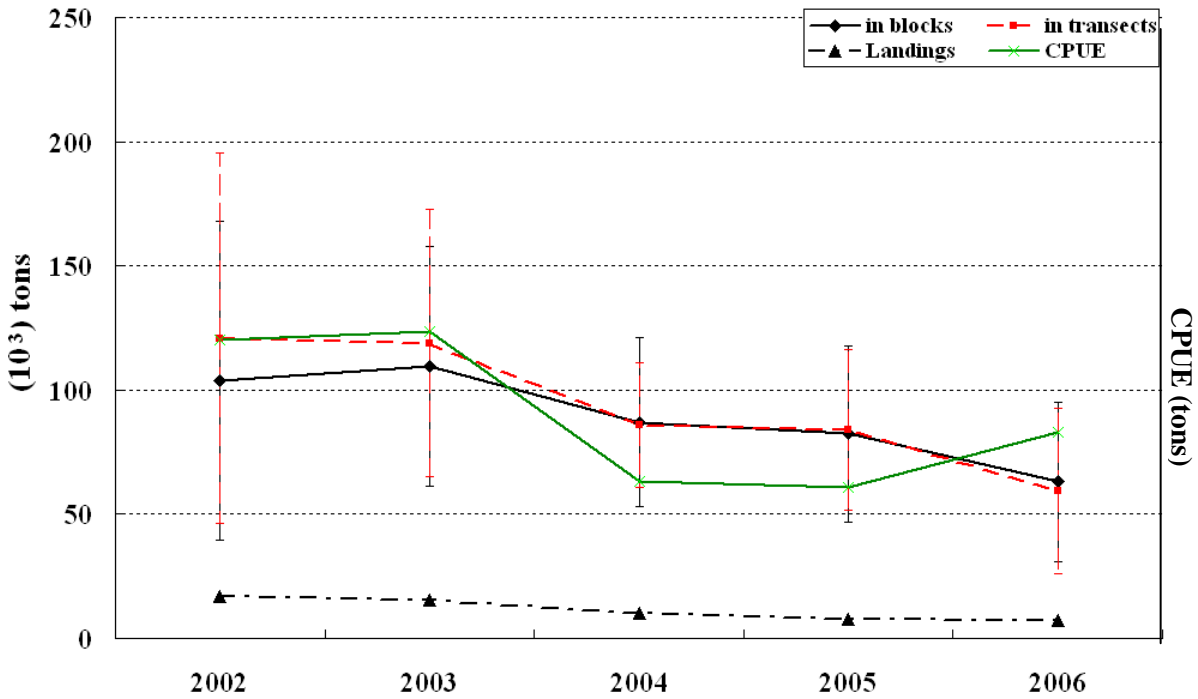


Fig. 5.17 Biomass estimates of *Decapterus* spp resulted from stratification in blocks (bold line), in transects (red dashed line) and in comparison with CPUE results (green line) and landings (dashed line). Vertical bars represent standard error.

VI.1 Key steps in biomass estimation

This thesis has explored methods of acoustic estimates of pelagic fish biomass in the East China Sea based on five years data collected from stratified sampling scheme. The study has expanded the results of the few previous attempts on using acoustic methods to estimate abundance and biomass of pelagic fish in the East China Sea. Different steps of hydroacoustics application to estimate biomass were run.

The first defying step (c.f. chapter 3) was to discriminate among the diverse target species and to assign each echo-integral to a particular species. The key idea was to partition between scrutinized fish schools based on five acoustic descriptors into broad fish classes. Based on these features, two methods of supervised classification were applied, the discriminant function analysis (DFA) and the artificial neural network technique (ANN). Both methods showed satisfactory and about equally correct classification rates (ANN 87.6%; DFA 85.1%) and classified detected schools into three groups (G1, G2 and G3). Then, biological samples obtained from midwater trawling were required to identify acoustically monitored fish schools classified within each group to species level. Fish species were classified within three groups, the first group 1 consisted of three species occuring in the upper pelagic layer. The bulk of catch was made of Japanese anchovy, round herring and sardine. The group 2 included five species taking place in midwater layers and represented mainly by jack mackerel, chub mackerel and shortfin scad Japanese scad. The last group G3 comprised mesopelagic species (pearlsides and lanterfishes) occurring in demersal layers.

At this stage, it was interesting to explore and evaluate the influence of environmental factors on school characteristics (c.f. chapter 4). Good knowledge of the distribution

patterns of fish schools is crucial for successful ecosystem based fisheries management. Focusing on the two fish-groups including pelagic species (G1 and G2), generalized additive models were used to provide statistically quantitative description of the relationships between bottom depth, water temperature and salinity at various depth levels and the acoustic descriptors as indicators of school size, depth, abundance and packing density. Results of the correlation analyses confirmed the preference of G1 fish species to occur above the thermocline. The size, abundance and density of schools were only controlled by temperature and salinity in the upper layer, and the bottom topography. Notwithstanding their pelagic nature, G2 species exhibited preferential aggregation at deep layers. Furthermore, GAMs revealed optimal conditions for some school properties. Such reliable findings are essential for a better understanding of pelagic fish-ecosystem interactions and will provide leading indicators for a more efficient fish stock monitoring.

Once the assignment of acoustically monitored schools to fish species is concluded, the backscattered energy was converted to estimate fish density and biomass. This wouldn't be possible without the fulfillment of another step which was the post-survey stratification of the surveyed areas into strata. Two approaches were applied, stratification in blocks and stratification in transects. The first method consisted in the partition of the surveyed area into three blocks according to the hydrographic conditions and the horizontal distribution of backscatters. The second approach was based on the occurrence or absence of acoustic backscatter in each transect and hence, excluded transects including vacant samples where mean density is zero.

The last step was the combination of fish composition from trawling data with fish density estimated over each nautical mile, derived from partitioned acoustic data according to

post-stratification. Then, target-strength of each species, obtained from literature, was used to convert the calculated densities to biomass estimates, and its corresponding error margins. The results revealed that the jack mackerel was the most abundant species, followed by the Japanese anchovy.

VI.2 Future perspectives: toward accurate application of fisheries acoustics

The study presented here represents a leading attempt dealing importantly with discrimination of co-occuring pelagic species into fish-groups based on acoustic school properties. The study, hence, introduced a directive approach relevant to the case of ecosystems with high fish diversity. Concurrently, the work represents a contribution that will need to be considered as fisheries stock assessment progresses towards operational ecosystem based fisheries management in the East China Sea. Some other issues addressed to sources of liable errors in fisheries acoustics application, worthy to be considered are discussed below.

2.1 Sampling errors

The sources of error in acoustic abundance estimates have been more extensively investigated than appears to be the case for other methods, at least as regards the assessment of pelagic stocks (Simmonds and Maclennan, 2005). There were a number of challenges encountered during our application of fisheries acoustics method to estimate fish biomass: the combination of inaccuracy generated from the survey design, the spatial distribution of the population and the intrinsic variability in the densities (Anon, 1998).

Echo-trace classification

The most poorly understood errors are those related to the partitioning of the echo-integrals between species. The two objective discrimination methods (DFA and ANN) applied here yielded high classification rates and replaced the subjective expert-based discrimination, which was significant source of miss-identification. Despite the promising results, ANN technique required a large amount of data and time consuming training phase. Therefore, it is more recommended to be applied for automated identification during survey time. The deploy of automated echo-trace classification method will allow for objective, fast and repeatable species identification. For commercial fish a real-time fish identification system would be very beneficial for an environmental and economic point of view by increasing fish selectivity and reducing by-catch.

Using the independent data, the estimated biomass is heavily reliant on the ability to properly partition the catch amount between different species within the same fish-group. Zwolinski *et al*. (2009) suggested to derive biological information (maturity stage, age, length, etc.) obtained from trawling would help to elucidate the demographic structure of the fish target population. For instance, in spawning grounds and areas of intense recruitment, juveniles are scarcely discriminated from adults on the basis of acoustic data.

Sampling strategy

The random biases being sources of the overall quantifiable variance were mainly associated with the sampling strategy (Rose *et al*, 2000; Gimona and Fernandes, 2003; Demer, 2004). The use of post-stratification stratified sampling design combining acoustic and midwater trawl surveys was crucial, as regards the even distribution of pelagic fish. Concurrently, the degree of coverage was useful to investigate the systematic relationship

between the sampling error and the monitored fraction of the stock.

After the delimitation of areas of high fish density in each block in this work, further effort should be focused on the execution of adaptive sampling design, which aims to reduce the estimates uncertainty by more intensively surveying these concentrations zones and by adjusting the coverage during the survey. It is recommended generally to find balance between the stratification and the optimal allocation of sampling effort. Midwater trawls were deployed to target patches of fish indicated by acoustic echoes in real time. As a result, information from trawl catches were not uniformly expanded to the entire surveyed area. Optimal allocation of sampling effort depends not only on their respective costs but on the relative importance placed on estimates of fish biomass and catch composition. (Godø *et al*. 1998) investigated the benefits of different allocations of effort in taking more trawl tows than is typically deemed necessary, so as to assess the effect of various levels of trawling effort on the precision of the results. The conclusion was to spent greater proportion of the midwater trawling effort in areas where variability in catch composition is high.

Therefore, the adoption of adaptive strategy in the surveyed area would allow to reduce the distance between transects by taking extra, uncorrelated observations in each stratum when the original observation exceeds the predetermined threshold. Additional transects should be tracked between the existing transects.

2.2 Systematic errors

Systematic biases are considered also as major contributor in the uncertainty because they might affect all the observations equally. Unlike the random error, the systematic bias cannot be reduced by collecting more samples.

Target strength

The target strength is an important factor in this context (Hazen and Horne, 2003). In the present work, TS to fish length relationships were deduced from the literature and the assumption was that jack mackerel and two species of *Scomber* have the same relationship. Both species of *Decapterus* spp were also assumed to have similar relationships. Estimating appropriate target strength to fish size relationships for each species and applying them to acoustic assessments might result in considerably different estimates and substantial differences in stock size.

Acoustic instrument

The acoustic data was collected using only one frequency 38 kHz. The use of developed acoustic equipment for instance the multifrequency echo-sounder would be advantageous to establish a truthful classifier which provides high rates of discrimination among fish species. In general, backscatter from individuals of various species and sizes produces variation in frequency response from their aggregations. The classification of pelagic species from their acoustic responses recorded at several frequencies would facilitate the effective identification of fish schools. Developed technologies such as optical devices could also be employed to more precisely identify fish species. The use of such advanced technology will reduce the random error of acoustic estimates for fisheries resources.

Vessel noise

The vessel noise is another factor that should be checked because it can limit the performance of the acoustic equipment. It is known that the ability of fish to avoid ships can bias acoustic biomass estimates (Fréon and Misund, 1999), in particular in shallow

waters, such as the East China Sea off Japanese coasts. Therefore, it is needed to investigate the reactions of fish if approaching research vessels.

The reduction of the noise in existing vessels is difficult and expensive. However, since the new R.V. Yoko maru is to be built soon and designed for acoustic surveying, it should ensure that the radiated noise level is below some limit. The installation of machinery in the new vessel should obey a scientifically-based noise specification to ensure that the budget noise is maintained. This question was addressed by an ICES Study Group, leading to a report on the acceptable noise performance of research vessels (Mitson, 1995). This study examined data on ambient noise, fish hearing and sound-induced behaviour to provide an objective methodology for setting noise levels in the audio range appropriate to fish observation. In addition, limits on the ultrasonic noise were specified to avoid degradation of echosounder performance. It is worth noting that the worst vessels, built without any noise specification, are likely to disturb herring schools up to 400 m distant (Diner and Masse, 1987), while the corresponding limit for the best is around 15 m. This difference shows that noise reduction is both achievable and effective (Fernandes *et al.*, 2000).

For subsequent studies, the previous suggestions should be taken in consideration. Furthermore, the above mentioned sources of error (random and systematic) should be carefully evaluated and ordered by the magnitude of contribution in the overall uncertainty. Consequently, it would be advantageous to tackle these sources by priority and to yield more refined and accurate biomass estimates.

Applying different methods of stock assessment (e.g., VPA) in parallel might lead to produce an average result whose confidence interval is acceptably small. It is advisable,

when independent results are to be combined, to define error factors in each method to obtain the best overall estimate of pelagic fish biomass in the East China Sea.

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