

Using geostatistics to quantify annual distribution and aggregation patterns of fishes in the Eastern English Channel.

S. Vaz, C. S. Martin, B. Ernande, F. Coppin, S. Harrop and A. Carpentier.

The Eastern English Channel is an area with strong hydrodynamic features supporting, among other human activities, an important fishery exploitation. Since 1988, IFREMER (French Research Institute for Exploitation of the Sea) has been carrying out an essential ground fish survey primarily dedicated to ICES annual assessment of major commercial fish stocks in this area. However, these fisheries independent data also offer the opportunity to study of the distribution patterns of observed fish species using geostatistical techniques. Geostatistics embody a suite of methods for analysing spatial data and allow the estimation of the values of a variable of interest at non sampled locations from more or less sparse sample data points. Geostatistical estimation (kriging) is different from other interpolation methods because it uses a model describing the spatial structure and variation in the data – the variogram. The latter is the central tool of geostatistics and is essential for all of the other geostatistical methods. Kriging was used to produce distribution maps of several fish species over 17 years (1988-2004) and variogram parameters reflected changes in distribution patterns over time. Fish aggregation patterns and inter-annual variability were examined in the light of geostatistical analyses of fish distribution and a few example of this study will be presented.

Key-words: Eastern English Channel, CHARM, Fish spatial distribution patterns, geostatistics

Contact author:

S. Vaz: Ifremer, Laboratoire Ressources Halieutiques, 150 quai Gambetta, BP699, 62321, Boulogne/mer, France [tel: (+33) 3 21 99 56 00, fax: (+33) 3 21 99 56 01, e-mail: svaz@ifremer.fr]

S. Vaz, F. Coppin and A. Carpentier: Ifremer, Laboratoire Ressources Halieutiques, 150 quai Gambetta, BP699, 62321, Boulogne/mer, France [tel: (+33) 3 21 99 56 00, fax: (+33) 3 21 99 56 01, e-mail: svaz@ifremer.fr]. B. Ernande: Ifremer, Laboratoire Ressources Halieutiques, avenue du Général de Gaulle, 14520 Port-en-Bessin, France [tel: (+33) 2 31 51 56 00, fax: (+33) 2 31 51 56 01, e-mail: [Bruno.Ernande@ifremer.fr](mailto: Bruno.Ernande@ifremer.fr)]. C. S. Martin: Department of Geographical and Life Sciences, Canterbury Christ Church University, Canterbury CT1 1QU, U. K. [tel: (+44) 1227 767700 (ext. 2324), e-mail: c.s.martin@canterbury.ac.uk].

INTRODUCTION

The analysis of spatial patterns is of prime importance since most natural phenomena are affected by processes that have spatial components generating spatially recognisable structures, such as patches or gradients, which can be analysed. Ecological data may include several types of spatial patterns occurring at different scale such as trends at larger scale, patchiness at intermediate and local scales and random fluctuation or noise at smaller scale (Fortin and Dale, 2005).

Species distribution results from the combined action of several forces, some of which are external (environmental), whereas others are intrinsic to the community (Legendre and

Legendre, 1998). Community structure and environmental attributes, result from many physical and biological processes that interact, some in non-linear or chaotic ways. The outcome is so complex that the variation over a region, of almost any size, appears to be random (Webster and Oliver, 2001). This requires the probabilistic approach, which underpins geostatistics. The randomness, which is embodied in the random function model on which geostatistics are based, is not a property of the physical world (Webster and Oliver, 1990). In reality, ecosystem spatial heterogeneity is deterministic and is not the result of some random, noise-generating process (Legendre and Legendre, 1998).

Originally developed for the mining industry, geostatistics were first developed to address specific needs of spatial prediction of geological resources over two or three dimensional areas. This last feature made the technique known rapidly in oceanography (Fortin and Dale, 2005) but it took longer to become widespread in ecology (Rossi *et al.*, 1992) and longer still to find its way to marine ecology. Many demersal and benthic fishes exhibit particular distribution and aggregation patterns at annual time scale in association with particular habitats or phases of their life cycle (Mello and Rose, 2005). Although there is a limited understanding about how geostatistics may be used for such end, they are particularly suited for fishes exhibiting gregarious behaviour but seasonally variable distributions. Spatial structures, in particular that of fish distribution, can be identified and described quantitatively using geostatistics (Petitgas, 1993 and 2001, Mello and Rose, 2005).

This study investigated the use of geostatistical methods to quantify annual distribution patterns over a broad range of species obtained from scientific survey. An overview of geostatistical concepts and result interpretation is presented here with little detail about the statistical computation involved. A simple methodology enabling geostatistical analyses and

kriging interpolation for cartography and suiting many species data, over a large range of years and originating from the same survey, is proposed. The results are discussed in relation to season, habitat, and migration patterns.

METHODS

Survey design and data collection

IFREMER contributes to the acquisition of basic biological data through its annual experimental trawling survey called CGFS (Channel Ground Fish Survey). The CGFS has been carried out each year since 1988 on-board the research vessel Gwen Drez in October. The survey extends from the Eastern English Channel to the south of the North Sea, which corresponds to ICES divisions VIIId and IVc. The study area is divided into rectangles of 15' latitude and 15' longitude using a systematic sampling strategy. The sampling gear is a high opening bottom trawl well adapted for catching demersal species, with a 10 mm mesh size (side knot) for catching juveniles. This sampling gear is polyvalent and is well adapted to the varying seabed types encountered in the study area. One or two 30 minutes hauls are performed within each rectangle of the CGFS grid. The fishing hauls are chosen using professional fishing plans or found by prospecting. The fishing method is standardised: sampling stations are each year at similar locations each year and identical sampling gear is used. At each sampling station, all the fish species are sorted, weighed, counted and measured. Data available for the period 1988 to 2004 were used to compute variograms and map species distribution (Fig.1).

Statistical analyses

Statistics and methods in ecology require the careful examination of the data distribution, because ecological variables (descriptors) are assumed not to have a uniform scale. Although

most of the methods do not require full normality, they perform better if the distribution is as near to normal as possible. Moreover, the statistical distribution of the data must be examined to determine whether the assumptions upon which geostatistics are based hold (Rossi *et al.*, 1992). The statistical distribution of environmental or biological data were tested for normality using histograms, skewness and kurtosis. The data were transformed when skewness value exceeded $|1|$ and/or kurtosis exceeded 1 and when a normalising function that could improve the data distribution was found. Biological variables were measured on scales based on analytical conventions and they are unrelated to the natural processes that generate them. Therefore, any transformed scale is as appropriate as those on which these data were originally recorded (Legendre and Legendre, 1998). Species abundance were expressed as density values (nbr.km^{-2}) and always required to be log-transformed using $\log_{10}(x+1)$ transformation (where x is the species abundance value).

Geostatistics

Geostatistical methods were developed for spatially structured mining data during the 1960s (Matheron, 1965) and embody a suite of methods for analysing spatial data and allow the estimation of the values of a variable of interest at non sampled locations from more or less sparse sample data points.

The variogram

The variogram, the central tool of geostatistics, is a function that measures the relation between pairs of observations a certain distance apart. It summarises the way in which the variance of a variable changes as the distance and direction separating any two points varies. Typically, for spatially structured data, the variance is small at short lags and increase with larger separating distance (monotonic increasing) (Fig.2). The variogram may increase to a

maximum at which it remains thereafter. This upper bound, the sill variance, estimates the maximum variance of the data and indicates that the variances between points are no longer correlated. The lag distance at which the sill is reached (the range) marks the limit of spatial dependence i.e. it describes the extent of the observed pattern. The range size is related to the spatial continuity of the variable of interest and a variable with long-range is more spatially continuous than a short range one. The variogram often has a positive intercept on the ordinate known as the nugget variance. The nugget is the amount of variance not explained by the spatial model. This arises from a combination of error terms attributable to inappropriate sampling, measurement or analytical errors and random variation, but mostly from variation occurring over distances smaller than the sampling interval.

Modelling the variogram

Many variograms have simple forms that can be described by a limited set of *authorised* models (Fig.3a-e). These models must be capable of describing the main features of the variogram, i.e. the nugget, the shape of the monotonic increase and the sill. The most common way of fitting models is by the statistical procedure of least squares approximation. The chosen model should be the one with the best statistical and visual fit. The parameters of the model estimate the nugget and the sill variances, and the distance parameter. From the latter, the scale of variation of a particular variable can be determined, compared with that of others and can be used to determine the limit of spatial dependence of this variable.

Circular, spherical and pentaspherical models curve (in increasing order of gradation) more gradually than bounded linear models. All of them represents transition features that have a common extent and appear as patches, some with large values some with small ones. The range (r) of the model is the average diameter (D) of the patches (Webster and Oliver, 2001).

Exponential function approaches its sill asymptotically and does not have a finite range. The average diameter (D) of the patches can be approximated as $3r$, which is the distance at which the variogram has reached 95% of its sill. Variograms fitted by this model illustrate a transition process in which the structures have random extents. Such a variogram should be expected where differences in abundance level are the main contributors to abundance variation and where boundaries between levels occur at random (Webster and Oliver, 2001). Some variograms appear completely flat, i.e. “pure nugget”, meaning that there is no spatial dependence evident in the data (Fig. 3f).

Measure of the spatial structuration

The level of spatial structure can be inferred from the ratio, Q , given by:

$$Q = C / (C+C_0)$$

Where $C+C_0$ is the sill and C_0 is the nugget variance; hence C is the variance attributable to spatial dependence. The ratio Q varies between 0 and 1: a ratio of 0 indicates the absence of spatial structure at the sampling and support scale used; as Q approaches 1, a greater proportion of the variability is explained by the variogram model.

Kriging interpolation

The method of prediction embodied in geostatistics and for which the variogram parameters are essential, is known as “kriging”. Kriging produces optimal unbiased estimates that can be used for mapping by taking into account the way that a variable varies in space to predict the values at unsampled locations. It is a method of weighted averaging based on the variogram model of the spatial variation. Finally, estimation variance is known and is the minimum, whereas classical methods are based on arbitrary mathematical functions and provide no measure of error variances. Ordinary kriging is the most commonly used method. It can be

used to produce a large field of estimates at points or blocks and corresponding variances for mapping. The weights are obtained from the variogram model and are derived as to minimize the estimation variance. Generally, the weights of points near the point to be kriged are large and these decrease as the distance increases. The nearest four or five might contribute 80% of the total weight and the nearest 10 almost all the remainder. Similarly, clustered points carry less weight individually than isolated ones at the same distance. Finally, some data points may be screened by points lying between them and the point to be kriged. These effects are desirable and show that kriging is local. Block kriging, producing average estimate value within a prescribed area rather than punctual location, was preferred. Block size matched that of interpolation grid so that the grid nodes corresponded to the block centre and blocks did not overlap.

Spatial trend or drift

Local trend or drift violates the assumption of the random function model, because the values change in a smooth predictable way, they are deterministic and are no longer random (Isaaks and Srivastava, 1989). In this case, the variogram would have a concave upward form. Variables must be examined for trend at the outset by fitting a low-order polynomial (linear or quadratic regression) on the spatial coordinates (Webster and Oliver, 2001). Linear function for two dimensional trends corresponds to an inclined plane (such as a drift in depth value from inshore to offshore) whilst quadratic function correspond to a curved surface simulating an edge effect (such as depth value around an island or in an enclosed bay or strait surrounded by coastlines). When the fitted function accounts for over 20 % of the variance, a variogram should be computed using the residuals and compared to the variogram of the original data. When the presence of a gradual trend in the data is confirmed, universal kriging, an adaptation of ordinary kriging, allows one to accommodate such trend. Universal kriging was used to

produce good local estimate in the presence of a trend and like ordinary kriging the procedure was automatic once a satisfactory function for the variogram was found.

The kriged estimates can be used to map the variable of interest in order to interpret the spatial pattern described by the variograms. In the present study, the spatial variation of biological and environmental data were analysed using Genstat (Genstat 7 Committee, 2004), which is a GENeral STATistics package that includes the main geostatistical tools. It computes experimental variograms, fits these with various authorised mathematical models and uses them to calculate kriged estimates on a fine regular grid of 0.1 decimal degree mesh size.

Survey resolution and kriging search parameters

Prior any species analyses could take place, a preliminary data exploration resulted in optimised search parameters to suit the survey design across all years and were set constant for all kriging procedures. First the longitude coordinates were corrected so that longitude decimal degree were set to be the same metric distance as the latitude decimal degree. This is done by the following projection transformation:

$$\text{Corrected longitude} = \text{longitude} * \cos((\text{latitude} * \pi) / 180)$$

After geostatistical analyses and kriging interpolation have taken place, longitude was back-transformed to enable mapping with true coordinates. The average distance between close pair of observations, corresponding to the survey resolution, was 0.1° and was used to set the kriging grid mesh size. Search radius was set to 0.2 (twice the grid mesh size) and number of neighbours used for kriging were taken between a set minimum of 4 and maximum of 7 data points.

Mapping

Using ArcMap's Spatial Analyst extension, the grid of data points was then interpolated by kriging, using the default parameters of the software (ordinary kriging, spherical variogram model, variable search radius with 12 points) to create a continuous raster of 1 km² cell size (resolution). ArcMap's Raster Calculator extension was then used to cut out any portion of the raster that was "extrapolated", i.e. that was outside of the geographical area covered by the original data point grid. When the area surveyed varied across years, the resulting maps differ in geographical extent.

Geostatistical analyses and kriging were used extensively to analyse the spatial structure of sixteen fish species over 17 years (1988-2004). Their variogram parameters that reflected the changes in their distribution patterns over time were defined and the resulting maps illustrate the spatial distributions and their variation over time of the species in the Eastern English Channel.

RESULTS

Three species will be presented in this study as example of result and interpretation. These were *Microstomus kitt* (lemon sole), *Raja clavata* (thornback ray), *Scyliorhinus canicula* (lesser-spotted dogfish). Experimental variograms were computed and fitted with authorised models using Genstat software (Fig 3a-f).

***Microstomus kitt* (lemon sole)**

The geostatistical results for this species are presented in Table 1 and illustrate the case of a relatively strongly spatially structured distribution ($Q = 0.69$ corresponding to 69% of the data variability being explained by the variogram model in average over 17 years). The average diameter (D) of the observed patches was 0.7° over the entire period but varied greatly from year to year (from 0.3° up to 1.6°). Various type of models were used indicating that some years the patch sizes were relatively constant (boundedlinear, circular, pentaspherical) and some others spatial structures had random extent (exponential models). Often years with spatial distribution displaying large patch size ($D > 0.7$) were modelled with an exponential model illustrating their random extent. Trends sometimes occurred (1990, 1994-96, 2004) and corresponded to years with relatively small range ($D < 0.6$) illustrating the almost exclusively north-eastern distribution of this species for these years (Fig. 4). This species generally occurs on gravely seabeds mostly in the Dover strait and sometimes in the centre of the Eastern English Channel where tidal flows are at their greatest.

***Raja clavata* (thornback ray)**

The geostatistical results for this species are presented in Table 2 and illustrate the case of a species with a relatively small average diameter (D) of the observed patches (0.56° over the entire period). It was not as strongly structured as lemon sole (average $Q = 0.56$). Models indicating that patch sizes were relatively constant within a particular year (boundedlinear, circular, spherical, pentaspherical) were predominant however the average path extent varied greatly from year to year (0.1° up to 1.2°). Trend effect never occurred illustrating the patchy distribution of this species with no direct relation to coastal proximity or geographic preferences within the area of study (Fig. 5). Maps illustrate their preferences for central Eastern English Channel but also highlight how this species may be found more inshore some

years along both French and English coasts, near mouths of estuaries and in sandy bays along southern English Coast.

***Scyliorhinus canicula* (lesser-spotted dogfish)**

The geostatistical results for this species are presented in Table 3 and illustrate the case of a species with a relatively large average diameter (D) of the observed patches (1.04° over the entire period) that did not vary greatly from year to year (from 0.7° up to 1.4°). The model used indicated that the patch sizes were relatively constant within each years (boundedlinear, circular, spherical, pentaspherical). This species was not has spatially structure as the two previous ones (average $Q = 0.47$) due to three isolated years (1989, 1993, 2002) where no spatial structure could be found. These years also corresponded to the only times significant quadratic trends could be detected meaning that long-range drift was the only spatial structure that can be found in the data in these instances. This species displayed a relatively broad distribution across the central region of the Eastern English Channel that sometime extended in the Dover Strait (Fig 6).

DISCUSSION

The distribution maps reflected the species habitat preferences in this area of the English Channel. Lemon sole is a benthic species living on gravels or shelly sand between 40 and 200 m depth. In the Eastern English Channel its distribution is almost exclusively limited to the Dover Strait where hard seabed sediment and strong tidal current are found. Patch of variable extent and trend in their distribution for high abundance in this area could be quantified and identified through the geostatistical analyses process. Moreover, this study revealed that this species was strongly structured in space highlighting its strong affinity to a particular habitat in this area. Thornback ray is a demersal species preferring hard and sandy bottoms of the

continental slope and illustrated by its patchy and variable distribution in the area. Thornback ray was relatively well structured but although its affinity for hard sediment type was confirmed by its yearly distribution, it had no affinity for any particular area in the Eastern English Channel and its localisation and extent changed from year to year probably in relation to its total abundance. Geostatistical analyses enabled the quantification of this distribution and revealed that the patch extent where relatively small. Lesser-spotted dogfish is a benthodemersal species that inhabits gravel and sandy bottoms on the continental shelves. Its distribution extended largely in the deepest areas of the Eastern English Channel over large area of hard seabed sediments. Geostatistical results revealed the large extent of the observed patterns in this species distribution but also its relatively small spatial structuration. This result raise question about the survey resolution and design and its effectiveness to capture efficiently the true spatial heterogeneity of this species that may occur on a smaller scale than the one that could be observed.

CONCLUSION AND PERSPECTIVE

Many interpolation techniques may be used for illustration purpose. However, geostatistics enable to explore, characterise and quantify spatial structure as well as interpolation (Fortin and Dale, 2005) and should be preferred to other techniques. In the process of studying the variogram structure and modelling it for accurate interpolation, valuable information about the spatial process taking place is obtained. Measure of patch size, global trends and spatial structuration are made and can be used to support the description of the species distribution patterns in relation to their habitat preferences and spatial behaviour. Moreover, generic and relatively simple methods and softwares now enable its use and bring geostatistics to novice reach without loosing its accuracy and risking the “black-box” approach often proposed in GIS software. In the framework of an international project (CHARM project,

<http://charm.canterbury.ac.uk>), 16 fish species spatial distribution could be analysed and mapped based on 16 years data and two seasons (Carpentier *et al.*, 2005) in a relatively short time span proving that geostatistics could be efficiently used for large scale studies aimed at ecosystemic understanding of marine living resources.

Further to geostatistical analyses, other spatial analyses may be used to quantify the aggregation patterns of fish (see Fortin and Dale, 2005 for full review). However, some techniques such as geostatistical aggregation curves (Petitgas, 1998) may give useful insight about how the spatial distribution changes as the population abundance varies linking fish distribution to density-dependent population dynamics. Based on these aggregation curves, patch gravity centre and boundaries may be defined and compared across years to further characterise the link between the population demography and its spatial distribution behaviour.

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Table 1 Geostatistical analyses results for *Microstomus kitt* (lemon sole)

Year	Trend type	Trend fit (%)	MODEL	Model fit (%)	Q	D (decimal °)
1988			exponential	9.4	0.18	1.2
1989			exponential	94.7	0.85	0.6
1990	Linear	20.4	circular	73.6	0.54	0.4
1991			exponential	92.3	0.88	0.8
1992			circular	96.1	0.52	0.4
1993			circular	96.4	0.64	0.9
1994	Quadratic	34.1	pentaspherical	45.7	0.33	0.5
1995	Quadratic	33.3	circular	95.7	0.84	0.4
1996	Quadratic	47.7	pentaspherical	18.1	0.53	0.5
1997			pentaspherical	83.7	0.82	0.8
1998			circular	10.7	0.63	0.5
1999			boundedlinear	93.7	1.00	0.4
2000			circular	59.2	0.60	0.4
2001			exponential	98	0.64	1.6
2002			exponential	93	0.89	0.8
2003			exponential	91	0.90	1.4
2004	Quadratic	38.7	circular	91.5	1.00	0.3
Interannual average (standard deviation)					0.69 (0.23)	0.70 (0.39)

Level of spatial structure, $Q = C / (C+C0)$; Average diameter of the patches (D); highlighted values have spatial extent superior to the inter-annual average patch diameter

Table 2 Geostatistical analyses results for *Raja clavata* (thornback ray)

Year	Trend type	Trend fit (%)	MODEL	Model fit (%)	Q	D (decimal °)
1988			circular	62.4	0.38	0.7
1989			pentaspherical	52.7	0.53	0.7
1990			pentaspherical	76.7	0.36	0.3
1991			circular	96.6	0.16	0.9
1992			spherical	83.5	1.00	0.1
1993			pentaspherical	99.6	0.76	0.3
1994			pentaspherical	99	0.70	0.7
1995			exponential	99.8	0.68	0.4
1996			pentaspherical	100	0.54	0.4
1997			pentaspherical	83.5	0.65	0.1
1998			boundedlinear	100	0.50	0.4
1999			boundedlinear	95.1	0.35	0.2
2000			pentaspherical	99.9	0.47	0.6
2001			circular	99.7	0.39	0.9
2002			pentaspherical	99.1	0.50	1.2
2003			spherical	96.3	0.48	1.0
2004			boundedlinear	62.5	0.52	0.7
Interannual average (standard deviation)					0.53 (0.19)	0.56 (0.31)

Level of spatial structure, $Q = C / (C+C0)$; Average diameter of the patches (D); highlighted values have spatial extent superior to the inter-annual average patch diameter

Table 3 Geostatistical analyses results for *Scyliorhinus canicula* (lesser-spotted dogfish)

Year	Trend type	Trend fit (%)	MODEL	Model fit (%)	Q	D (decimal °)
1988			boundedlinear	99.2	0.67	1.0
1989	Quadratic	36.5	pure nugget		0.00	
1990			boundedlinear	98.1	0.71	1.2
1991			spherical	98.7	0.63	1.4
1992			boundedlinear	98.1	0.71	0.8
1993	Quadratic	33.3	pure nugget		0.00	
1994			boundedlinear	97.9	0.57	1.3
1995			boundedlinear	96.2	0.27	0.7
1996			boundedlinear	99.4	0.41	0.8
1997			circular	99.3	0.68	1.2
1998			boundedlinear	98	0.49	1.1
1999			boundedlinear	99	0.64	1.1
2000			boundedlinear	98.7	0.54	1.1
2001			boundedlinear	91.8	0.56	1.2
2002	Quadratic	32.4	pure nugget		0.00	
2003			boundedlinear	95	0.59	0.8
2004			boundedlinear	93.8	0.55	0.9
Interannual average (standard deviation)					0.47 (0.25)	1.04 (0.21)

Level of spatial structure, $Q = C / (C+C0)$; Average diameter of the patches (D); highlighted values have spatial extent superior to the inter-annual average patch diameter

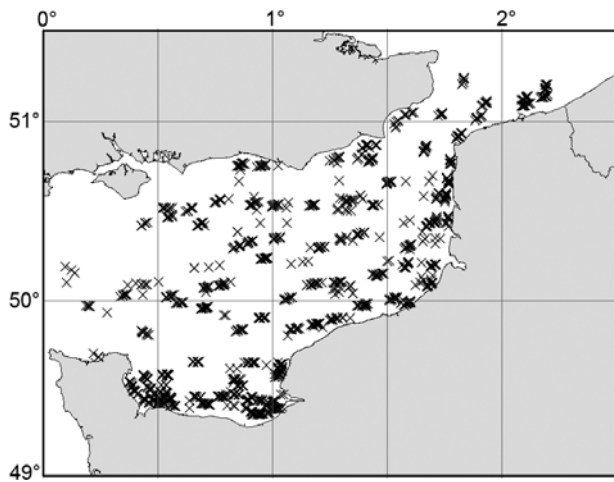


Figure 1 CGFS data available for the period 1988 to 2004

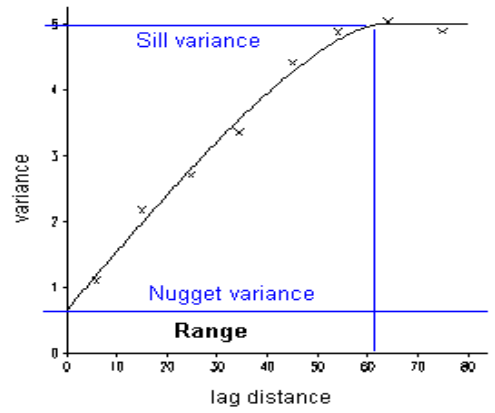


Figure 2 Example of variogram

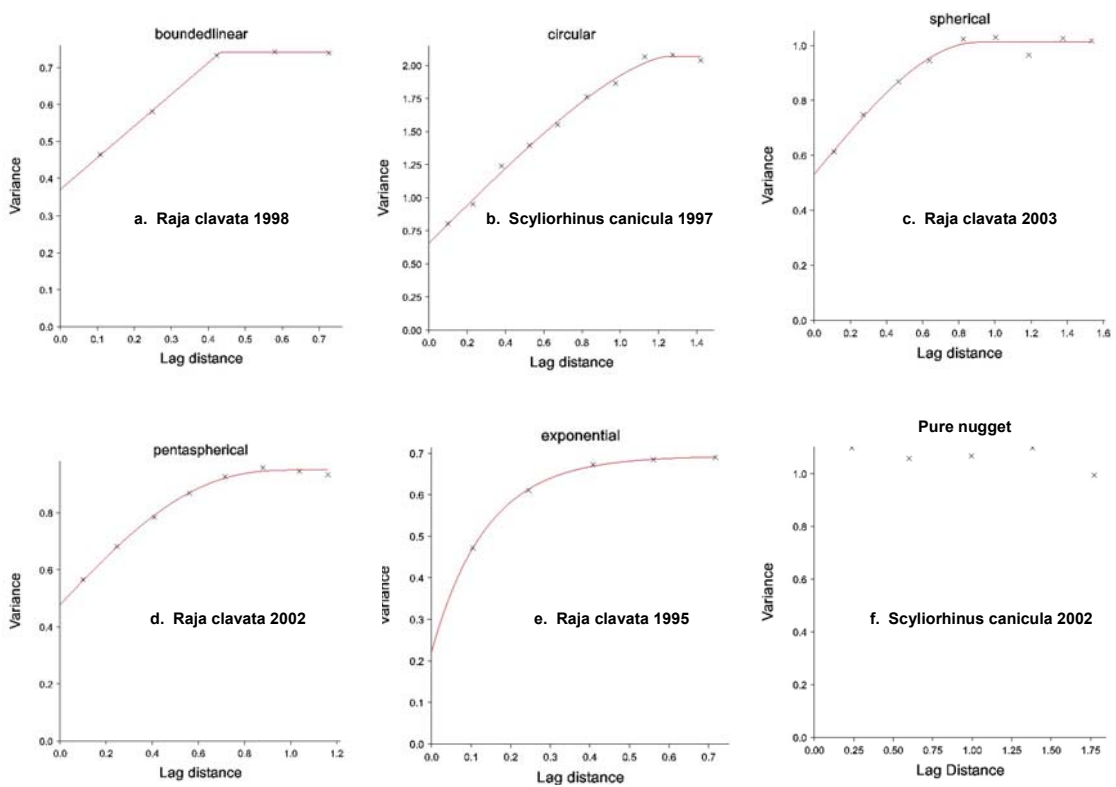


Figure 3 A few example of experimental variograms and fitted models

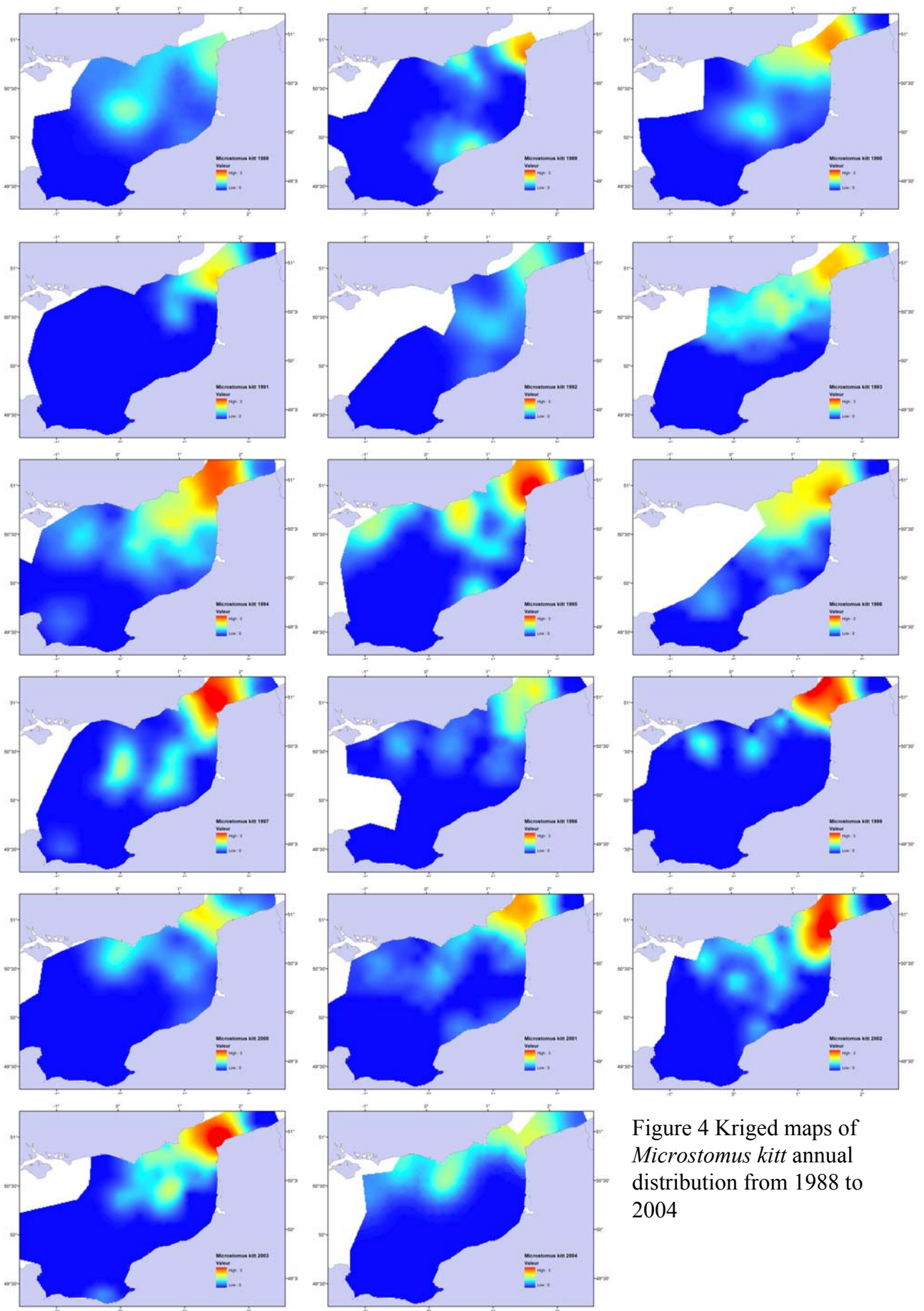
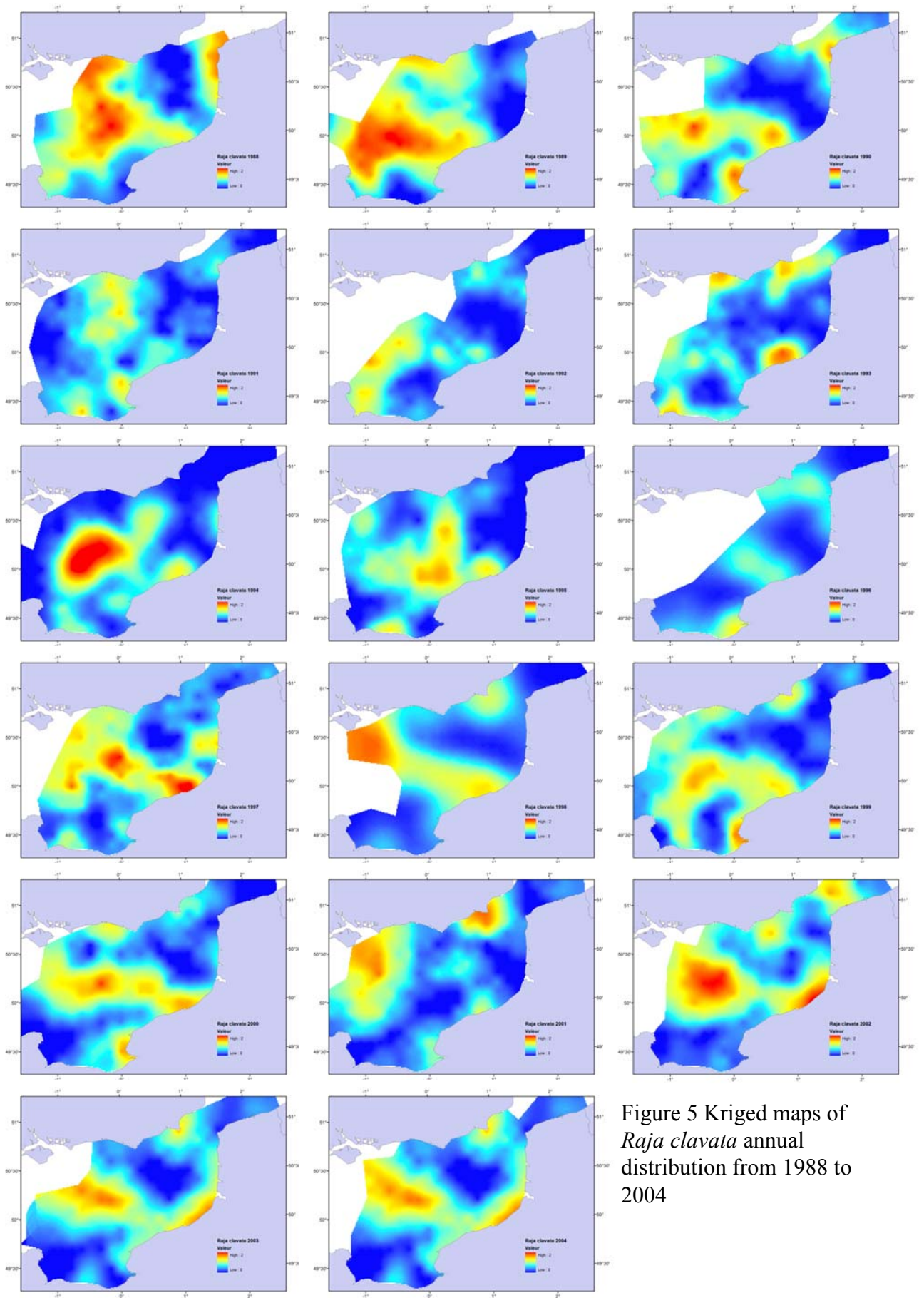


Figure 4 Kriged maps of *Microstomus kitt* annual distribution from 1988 to 2004



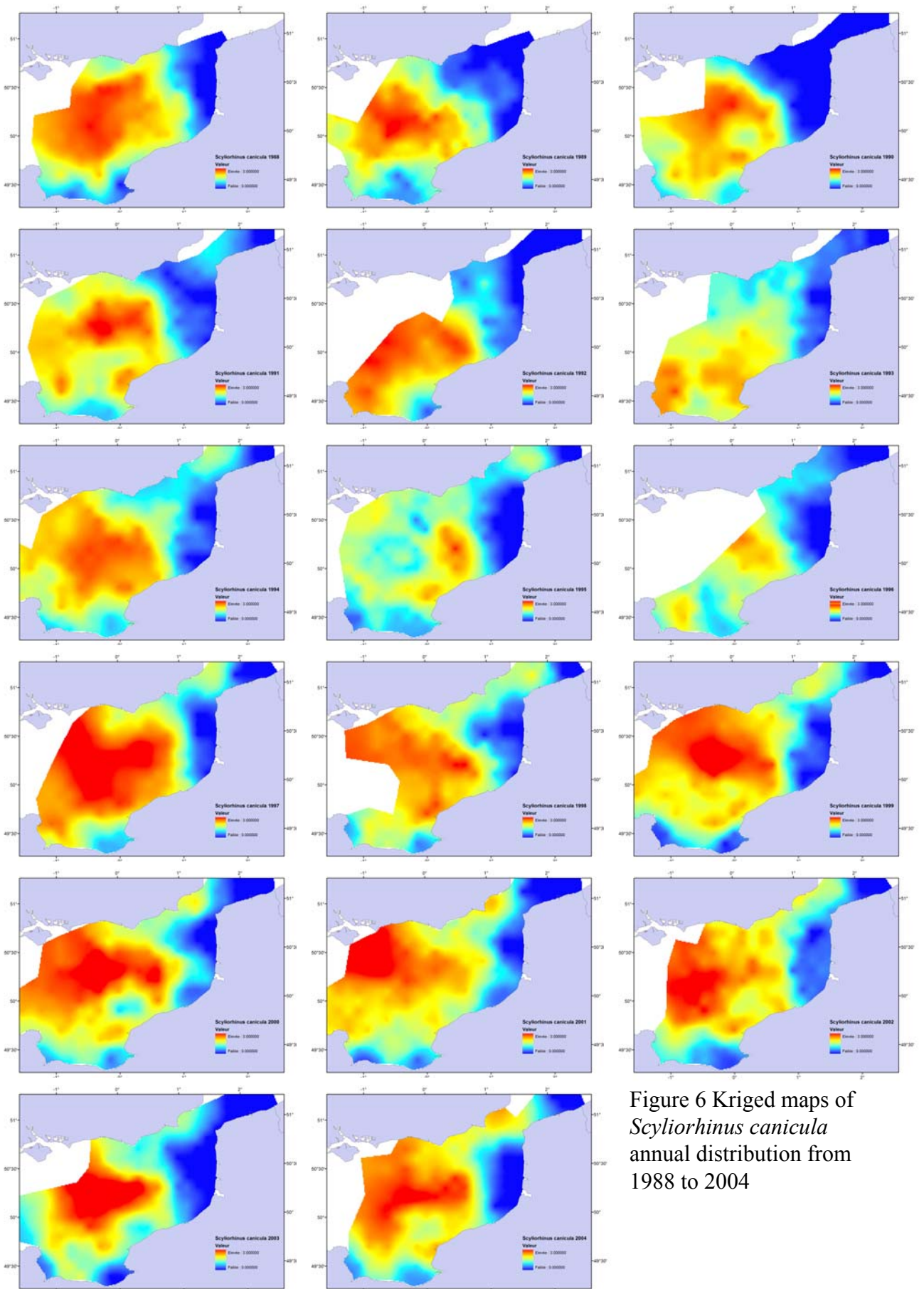


Figure 6 Kriged maps of *Scyliorhinus canicula* annual distribution from 1988 to 2004