CARL VON OSSIETZKY universität OLDENBURG

ICBM

Möglichkeiten und Grenzen geostatistischer Verfahren in den Fischereiwissenschaften: Analyse räumlicher und zeitlicher Variabilität von Fischpopulationen

Von der Fakultät für Mathematik und Naturwissenschaften der
Carl von Ossietzky Universität Oldenburg angenommene

Dissertation

zur

Erlangung des Doktorgrades der Naturwissenschaften

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geb. am 05.08.1975 in Worms

Oldenburg im Oktober 2004

Gefördert durch das Stipendienprogramm der Deutschen Bundesstiftung Umwelt
DBU
Deutsche Bundesstiftung Umwelt

In Kooperation mit BFA,
Institut für Seefischerei

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Tag der Disputation: 19.01.2005

INHALTSVERZEICHNIS

EINLEITUNG

Der enorme Zuwachs an Nutzungsarten in der Nordseeregion sowie die zunehmende Ressourcenknappheit führten in den letzten Jahren zu immer intensiveren und vielschichtigeren Nutzungskonflikten. Mit dem Anstieg der Nutzungsvielfalt geht auch ein steigender Bedarf an genauer Planung der Flächennutzung in Form von Raumordnungsplänen und europäischen Direktiven einher (Wirtz *et al.* 2003). Im Besonderen ist beispielsweise durch die Bauvorhaben von Offshore Windkraftanlagen in Nord- und Ostsee die Notwendigkeit der räumlichen Abgrenzungen ökologisch wertvoller Flächen von potentiellen Antragsflächen deutlich geworden. Die Entwicklung einer Managementstrategie, welche die teilweise konträren Nutzungstypen langfristig vereint, ohne dabei Naturschutzziele oder wirtschaftliche bzw. technologische Entwicklungen zu beeinträchtigen, ist eine herausfordernde Aufgabe für die Entscheidungsträger.

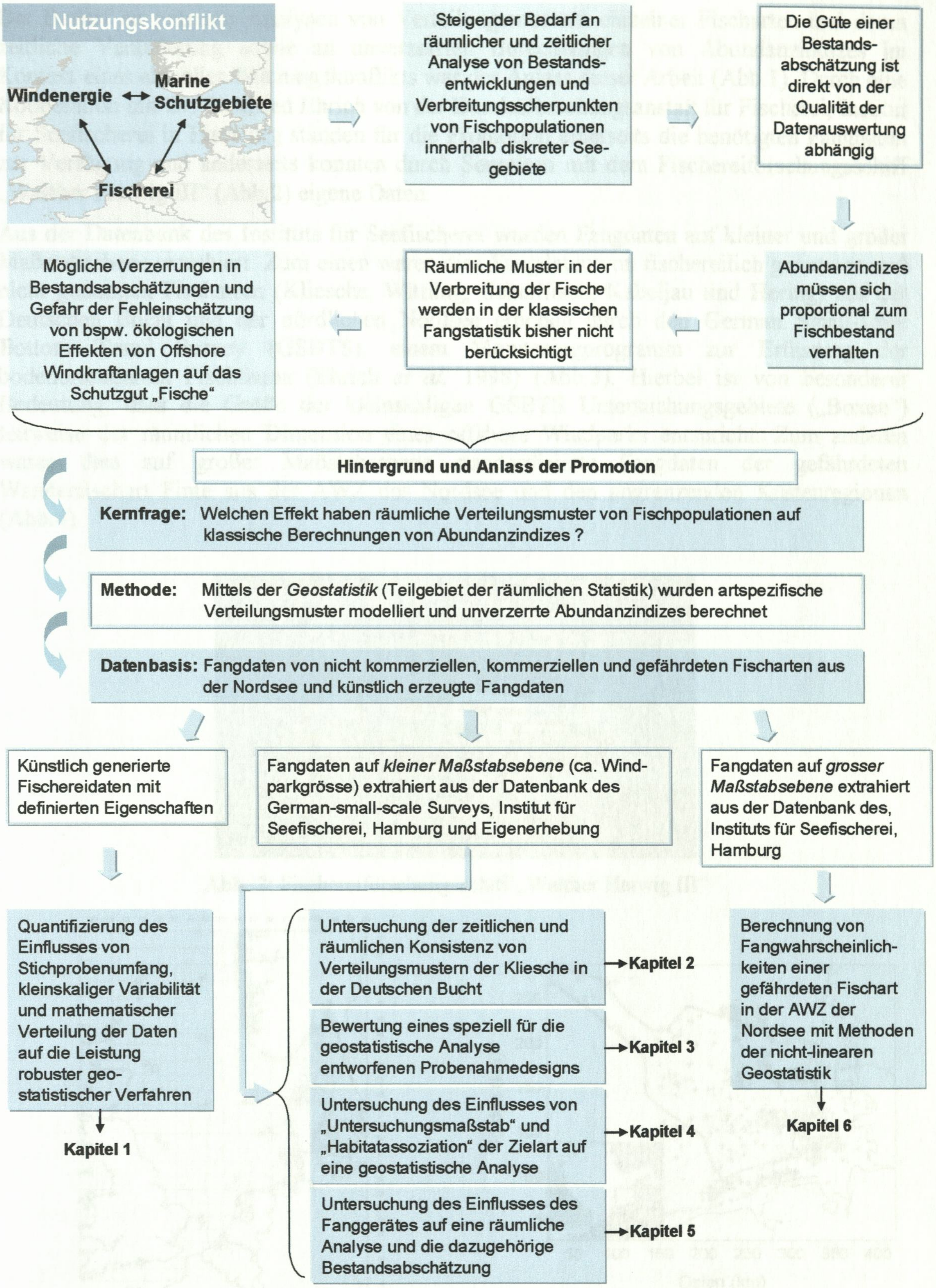
Gegenstand vieler wissenschaftlicher und politischer Diskussionen war in jüngster Zeit der Konflikt zwischen „Offshore Windkraftanlagen", „Meeresschutzgebieten" (Ehrich *et al.* 2003) und „Fischerei" innerhalb der Ausschließlichen Wirtschaftszone (AWZ) der Nordsee. In diesem Zusammenhang wurden viele wissenschaftliche Projekte initiiert, die zum einen ökologisch wertvolle Flächen definieren und zum anderen mögliche Effekte von Windkraftanlagen auf die marine Umwelt in der AWZ der Nord- und Ostsee untersuchen sollten. Zu den speziell untersuchten Schutzgütern zählen Makrozoobenthos, Vögel, Säugetiere, Landschaft und Fische. Das Schutzgut „Fische" besteht vor allem aus der bodenorientierten (demersalen) Fischfauna, da deren Vorkommen, im Gegensatz zur pelagischen Fischfauna, geringeren räumlichen und zeitlichen Schwankungen unterliegt (Ehrich *et al.* 1998). Eine der Entscheidungsgrundlagen für einzelne Managementstrategien bilden daher die Ergebnisse von räumlichen und zeitlichen Analysen von Bestandsentwicklungen und Verbreitungsschwerpunkten von demersalen Fischpopulationen auf verschiedenen Maßstabsebenen. Nicht nur durch den oben beschriebenen Nutzungskonflikt, sondern auch durch den Konflikt zwischen Ausbeutung und nachhaltigem Umgang mit der natürlichen Ressource „Fisch" gewinnt eine präzise Bestandsabschätzung („fisheries-assessment") immer mehr an Bedeutung (Jennings *et al.* 2001).

Das primäre Ziel einer Bestandsabschätzung in der Fischerei besteht in der Bewertung des Befischungszustands einer Art, um bestimmen zu können, bis zu welchem Grad diese nachhaltig ausgeschöpft werden kann (King 1995). Daher besteht eine wichtige Aufgabe darin, festzustellen, ob die statistische Auswertung von Fangdaten die aktuelle Situation der Abundanz einer Fischart widerspiegelt (Hilborn & Walters 1992). Für eine Bestandsabschätzung werden Informationen über Artenzusammensetzung, Verteilung von Biomasse, Abundanz der Fische, biologische Daten (Alter, Geschlecht und Reifegrad) sowie weiteren Umgebungsvariablen wie Temperatur, Salzgehalt oder Fangtiefe benötigt. Ein weit verbreitetes Monitoringwerkzeug sind jährliche Grundschleppnetz-Surveys (Gunderson 1993), bei denen Werte für die gewünschten biologischen Variablen wie die Längen- bzw. Altersverteilung innerhalb einer Fischpopulation oder Abundanzindizes wie der "Catch per Unit Effort" (CPUE; Einheitsfang; z. B. kg pro 30 min Schleppzeit, Anzahl der Tiere pro Fang) mit Standardverfahren bestimmt werden. Zum einen werden die Ergebnisse der wissenschaftlichen Surveys benötigt, um die Stärken der rekrutierenden Jahrgänge für eine Fangmengenvorhersage abzuschätzen zu können. Zum anderen dienen die Häufigkeitsindizes der höheren Jahrgänge dazu, die Berechnungen von Bestandsgrössen, die auf den durch Fischerei entnommenen Mengen basieren, zu verbessern. Die Güte einer Bestandsabschätzung ist direkt von der Qualität der Datenauswertung von Abundanzen und Altersverteilungen einer Art in den spezifizierten Untersuchungsgebieten abhängig.

Eines der zentralen Probleme bei der Bestandsabschätzung ist es, einen Abundanzindex zu finden, der sich proportional zum Fischbestand verhält und somit Entwicklungstendenzen im Bestand reflektiert. Eine Nichtberücksichtigung dieses Problems kann dazu führen, dass z.B. hohe CPUE-Werte vorliegen, obwohl der Bestand einer Art in der Realität kurz vor dem Zusammenbruch steht, bedingt durch veränderte räumliche Muster in der Verteilung der Tiere und dem Fang aus einer aggregierten Fischpopulation (Hilborn & Walters 1992). Da die Präsenz derartiger räumlicher Muster und ihre Veränderungen innerhalb eines Management-Gebietes (z.B. Nordsee) in der Fangstatistik derzeit jedoch nicht berücksichtigt wird, kann dies zu einer katastrophalen Situation führen (Hilborn & Walters 1992). Ein Beispiel dafür ist der Zusammenbruch der Kabeljaupopulation in den Gewässern Neufundlandes. Dort wurden hohe CPUE-Werte gemessen, während dessen sich der Zusammenbruch der Population durch Veränderungen in der räumlichen Verteilungsmuster ankündigte (Hutchings 1996).

Dies gilt beispielsweise auch für Untersuchungen innerhalb von Antragsgebieten für Offshore Windkraftanlagen. Wenn die räumliche und zeitliche Dynamik einer Fischpopulation nicht adäquat abgeschätzt wird, kann dies zu Fehleinschätzungen möglicher ökologischer Auswirkungen führen. Im allgemeinen sind ökologische Daten durch räumliche Muster charakterisiert, welche eine räumliche Abhängigkeit (Autokorrelation) herbeiführen (Legendre 1993; Fortin *et al.* 2002). Die Intensität der Musterbildung ("patchiness") wird durch den Untersuchungsmaßstab bestimmt. Ökologische Daten sind eine Verbundsstruktur von mehreren räumlichen Prozessen, die auf unterschiedlichen Maßstäben operieren. So wird das Ausmaß der räumlichen Abhängigkeit in den Daten durch die unterschiedlichen Prozesse und Muster, welche nicht notwendigerweise additive oder linear sind, bestimmt (Fortin *et al.* 2002).

Die klassische Methode zur Bestandsabschätzung einer Bodenfischart in einem definierten Untersuchungsgebiet umfasst einen Survey mit Standardnetz und einer speziellen Beprobungsstrategie. Die Probenahmestationen werden zufällig im Untersuchungsgebiet positioniert, um so unverzerrte Abschätzungen des Vorkommens einer Fischart zu erhalten. Wenn das zufällige Beprobungsmuster dabei auf einer passenden räumlichen Skala angewendet wird, können zugrundeliegende räumliche Strukturen in der Verteilung „ausgelöscht" werden, jedoch ohne dass der Bearbeiter hiervon Kenntnis erlangt. In diesem Fall wären dann Auswertungsmethoden der klassischen Fangstatistik (arithmetischer Mittelwert, Varianz und Standardabweichung der Fangdaten in der Untersuchungseinheit) anwendbar. Bedingt durch die Tatsache, dass die Skala der räumlichen Verteilung einer zu untersuchenden Fischart meist unbekannt ist, wird die Anwendung klassischer Methoden allerdings vielfach zu Verzerrungen in der Berechnung von Abundanzindizes führen (Petitgas 1996; Maynou 1998). Das Vorhandensein eines Musters in der räumlichen Verteilung einer Fischpopulation verursacht eine räumliche Abhängigkeit (Autokorrelation) in den erhobenen Fangdaten, die auch durch eine zufällige Auswahl der Stationen nicht beseitigt werden kann (Maynou 1998). Die Präsenz einer solchen räumlichen Abhängigkeit lässt die Zufälligkeit in der Verteilung der Probenahmeorte quasi „verschwinden". Zufällig gewonnene Daten sind aber die Voraussetzung für eine unverzerrte Berechnung der Varianz der mittleren Biomasse (Aubrey & Debouzie 2000). Durch die Präsenz einer räumlichen Abhängigkeit in den Daten kann die Grundannahme für viele klassische statistische Verfahren verletzt werden, nämlich die der Unabhängigkeit der Messwerte (Fortin *et al.* 2002).



Nutzungskonflikt

Steigender Bedarf an räumlicher und zeitlicher Analyse von Bestandsentwicklungen und Verbreitungsscherpunkten von Fischpopulationen innerhalb diskreter Seegebiete

Die Güte einer Bestandsabschätzung ist direkt von der Qualität der Datenauswertung abhängig

Abundanzindizes müssen sich proportional zum Fischbestand verhalten

Räumliche Muster in der Verbreitung der Fische werden in der klassischen Fangstatistik bisher nicht berücksichtigt

Mögliche Verzerrungen in Bestandsabschätzungen und Gefahr der Fehleinschätzung von bspw. ökologischen Effekten von Offshore Windkraftanlagen auf das Schutzgut „Fische“

Hintergrund und Anlass der Promotion

Kernfrage: Welchen Effekt haben räumliche Verteilungsmuster von Fischpopulationen auf klassische Berechnungen von Abundanzindizes ?

Methode: Mittels der *Geostatistik* (Teilgebiet der räumlichen Statistik) wurden artspezifische Verteilungsmuster modelliert und unverzerrte Abundanzindizes berechnet

Datenbasis: Fangdaten von nicht kommerziellen, kommerziellen und gefährdeten Fischarten aus der Nordsee und künstlich erzeugte Fangdaten

Künstlich generierte Fischereidaten mit definierten Eigenschaften

Fangdaten auf *kleiner Maßstabsebene* (ca. Windparkgrösse) extrahiert aus der Datenbank des German-small-scale Surveys, Institut für Seefischerei, Hamburg und Eigenerhebung

Fangdaten auf *grosser Maßstabsebene* extrahiert aus der Datenbank des, Instituts für Seefischerei, Hamburg

Quantifizierung des Einflusses von Stichprobenumfang, kleinskaliger Variabilität und mathematischer Verteilung der Daten auf die Leistung robuster geostatistischer Verfahren → **Kapitel 1**

Untersuchung der zeitlichen und räumlichen Konsistenz von Verteilungsmustern der Kliesche in der Deutschen Bucht → **Kapitel 2**

Bewertung eines speziell für die geostatistische Analyse entworfenen Probenahmedesigns → **Kapitel 3**

Untersuchung des Einflusses von „Untersuchungsmaßstab“ und „Habitatassoziation“ der Zielart auf eine geostatistische Analyse → **Kapitel 4**

Untersuchung des Einflusses des Fanggerätes auf eine räumliche Analyse und die dazugehörige Bestandsabschätzung → **Kapitel 5**

Berechnung von Fangwahrscheinlichkeiten einer gefährdeten Fischart in der AWZ der Nordsee mit Methoden der nicht-linearen Geostatistik → **Kapitel 6**

Abb. 1: Darstellung der thematischen Positionierung der hier vorliegenden Arbeit und Charakterisierung der Methodik und Arbeitshypothesen.

Der Bedarf an präzisen Analysen von Verteilungsmustern einzelner Fischarten und deren zeitliche Veränderung sowie an unverzerrten Berechnungen von Abundanzindizes im Kontext eines aktuellen Nutzungskonflikts war der Anlass dieser Arbeit (Abb.1). Durch eine Kooperation mit Dr. Siegfried Ehrich von der Bundesforschungsanstalt für Fischerei, Institut für Seefischerei in Hamburg standen für die Promotion einerseits die benötigten Fangdaten zur Verfügung und anderseits konnten durch Seereisen mit dem Fischereiforschungsschiff „Walther Herwig III“ (Abb.2) eigene Daten.

Aus der Datenbank des Instituts für Seefischerei wurden Fangdaten auf kleiner und großer Maßstabsebene extrahiert. Zum einen waren dies Fangdaten von fischereilich genutzten und nicht genutzten Fischarten (Kliesche, Wittling, Schellfisch, Kabeljau und Hering) aus der Deutschen Bucht und der nördlichen Nordsee erhoben durch den German Small-scale Bottom Trawl Survey (GSBTS), einem Monitoringprogramm zur Erfassung der bodenorientierten Fischfauna (Ehrich *et al.* 1998) (Abb.3). Hierbei ist von besonderer Bedeutung, dass die Größe der kleinskaligen GSBTS Untersuchungsgebiete („Boxen“) teilweise der räumlichen Dimension eines offshore Windparks entspricht. Zum anderen waren dies auf großer Maßstabsebene standardisierte Fangdaten der gefährdeten Wanderfischart Finte aus der AWZ der Nordsee und den angrenzenden Küstenregionen (Abb.4).

Abb. 2: Fischereiforschungsschiff „Walther Herwig III“

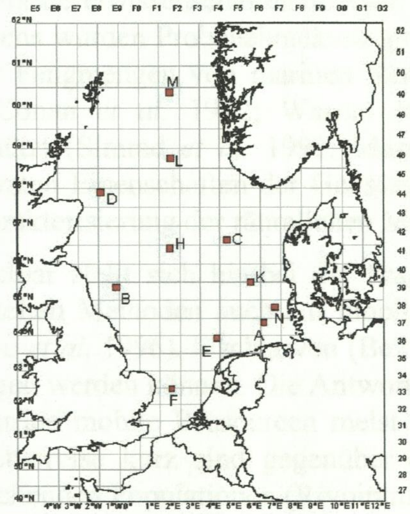


Abb. 3: Räumliche Verteilung der Standartuntersuchungsgebiete („Boxen“) des German Small-scale Bottom Trawl Survey (GSBTS) in der Nordsee.

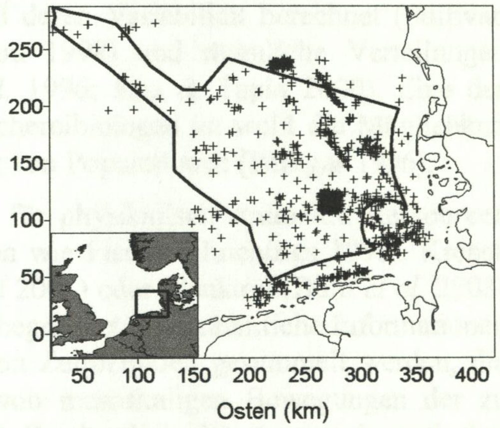


Abb. 4: Ausschließliche Wirtschaftszone (AWZ) der Nordsee und Darstellung der Fangstationen (+) der anadromen Wanderfischart Finte (*Alosa fallax*).

Durch eine weitere Kooperation mit Dr. Francesc Maynou vom Institut de Ciències del Mar in Barcelona, Spanien wurde nicht nur die Arbeitsmethodik optimiert, sondern zusätzlich auch künstliche Fangdaten mit definierten Eigenschaften generiert, um robuste geostatistische Verfahren zu testen.

Die Arbeit beschäftigt sich mit der räumlichen Analyse von Verteilungsmustern einzelner Fischarten und deren zeitliche Veränderung innerhalb diskreter Seegebiete, wobei die Kliesche (*Limanda limanda*) die hier am intensivsten untersuchte Art ist. Sie ist die häufigste Plattfischart in der Nordsee bzw. Deutschen Bucht (Daan *et al.* 1990; Rijnsdorp *et al.* 1992) und repräsentiert eine Art mit geringen Schwankungen in der Populationsgröße in den letzen Jahren (Heessen & Daan 1996). Aufgrund der Annahme, dass stabile Populationen artspezifische Verteilungsmuster ausbilden (Hutchings 1996; Warren 1997), eignet sich diese Art also besonders gut, um artspezifische Strukturausbildungen genauer zu untersuchen.

Einerseits werden in dieser Arbeit einzelne Faktoren untersucht, die eine adäquate räumliche Analyse im Hinblick auf akkurate und präzise Abschätzungen, beeinflussen können, andererseits ist von besonderem Interesse welchen Einfluss artspezifische Verteilungsmuster („Patches“) auf die Berechnung von Abundanzindizes haben und wie sich diese von den klassischen unterscheiden. Denn artspezifische Verteilungsmuster und deren Veränderung mit der Zeit, wie oben schon beschrieben, werden in den Methoden der klassischen Fangdatenauswertung nicht berücksichtigt.

Um adäquate Analysen von räumlichen Verteilungen der Fischpopulation in den Untersuchungsgebieten zu erhalten und die dazugehörigen unverzerrten Biomasseindizes berechnen zu können, wurden Methoden der Geostatistik eingesetzt. Die Geostatistik ist ein Teilgebiet der räumlichen Statistik (Chilès & Delfiner 1999). In den 60er Jahren wurden diese Methoden entwickelt, um die Ausbeute von Erzreserven zu optimieren (Matheron 1963; Matheron 1971; Journel & Huijbregts 1978). Die Anwendung von geostatistischen Methoden weitete sich dann auch auf andere Gebiete der Naturwissenschaften wie die der Ökologie aus (Sokal & Oden 1978b; Sokal & Oden 1978a; Legendre & Fortin 1989; Rossi *et al.* 1992; Legendre 1993). Erst in den letzten Jahren ist der Einsatz der Geostatistik speziell in den Fischereiwissenschaften deutlich angestiegen (Rivoirard *et al.* 2000). Mit Hilfe dieses Verfahrens wurden Probenahmekonzepte optimiert (Warrick & Myers 1987; Petitgas 1996), mittlere Fangmengen von marinen Ressourcen und deren Variabilität berechnet (Sullivan 1991; Conan *et al.* 1992; Warren 1997; Maynou 1998) und räumliche Verteilungen abgeschätzt (Simrad *et al.* 1992; Maravelias *et al.* 1996; Roa & Tapia 2000). Eine der attraktivsten Eigenschaften der Geostatistik für Fischereibiologen ist wohl die Möglichkeit der Charakterisierung der räumlichen Musterbildung von Populationen (Petitgas 1996).

Unmittelbar stellt sich hierbei die Frage, wie die für physikalisch stationäre Ressourcen entwickelten Methoden auch auf mobile Ressourcen wie Fische (Hutchings 1996), Krebse (Maynou *et al.* 1996), Fischlarven (Bez & Rivoirard 2001) oder Plankton (Bulit *et al.* 2003) übertragen werden können. Die Antwort liegt darin begründet, dass räumliche Informationen über marine mobile Ressourcen meist innerhalb von Zeitperioden gesammelt werden, die vergleichsweise kurz sind gegenüber der Dauer von mesoskaligen Bewegungen der zu untersuchenden Populationen (Rivoirard *et al.* 2000). Da räumliche Muster aus theoretischer Sicht als Ergebnis eines Zufallsexperiments angesehen werden, bedeutet dies für alle raumbezogenen ökologischen Untersuchungen, dass während der Probennahme kein neues Zufallsexperiment "ausgeführt" wird, unabhängig davon, ob die Daten mit Hilfe der Geostatistik ausgewertet werden oder nicht.

Durch den besonders geringen Stichprobenumfang, wie er in der Fischereiforschung meist üblich ist, und der mathematischen Verteilung der Fangdaten entstehen oftmals Probleme bei der Verwendung geostatistischer Methoden (Maravelias *et al.* 1996; Rivoirard *et al.* 2000). Eine Mindestanzahl von 30-50 Stichproben werden von Legendre (1993) empfohlen. Doch durch den Konflikt zwischen den Kosten eines Surveys und dem theoretischem Bedarf an Stationen stehen in der Fischereipraxis oftmals weniger als 30-50 Stichproben für eine geostatistische Analyse zur Verfügung. Kenntnisse über den Einfluss von Stichprobenumfang und mathematischer Verteilung der Daten auf die Leistung gängiger Verfahren der Geostatistik sind somit fundamental. Um akkurate und präzise Abschätzungen zu gewährleisten, erwies es sich somit als notwendig, diese Problematik durch eine geostatistische Simulationsstudie mittels künstlich erzeugter Fangdaten zu analysieren und mögliche Fehler zu quantifizieren. In Zusammenarbeit mit Dr. Maynou, ICM Barcelona, wurde ein „Leitfaden“ entwickelt, anhand dessen ein Anwender die für seine Datenlage geeigneten Verfahren auswählen kann, um die Modellierung und somit die Abschätzung der mittleren Fangmenge einer Art optimieren zu können (Kapitel 1).

Eine Methodik, mit deren Hilfe mögliche Effekt von Offshore Windkraftanalgen auf das Schutzgut „Fisch“ anhand von Langzeit-Messdaten erfasst werden können, wurde auf Basis von kleinskaligen Langzeit-Monitoringdaten (GSBTS) entwickelt (Kapitel 2). Für Fangdaten der Kliesche (*Limanda limanda*) wurde die zeitliche Konsistenz der räumlichen Musterbildung in der Deutschen Bucht (Box A) untersucht. Artspezifischer Verteilungsmuster von drei Größenklassen von Kieschen wurden auf dieser Maßstabsebene charakterisiert und deren Effekt auf die klassische Abundanzabschätzung quantifiziert.

Auf Basis bereits gewonnener Erkenntnisse über räumliche Muster von Fischpopulationen innerhalb mesoskaliger Seegebiete und über robuste Verfahren der Analysemethode wurde ein speziell für eine geostatistische Analyse optimiertes Probenahmedesign entwickelt, das im Januar 2002 und 2003 während einer Forschungsfahrt mit der Walther Herwig III (Abb. 2) in die Deutsche Bucht (Box A) getestet wurde (Kapitel 3). Dabei wurde untersucht, ob sich die Modellierung der kleinskaligen Variabilität in den Fangdaten von Kliesche und Wittling (*Merlangius merlangus*) durch zusätzliche Stationen, mit geringem Abstand zueinander, optimieren lässt ("star-survey") und welchen Effekt dieses Probenahmekonzept ggf. auf die räumliche Analyse der Fangdaten hat. Zusätzlich wurde eine räumliche Analyse der Fangdaten verschiedener biologischer Gruppen von Klieschen (Größenklassen und Geschlecht) durchgeführt und die Unterschiede bzw. Übereinstimmung in der Ausbildung von räumlichen Aggregationen bewertet.

Grundsätzlich spielt der Untersuchungsmaßstab eine große Rolle in räumlichen und zeitlichen Analysen von fleckenhaften Verteilungen („patches“). Ein „patch“ impliziert dabei ein relatives diskretes Muster, doch diese Definition ist immer relativ zu dem untersuchten System zu sehen (Pickett & White 1985). So sind die hier untersuchten und modellierten Muster in der Verteilung der Fangdaten für die jeweilige Maßstabsebene zu interpretieren. Daher war es notwendig, auch den Einfluss der „räumlichen Dimension des Untersuchungsgebietes“ auf eine geostatistische Analyse zu untersuchen (Kapitel 4). Die Aggregation von Tieren als Reaktion auf die fleckenhafte Verteilung wichtiger Ressourcen ist ein häufiger Grund für kleinskalige räumliche Populationsmuster (Hanski 1999). Aus diesem Grund wurde auch der Einfluss der Habitatassoziation (definiert durch die Wassertiefe) auf die räumlichen Muster in den Fangdaten in die Analyse einbezogen (Kapitel 4). Für diese Untersuchung standen besondere Fangdaten von Kabelajau (*Gadus morhua*), Schellfisch (*Melanogrammus aeglefinus*), Wittling, Kliesche und Hering (*Clupea harengus*) aus der nördlichen Nordsee zur Verfügung. Dieser in der Fischerei einzigartiger

Datensatz wurde im Rahmen eines Vergleichsfischereiexperiments in der nördlichen Nordsee (Box D) im Sommer 1986 erhoben. Dabei wurden 127 Stationen in zwei sich überlappenden Seegebieten mit unterschiedlichen räumlichen Dimensionen befischt. Unter anderem wurden Empfehlungen zur Modifikation von bestehenden Monitoringkonzepten formuliert, um verbesserte Bestandsabschätzungen erzielen zu können.

Um räumliche Daten aus unterschiedlichen Fischerei-Surveys sinnvoll vergleichen zu können, ist es notwendig, Unterschiede in der Erfassungsgüte räumlicher Muster von Fischpopulationen in Abhängigkeit vom eingesetzten Fanggerät zu analysieren. So wurde im Rahmen meiner Dissertation auch der Einfluss des Fanggerätetypes auf die räumliche Analyse von Fangdaten am Beispiel dreier Größenklassen von Klieschen untersucht (Kapitel 5). Die zu vergleichenden Fangdaten wurden mit der 7m-Baumkurre und dem Kabeljauhopser im Winter 2001 mit dem Forschungskutter „Solea“ in der Deutschen Bucht erhoben. Ein Resultat dieser Untersuchung war die qualitative Entwicklung von Anforderungen an das Fanggerät und die zu untersuchende Zielart, um eine präzise geostatistische Bewertung von Monitoringdaten zu gewährleisten.

Die Hauptverbreitungsmuster der gefährdeten anadromen Wanderfischart Finte (*Alosa fallax*) wurden für mehrere Jahre auf großer Maßstabsskala (AWZ der Nordsee) untersucht (Kapitel 6). Hierzu wurden Methoden der nicht-linearen Geostatik verwendet, um potentielle Schutzgebiet zu definieren. Im Rahmen der Kooperation mit Dr. Maynou wurden für die AWZ der Nordsee und den angrenzenden Küstengebieten Wahrscheinlichkeiten berechnet, mehr als eine bestimmte Anzahl von Finten zu fangen. So konnten Verbreitungsschwerpunkte definiert und Empfehlungen zum nachhaltigen Schutz dieser Art formuliert werden.

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KAPITEL 1

Assessing the performance of linear geostatistical tools applied to artificial fisheries data

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Abstract

The geostatistical analysis of fisheries survey data often presents problems due to the skewed distributions characteristic of such data as well as to the restricted number of samples, both of which severely affect the reliability of the experimental variograms and kriging results obtained. To analyse this problem, simulated catch data were generated with an underlying spherical covariance function, two types of distribution function (Gaussian and log-Gaussian), three levels of nugget variability (0 %, 30 % and 50 %) and different numbers of samples (from 20 to 200). The degree to which the originally defined covariance structure is recovered by common least squares and maximum likelihood methods, as well as the performance of two commonly used estimators for the empirical variogram (classical and robust), were assessed. Furthermore, the reliability of several goodness-of-fit criteria in detecting the original model type was evaluated. Our results showed that employing maximum likelihood methods instead of least-squares-based methods is advisable, especially when dealing with a low number of samples and a high level of nugget variability. This is true even for log-Gaussian distributed data, in view of the fact that these methods always showed higher precision and greater accuracy in the estimated parameters, especially when few samples are available. In all cases, the number of samples had a strong influence on the methods tested. Both estimator types behaved similarly in the Gaussian case, although the robust estimator performed considerably worse for log-Gaussian data. The Akaike Information Criterion and a goodness-of-fit criterion with weights according to numbers of pairs were the most powerful criteria for choosing the appropriate model type. Additional, non-linear models are presented which may be used to calculate correction factors depending on the sample size for the parameters nugget and sill of a spherical model fitted to any fisheries data. In general, we recommend that more attention is devoted to the combination of data distribution and number of samples for selecting the tools for structural variogram analysis. Thus, the appropriate choice of geostatistical tools in the analysis of fisheries data to obtain more accurate and precise abundance indices is essential.

Key Words: geostatistics, non-conditional simulation, robust estimator, goodness-of-fit criteria, least squares methods, maximum likelihood, nugget variability.

In review: ICES Journal of Marine Science

1 Introduction

In fisheries science, geostatistical analysis is mainly used to estimate species abundance (Conan *et al.*, 1992; Petitgas, 1993), to assess spatial structures and to derive ecological parameters of the population studied (Petitgas, 1996). Mostly intrinsic linear geostatistical methods are applied to evaluate fisheries survey data. Variograms based on sampling data, possibly transformed to normality (Guiblin *et al.*, 1995; Rivoirard *et al.*, 2000), are computed by using different estimator types for the empirical variograms. In most cases the classical estimator (Journel and Huijbregts, 1978) is used to calculate the variogram (Lembo *et al.*, 1998; Maynou, 1998), although the robust estimator (Cressie and Hawkins, 1980) has also been adopted, in order to reduce the influence of outlying observations (Maravelias *et al.*, 1996). The fit of the variogram model can be done visually (fitting by eye) (Petitgas, 1996) or automatically, using for example weighted least squares methods (WLS) (Fernandes and Rivoirard, 1999; Pelletier and Parma, 1994; Rueda and Defeo, 2001). Although both procedures often yield similar results, the semi-automatic procedure using software is most generally advised. Problems in the geostatistical analysis of fisheries data often arise due to the skewed distributions of fisheries catch data and to the restricted number of samples, which greatly affects the accuracy and precision of the variograms and kriging results obtained (Chilès and Delfiner, 1999; Cressie, 1991; Webster and Oliver, 2001).

To overcome the problem of skewed distributions, some authors have recommended alternative approaches, such as removing the statistical outliers (Armstrong, 1984), computing robust variograms (Cressie and Hawkins, 1980; Cressie, 1991), transforming the data (Guiblin *et al.*, 1995), and other *ad hoc* methods. Regarding fisheries data, large-value observations (sometimes inappropriately considered as outliers) are representative of the population and should not be omitted in the geostatistical analysis (Rivoirard *et al.*, 2000). In case of a log-normal distribution, transformation of the data to normality and back-transformation of the empirical variogram is possible, although the common presence of "zero" densities within the study area makes this approach difficult (Guiblin *et al.*, 1995). Rivoirard (2000) proposed an improvement of the parameter estimation for back-transformed variograms, which agrees well with the general observation that spatial autocorrelation is detected more easily with normally distributed data. Thus, the choices, depending on the characteristics of the spatial phenomenon under study (Matheron, 1989), among the several approaches recommended to overcome limitations due to the data distribution may be the first step in which bias might be introduced into the analysis.

Different methods are recommended to estimate the underlying spatial covariance model, either based on least squares fit of the empirical variogram (i.e. Ordinary Least Squares (OLS), Weighted Least Squares (WLS) or Cressie's modification of WLS (Cressie, 1991) or based on maximum likelihood methods (Maximum Likelihood (ML) and Restricted Maximum Likelihood (REML)). OLS fitting is not recommended because it gives the same weight to each pair in the variogram (Cressie, 1991). However the first lags (short distances) of a variogram are particularly important for the fit, since the behaviour of the variogram near the origin determines the degree of regularity (Rivoirard *et al.*, 2000). Further recommendations about using different weights for the weighted least squares procedure were made by Cressie (1991), Fernandes (1999), and Webster (1992). Cressie (1991) advised maximum likelihood estimations in case of normally distributed data.

In fisheries, the spatial covariance model may vary with the species under study (González-Gurriarán *et al.*, 1993; Maynou *et al.*, 1996; Petitgas, 1997), the time of the day (Rivoirard and Wieland, 2001; Simmonds and Rivoirard, 2000), the sampling period (Freire *et al.*, 1991; Hutchings, 1996; Sobrino and Garcia, 1993), or the age of the individuals (Bez and Rivoirard, 2000; Rivoirard *et al.*, 2000; Stelzenmüller *et al.*, 2004). Thus the analysis of this variation is one of the main objectives of many such studies. For example, the collapse of the northern cod, *Gadus morhua*, in Newfoundland waters was preceded by a change in the covariance structure (Hutchings, 1996). However, it is almost impossible to determine *a priori* the underlying covariance structure, so that an objective criterion for model selection is urgently required. The use of a semi-automated procedure has the advantage of speed, reproducibility, and objectivity although an appropriate criterion has to be chosen (Fernandes and Rivoirard, 1999; Rivoirard *et al.*, 2000). The simplest criterion is to minimise the sum of squares of the fitting errors (minimisation function), so that the smallest value indicates the "best fit" (Barry *et al.*, 1997). However, other authors recommended application of some goodness-of-fit measures (by minimising the sum of squares errors divided by the sum of square experimental values), preferably weighted by the number of pairs (Fernandes and Rivoirard, 1999) or by the inverse power of distance *h* (Rivoirard *et al.*, 2000). Another recommended criterion for model selection is Akaike`s Information Criterion (Akaike, 1973; Webster and McBratney, 1989; Webster and Oliver, 2001), although this method is mainly used for comparing the goodness-of-fit of different models. Finally, based on the model defined, the estimation of the variables at the grid nodes of the spatial phenomenon is commonly done by Ordinary Kriging (Matheron, 1971). As a result, a continuous contour map displaying estimated species density is obtained as well as estimations of the global mean and its variation, but the same arguments apply to the case of obtaining block estimates of density or total abundance.

Often, in fisheries studies, data are restricted to the currently measured values, and no additional sampling can be done. Therefore fishery surveys often have a relatively low number of samples, sometimes much less than 100. Webster (1992), using sequential Gaussian simulations with Monte Carlo methods (Deutsch and Journal, 1998), found that a sample of 100 points gives moderate variogram confidence intervals, whereas at least 144 measurements were necessary for a good estimation. The authors concluded that variograms based on less than 50 samples will be erratic and will not show the evident structure, while the form of the variogram became clearer with increasing sample size. Still, in fisheries this problem is difficult to overcome and leaves the researcher in a position of not applying geostatistics at all or of doing it despite the problems stated above. Thus, knowledge of the exact effects of reduced sample sizes in the estimation of the geostatistical model parameters and a quantification of this variation is fundamental for the application of geostatistics to fishery data.

Little work has been done on geostatistical simulation to test common methods and tools in a fisheries context. One application of non-conditional simulations was done by Simmonds (1992), who used three methods to generate a realisation of a random field with different degrees of spatial correlation in order to investigate the relationship between survey strategies and different spatial structures. Rivoirard (2000) employed a geostatistical simulation study to explore different variogram estimators and methods to estimate the variogram parameters. Employing the kriging method, simulations of fish and plankton patches were performed by Kalikhman (2001) and Kalikhman (1997) to examine the effects of various units of sampling distance on the adequacy of reconstruction of patchy distribution fields.

The objective of this study is to obtain test the robustness of commonly used structural variogram tools in fisheries data in recovering the underlying reference covariance function.

The behaviour of estimation methods and goodness-of-fit criteria was assessed regarding different combinations of factors such as distribution of the data (Gaussian and log-Gaussian), the value of the relative contribution of nugget variability (0 %, 30 % and 50 %), the type of estimator for the empirical variogram (classical and robust), the fitting method (WLS, Cressie, ML and REML) and number of samples (20, 30, 40, 50, 70, 100 and 200). For this assessment a non-conditional simulation of isotropic random fields was performed following a random sampling scheme with known covariance function, data distribution and different numbers of samples. In particular the following questions were addressed: *i)* which fitting method best recovers the initially specified covariance function, taking into account the factors considered, *ii)* which goodness-of-fit criterion better identifies the initially specified covariance model, again taking into account the factors of influence mentioned above, *iii)* which factors result in a lower bias in the estimation of the parameters, *iv)* what is the minimum number of samples needed to recover the original covariance structure and which degree of variability in the parameters can be expected with smaller sample sizes, and *v)* is it possible to obtain an adjustment model depending on sample size to correct the estimated model parameters in order to recover the true values of the parameters.

2 Material and Methods

2.1 Simulation of the data

Artificial catch data were computed by non-conditional simulations, following the second order definition in Chilès (1999). The non-conditional simulation of the random function $\{Z(x): x \in R^n\}$ is a realisation of a random field (RF *S(x)*), randomly selected in the class of all RFs with the same second-order moments as $Z(x)$, namely with the same covariance and variogram. The realisations $S(x)$ were computed employing the Cholesky decomposition method (Harbitz and Aschan, 2003; Press *et al.*, 1992), using the geoR library of the R package (Gentleman and Ihaka, 2000; Ribeiro JR. and Diggle, 2001). This method consists of multiplying a vector of standardised normal deviates by the square root of the covariance matrix. This classical method has been introduced in geostatistical applications by Davis (1987). To match one of the goals of this study, namely to assess the robustness of estimation methods and goodness of fit criteria also for a skewed distribution of the parameters, more than 100 realisations of the simulated random field should be generated (Chilès and Delfiner, 1999). Thus for each case studied, we computed 200 realisations. The realisations were generated on a grid of 50 by 50 cells, both for the Gaussian and the log-Gaussian RFs, of unit length.

For both types of RF, the reference covariance function was specified as composite function consisting of a nugget model plus a spherical model, commonly used in fisheries geostatistics (Cressie, 1991; Rivoirard *et al.*, 2000), with a total sill of 0.3 and range 0.3. The range was chosen as approximately 20% of the maximum distance of the random field to avoid statistical fluctuations (Lantuéjoul, 2002). Fig. 1 shows an example of a realisation of the RFs generated (left panel). The empirical variograms fitted to a sample of one realization of the RF are also shown, with a plot of the reference variogram (Fig. 1, middle panel) showing that for a given realization of the RF statistical fluctuations are present. Due to the relatively low range specified (with respect to the maximum distance of the field) and the large number of replicate sample we expect that the influence of statistical fluctuations is minimum. The histograms of the process distribution of the artificial catch data, both for the Gaussian and log-Gaussian processes, are shown in Fig. 1 (right panel). Further the Gaussian RF had a mean of 3.0 and a standard deviation of 0.53 (Fig. 1). The log-Gaussian RF was slightly modified to include 10% of internal zeros, to provide a more realistic artificial catch data set, with a mean of 1.17, a standard deviation of 0.67 and a skewness of 2.25 (Fig. 1). We studied the importance of the following factors: (*i*) the height of the relative nugget (nugget (C_0) / nugget (C_0) + partial sill (C_s) [%]) with 0, 30 and 50 % levels, and (*ii*) the sample size with a number of 20, 30, 40, 50, 70, 100 and 200 random samples taken from the generated RF.

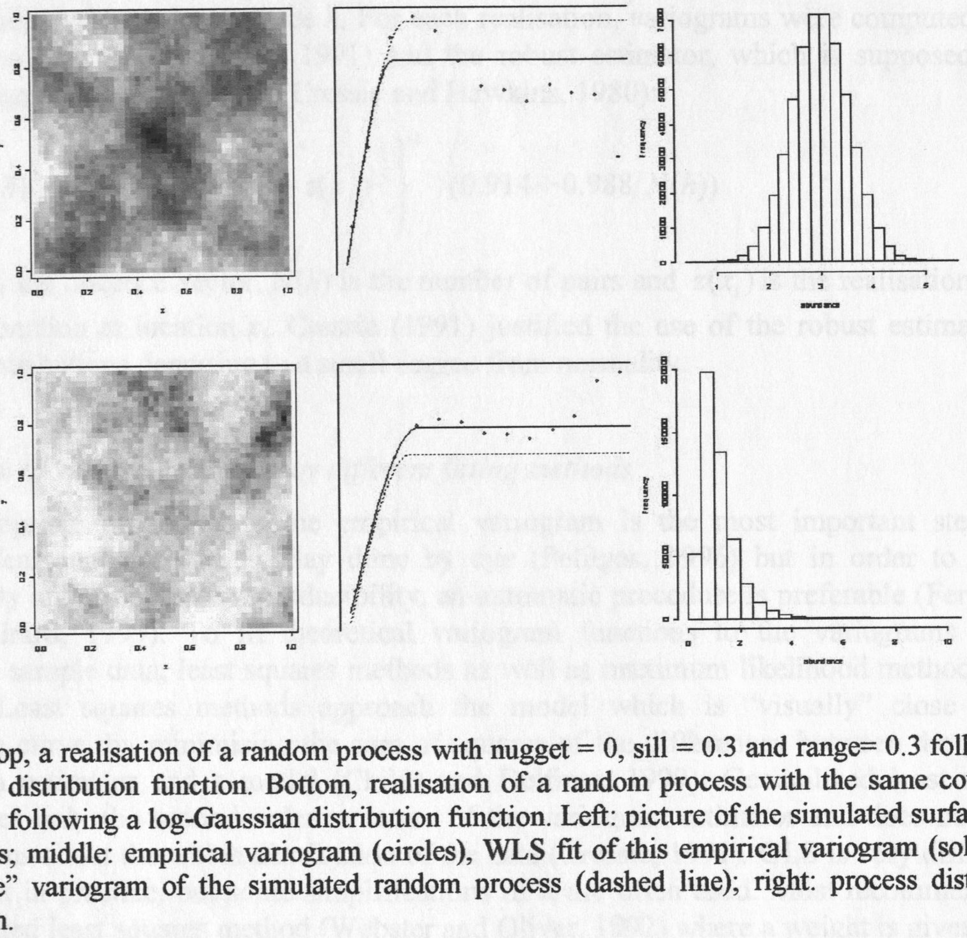


Fig. 1: Top, a realisation of a random process with nugget = 0, sill = 0.3 and range= 0.3 following a Gaussian distribution function. Bottom, realisation of a random process with the same covariance structure, following a log-Gaussian distribution function. Left: picture of the simulated surface of 50 x 50 cells; middle: empirical variogram (circles), WLS fit of this empirical variogram (solid line), and "true" variogram of the simulated random process (dashed line); right: process distribution histogram.

2.2 *Detection of spatial autocorrelation*

For each of the case studies, the Mantel test statistic (Legendre and Legendre, 1998; Mantel, 1967; Sokal, 1979) was computed to test its power in detecting spatial structures, especially when they are constrained by the underlying covariance structure, the relative nugget or the number of samples. We used the Euclidean distance to compute the matrix of geographical distances and the Manhattan distance for the matrix of biological distance, as recommended by Legendre (1998) for animal abundance data. To compute the Mantel Test it is typically recommended to use 500-2000 permutations of the matrices to generate the statistical distribution and to estimate the probability of obtaining a significant association between two matrices (Jackson and Somers, 1989). To assess the performance of the test statistic, we used 1000 permutations. Simulated sample data were regarded as significantly spatially autocorrelated when the observed *p-value* was smaller than α=0.05.

2.3 Geostatistical analysis of the simulated data

Experimental variograms

The spatial structure within the data is explored by computing the empirical variogram, which is the basic structural tool of intrinsic geostatistics (Rivoirard *et al.*, 2000). It is a function of distance vector *h*, equal to the variance of all pairs of the variable measured at locations separated by the distance *h*. For each realisation, variograms were computed using the classical estimator (Cressie, 1991) and the robust estimator, which is supposed to be resistant against extreme values (Cressie and Hawkins, 1980):

$$\hat{\gamma}(h)=\left\{\frac{1}{N(h)}\sum_{x_i-x_j\sim h}\left|z(x_i)-z(x_j)\right|^{\frac{1}{2}}\right\}^4\Big/(0.914+0.988/N(h)) \qquad (1)$$

where *h* is the distance vector, N(*h*) is the number of pairs and $z(x_i)$ is the realisation of the random function at location x_i. Cressie (1991) justified the use of the robust estimator for sample distributions departing to a small degree from normality.

Estimation of variogram models by different fitting methods

The appropriate model fit to the empirical variogram is the most important step in a geostatistical analysis. Fitting may done by eye (Petitgas, 1996) but in order to reduce subjectivity and to increase reproducibility, an automatic procedure is preferable (Fernandes and Rivoirard, 1999). To fit theoretical variogram functions to the variograms of the simulated sample data, least squares methods as well as maximum likelihood methods were applied. Least squares methods approach the model which is "visually" close to the variogram curve, by minimising the sum of squares of the differences between the generic variogram estimator and a model (Chilès and Delfiner, 1999). Generalized least squares (GLS) uses only the second-order structure of the variogram estimator and does not make assumptions about the whole distribution of the data (Cressie, 1991). GLS is very difficult to implement in practice, but some simplifications of it are often used. Most recommended is the weighted least squares method (Webster and Oliver, 1992) where a weight is given to the difference between estimator variogram and model. In this study, we used two least squares fitting methods: weights equal to the number of pairs at each distance class (Cressie, 1991), referred to as WLS, and a modification of this method introduced by Cressie (1985), referred to as "Cressie".

The maximum likelihood (ML) and the restricted maximum likelihood method (REML) (Cressie, 1991), which do not require a computation of an empirical variogram, were also applied to all simulated sample data sets. The maximum likelihood estimation procedure relies on the assumption of a Gaussian distribution of the data. With ML estimation and small to moderate sample sizes the estimators of the parameters are biased (Matheron, 1971). The ML estimator is supposed to be more biased than the REML estimator (Cressie, 1991).

One objective of this study is to recommend a fitting method which recovers best the initial values of the parameter of the covariance functions specified, depending on the combination of the factors distinguished: distribution of the data, relative nugget, estimator type and number of samples. Therefore to follow the recommendations as well as to test the most common method, employing WLS spherical, exponential, gaussian and linear models

(Cressie, 1991) were fitted. In contrast with Cressie, ML and REML only spherical models were fitted. The estimation of the parameters was done by specifying initial start values for each fitting procedure. For normally distributed data a fitting was carried out with random initial values, within a 10 % variation around the true parameters.

2.4 *Assessment of selected goodness-of-fit criteria*

Several measures of the goodness-of-fit were computed to assess variogram models obtained by WLS. One criterion was the value of the minimising function (Barry *et al.*, 1997), derived from the fit procedure with WLS. The smaller the values, the closer the fit to the variogram curve. A number of goodness-of-fit statistics (*gof*) were used to identify the model function with the closest fit, regarding the squared difference between the variogram curve and the model (Rivoirard *et al.*, 2000):

$$gof1 = \frac{\sum_h [\hat{\gamma}(h) - \gamma(h)]^2}{\sum_h [\hat{\gamma}(h)]^2} \qquad (2)$$

where $\hat{\gamma}(h)$ is the empirical variogram and $\gamma(h)$ is the fitted model. The closer this *gof* to 0, the better the fit. Fernandes (1999) proposed weights for this approach.

$$gof2 = \frac{\sum_h \omega(h)[\hat{\gamma}(h) - \gamma(h)]^2}{\sum_h \omega(h)[\hat{\gamma}(h)]^2} \qquad (3)$$

where weights $\omega(h)$ used are proportional to the number of pairs used to compute $\hat{\gamma}(h)$ (*gof 2*) and to the inverse square of the distance *h* (*gof 3*). Additionally, Akaike`s information criterion (Akaike, 1973) (AIC) was computed, which uses the squared residuals between the experimental values and the fitted model (Webster and Oliver, 2001). Once again the smallest AIC indicates the best fit.

Furthermore, cross-validation procedure (Isaaks and Srivastava, 1989) was carried out, to compare the estimated and true values only using the information available in the simulated data set. This bootstrap method is often used to compare different variogram models (Isaaks and Srivastava, 1989; McBratney and Webster, 1986). The model with the closest values to the mean standardised error (*cros1*) (equal to 0) and its standard deviation (*cros2*) (equal to 1), is regarded as the best fit.

2.5 *Evaluation of the fitting procedures and gof criteria*

Assessment of the fitting methods

To assess the capability of the fitting methods applied to recover the initially specified values for the parameters nugget, sill and range of the spherical covariance function, medians (with a 95 % confidence interval) of the estimated values for the parameters were plotted *vs* number of samples for all factors (relative nugget, distribution of the data and estimator type used). Subsequently a Wilcoxon test (Sokal and Rohlf, 1994) was computed for each combination of fitting method and number of samples for both estimator types, to test if the median of the estimates of the parameters of the spherical model differed significantly from the initial ones. Furthermore Kruskal – Wallis tests (Zar, 1999) were carried out for each fitting method and estimator type (classical and modulus) to test the null hypothesis, that the median of the distribution of the estimated values (nugget, sill and range) are the same in each group (for each sample size). The alternative is that at least two groups are significantly different. It was thus tested if the factor sample size has a significant influence on the estimation procedure carried out by the different fitting methods described above.

Assessment of common goodness-of-fit criteria

The percentage of cases in which a goodness-of-fit criterion was able to identify the spherical model as "best fit" (relative to the exponential, Gaussian and linear variogram model), was plotted *vs* number of samples for the different factors of influence defined above. Thus a qualitative assessment of each criterion in relation to corresponding combinations of factors was achieved.

2.6 Evaluation of adjustment models to correct the estimated model parameters depending on sample size.

For this approach only those cases were considered in which the estimated model parameters indicated a non-linear relationship with increasing sample size. This particular example is of quite general applicability because it represents a commonly encountered situation in fisheries geostatistics: large amounts of small-scale (nugget) variability and skewed data. The estimated model parameters (nugget and sill) of the spherical models fitted to the simulated log-Gaussian data with initial relative nugget of 50 % were used. Extreme values were temporarily deleted from the data set and values of the nugget were subtracted from the estimated sill to obtain the partial sill. Finally, estimated values of the model parameters were standardised by the initial values of each parameter (nugget = 0.15 and sill = 0.15).

Several exponential functions, which describe a positive or negative asymptotic process, were selected and fitted to the standardised parameters using a non-linear regression (Bates *et al.*, 1997). The one with the lowest residual sum of squares (RSS) was selected as the best fit. Using these functions it is possible to achieve a correction for any sample size greater than 20, in order to estimate the reference values of the parameters nugget and sill of a spherical model fitted to any catch data displaying the above described characteristics.

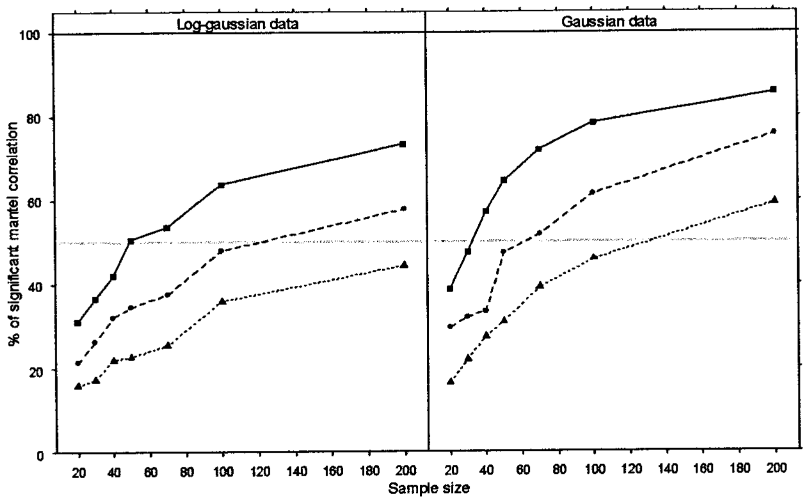
3 Results

3.1 Detecting spatial structure (Mantel test)

The percentage of spatial autocorrelations in the simulated data detected by the Mantel test statistic depending on the number of samples (20, 30, 50, 70, 100 and 200) is shown in Fig. 2a, regarding the factors "relative nugget" and "distribution type", respectively. For Gaussian-distributed data, the Mantel test indicates significant spatial autocorrelations in 40% to 80% of the cases, in the absence of a "relative nugget". Not surprisingly, with increasing nugget effects (30% and 50%) the power of the test is apparently decreasing. This tendency is less pronounced as sample size increases, due to the fact that more samples are taken within the radius of covariance of the field. For log-Gaussian-distributed data, the power of the test is generally lower, with chances of greater than 50% to detect spatial structures limited to cases without nugget effects and large sample sizes.

The median values for Pearson correlation coefficient provided by the Mantel test (with 95 % confidence intervals) depending on the number of samples are shown in Fig. 2b, again regarding the factors "relative nugget" and "distribution type", respectively. The degree of spatial autocorrelation detected using Pearson correlation index in the Mantel test was low and decreased for scenarios from 0% to 50% nugget effect; however, variation with sample size was marginal (Fig. 2b), unlike the percentage of significant cases. The low correlation values can be attributed to the non-linear behaviour of the spherical covariance model at medium distances, because the Mantel test using the Pearson correlation coefficient is only able to detect significant correlations for linear behaviour, i.e. at short distances of the spherical model. In the case of log-normally distributed data, the correlation detected was even lower, regardless of the initial percentage of nugget and sample size (Fig. 2b).

(a)



(b)

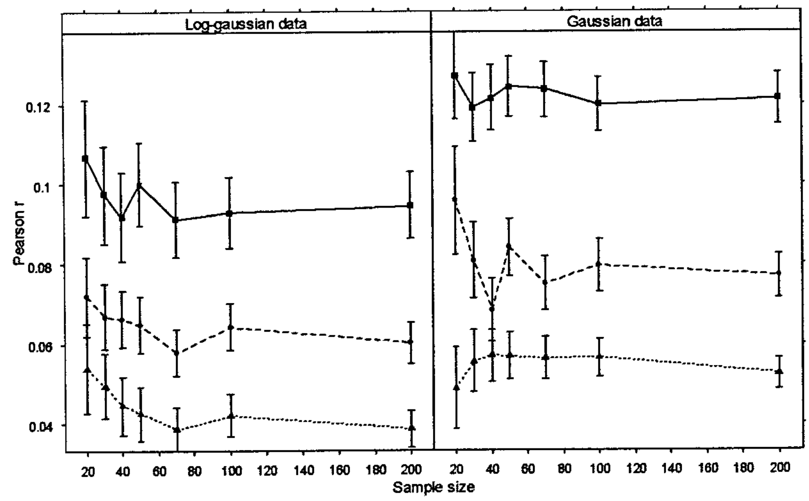


Fig. 2: (a) Percentage of trials in which the *p-value* from the spatial Mantel correlation was significant. (b) median (and respective 95% CI, calculated with the Wilcoxon test) of correlation index for the spatial Mantel test. ■ 0 % relative nugget, ● 30% relative nugget and ▲ 50% relative nugget.

3.2 *Qualitative assessment of the fitting methods employed*

Estimation of variogram parameters -nugget

Generally, for increased nugget variability more samples were needed to estimate the correct nugget value of the reference function in all estimation methods (Fig. 3a and b). In the case of the Gaussian-distributed process (Fig. 3a), Cressie's method performed best, since even with a small number of samples, correct nugget values were estimated. No significant difference was observed between the classical and the modulus estimator, except for very small sample sizes (n=20) and nugget values of 30 and 50%. The accuracy of WLS and Cressie methods was high for large sample sizes, but diminished in the presence of high nugget variability. The accuracy of the ML and REML methods followed a similar pattern, but their precision was higher than the WLS and Cressie methods. The results of the Kruskal-Wallis test showed that in the presence of nugget variability, the sample size was a significant factor determining the accuracy of the nugget estimation (chi-square between 13.66 and 119.27, $p<0.0001$).

For log-Gaussian distributed processes, the simulation results were similar for the classical estimator to the Gaussian-distributed process, but the modulus estimator performed very poorly in estimating the correct nugget (Fig. 3b). The classical estimator behaved similarly, in terms of precision and accuracy, to the case of the Gaussian process, both for WLS and Cressie's fitting methods. The behaviour of the ML and REML methods was also similar to the Gaussian process, with similar levels of precision and accuracy. The Kruskal-Wallis test detected a significant effect of sample size when the nugget component was 30 or 50% (chi-square between 47.86 and 124.29, $p<0.0001$).

Estimation of variogram parameters -sill

The influence of various factors (nugget, sample size, fitting method) on the estimation of the reference sill of the variogram is presented in Fig. 4a and b. Generally, the least square methods show less precision than likelihood methods, but their accuracy at large sample sizes is similar (Fig. 4a). For moderate amounts of nugget variability (30%), maximum likelihood methods could estimate the sill parameter with high accuracy for increased sample size. The importance of the nugget component does not have as much importance in the estimation of the correct value of the sill, converging asymptotically towards the reference value. The robust estimator performed different than the classical only for very small sample size (n=20). The results of the Kruskal-Wallis test showed that sample size was a significant factor with increasing nugget component (chi-square varied between 32.06 and 116.65, $p<0.0001$). Regarding the log-Gaussian distributed data, weighted least squares methods performed well asymptotically, although with lower precision than maximum likelihood methods. It is remarkable to note that the robust estimator converged quicker (i.e. at lower sample sizes) to the reference sill value for 30% nugget variability and 50% nugget variability. Maximum likelihood methods performed well, with high precision and accuracy for moderate to large sample sizes, although accuracy increased with increasing nugget variability. The REML estimator showed higher instances of bias than the ML estimator. The results of the Kruskal-Wallis test showed that sample size was a significant factor with increasing nugget component (chi-square 30.54 and 80.33, $p<0.0001$).

Estimation of variogram parameters -range

In general, the estimation of the range parameter produced the lower levels of accuracy and precision, both for Gaussian and log-Gaussian data (Fig. 5a and b). Further in both cases, increased accuracy was detected for the likelihood methods than for the least squares methods. Between least squares methods, WLS and Cressie performed equally for both types of data distribution. The robust estimator showed accuracy in estimating the range parameter for Gaussian data, but systematically overestimated the range in the presence of nugget variability in the case of log-Gaussian data. The results of the Kruskal-Wallis test for the Gaussian data showed that sample size was a significant factor (chi-square between 24.29 and 91.58, $p<0.0001$). For the log-Gaussian data, sample size not in general a significant factor, being significant only for the REML estimator (chi-square: 34.74, $p<0.0001$).

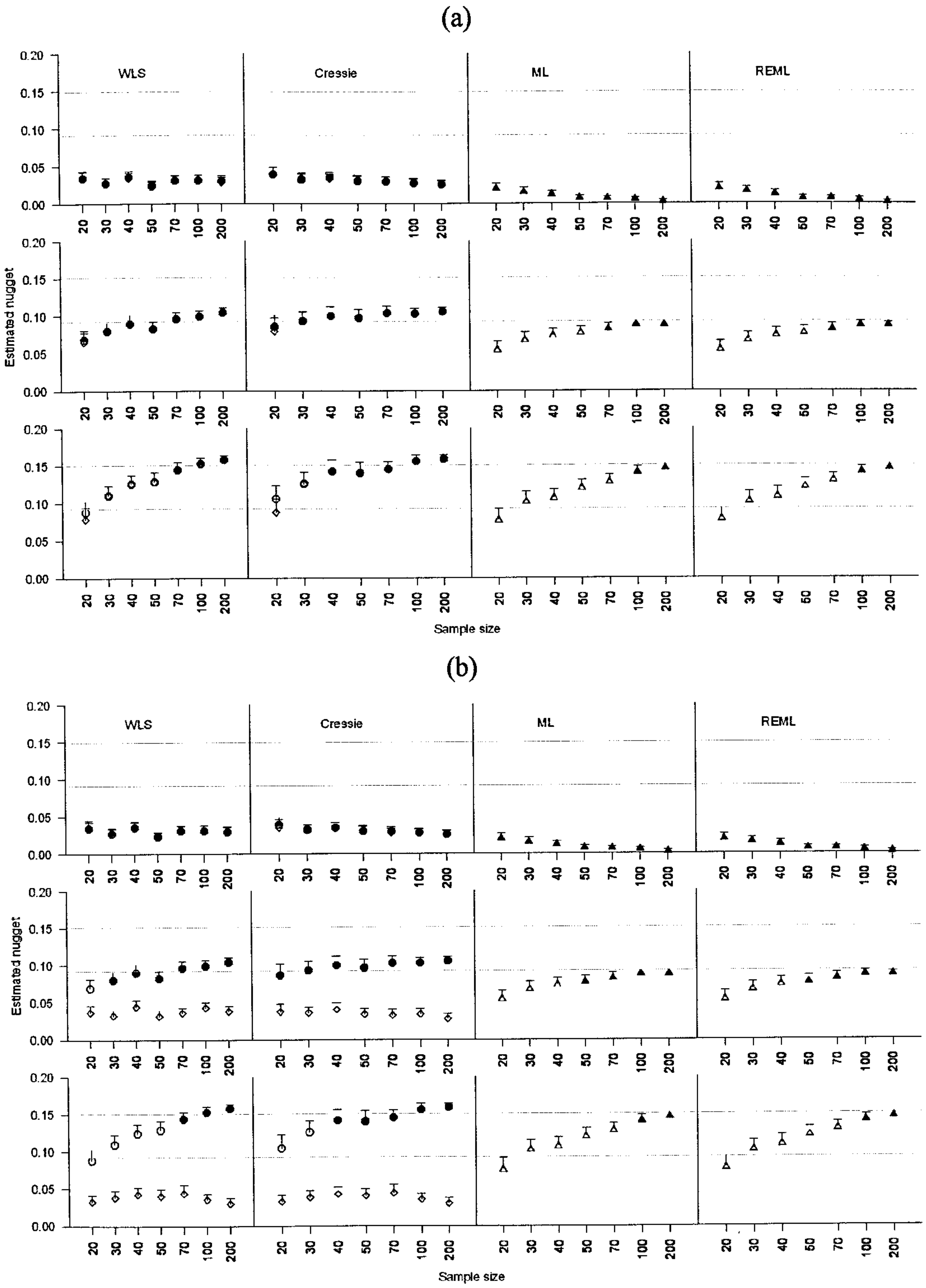


Fig. 3: Median values and 95% confidence intervals of the estimated variogram nugget parameter, regarding Gaussian distributed data (a) and log-Gaussian distributed data (b). Factors of influence and levels considered: fitting methods WLS, Cressie, ML and REML; nugget variability of 0%, 30% and 50%. ● classical estimator, ◆ modulus estimator and ▲ fitting methods ML and REML.: Estimates significantly different from the reference value (Wilcoxon test) are denoted by open symbols, values not significantly different by closed symbols.

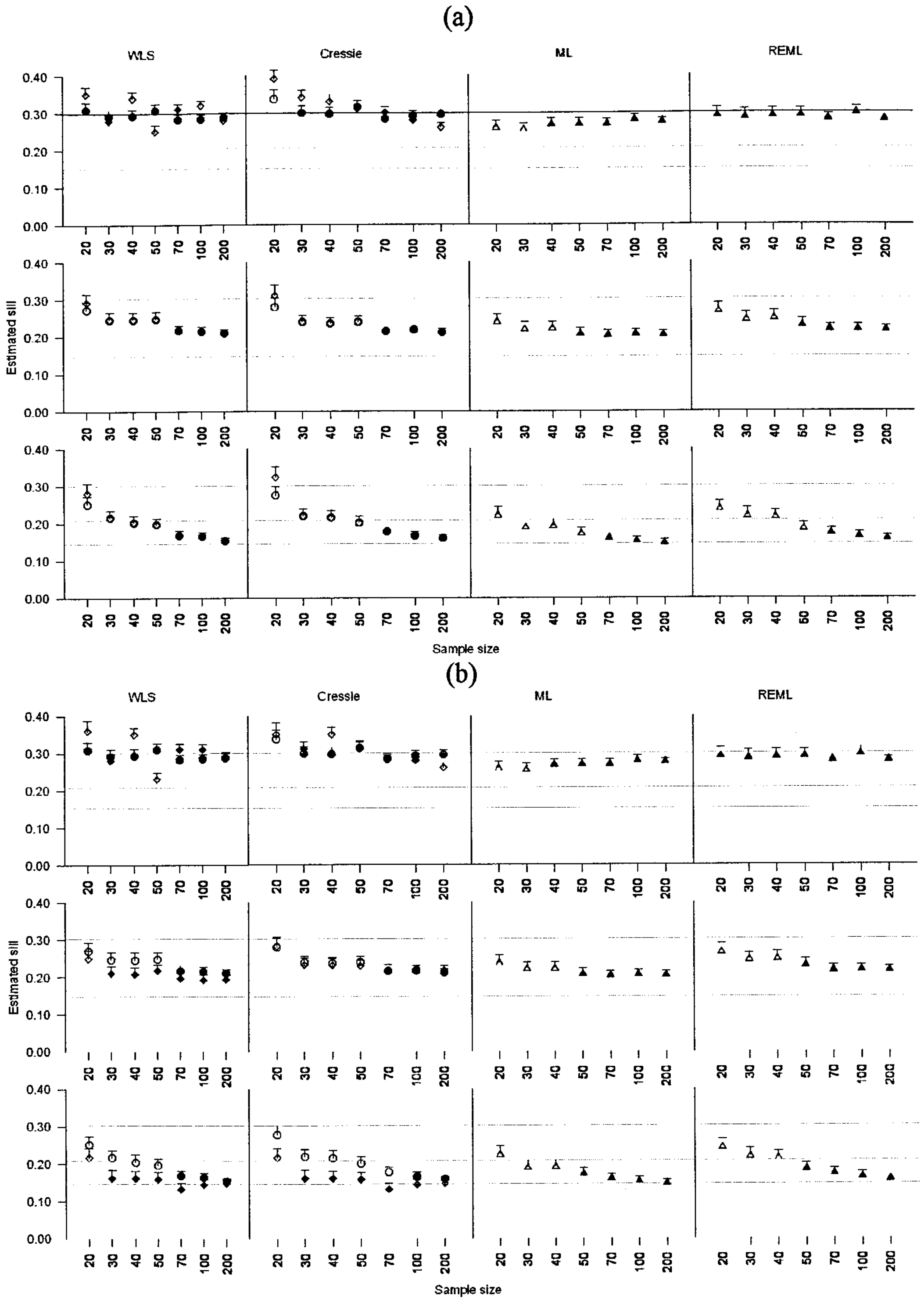


Fig. 4: Median values and 95% confidence intervals of the estimated sill, regarding Gaussian distributed data (a) and log-Gaussian distributed data (b). Factors of influence and levels considered: fitting methods WLS, Cressie, ML and REML; variability of 0%, 30% and 50%. ● classical estimator, ◆ modulus estimator and ▲fitting methods ML and REML.: Estimates significantly different from the reference value (Wilcoxon test) are denoted by open symbols, values not significantly different by closed symbols.

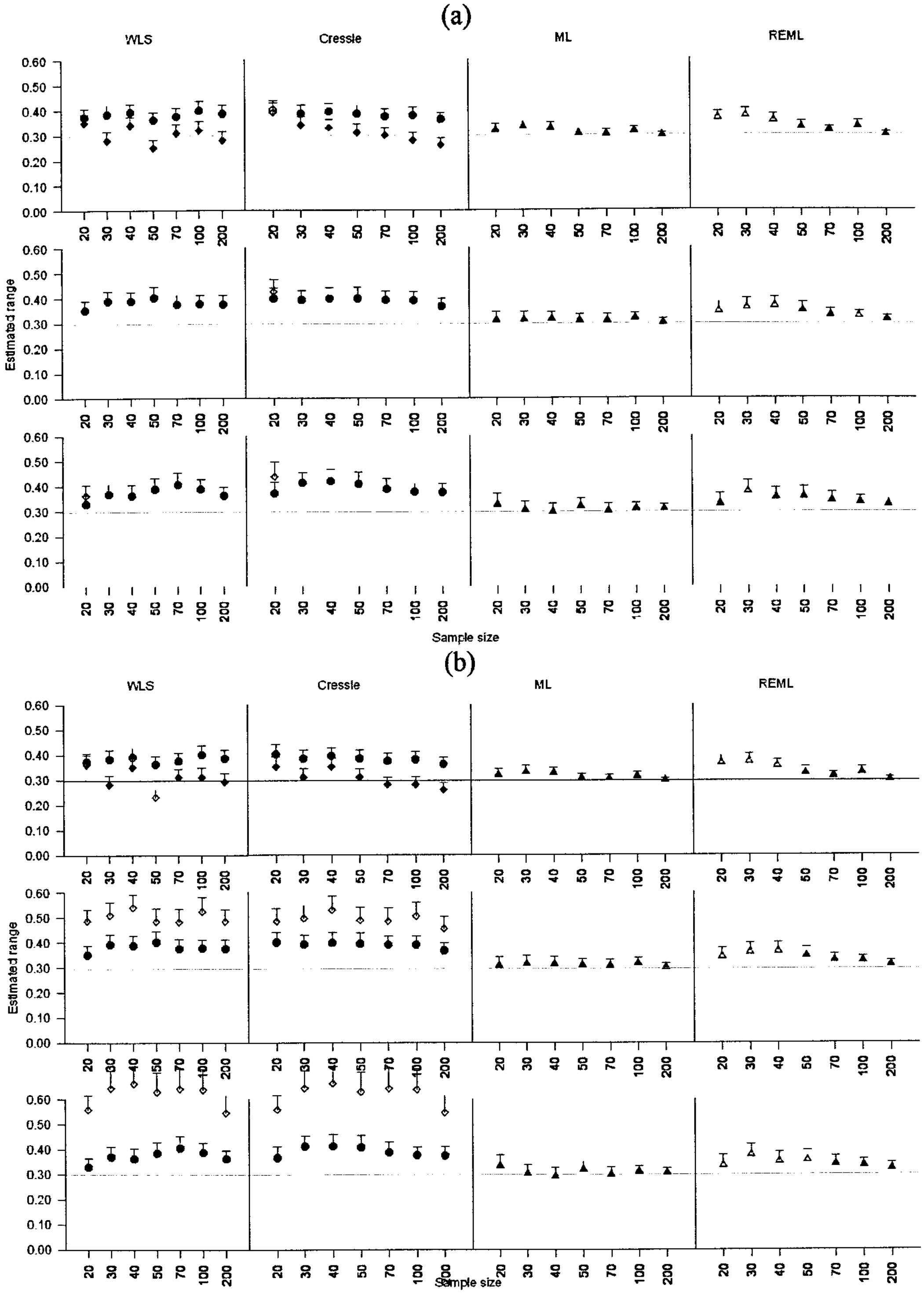


Fig. 5: Median values and 95% confidence intervals of the estimated values of the range, regarding Gaussian distributed data (a) and log-Gaussian distributed data (b). Factors of influence and levels considered: fitting methods WLS, Cressie, ML and REML; nugget variability of 0%, 30% and 50%. ● classical estimator, ◆ modulus estimator and ▲ fitting methods ML and REML.: Estimates significantly different from the reference value (Wilcoxon test) are denoted by open symbols, values not significantly different by closed symbols.

3.3 Assessment of selected goodness-of-fit criteria

In the absence of nugget variability (Fig. 6a, top panel), the criteria AIC, *gof2* and *min* performed relatively well in the case of normally distributed data. These methods helped identify the reference variogram in 40-50% of the cases, the proportion of correct fits increases with sample size. The criterion *gof1* ranks second regarding capability of detecting the reference variogram, with 50% of the cases for sample size 200. The criterion *gof3* is less powerful, detecting the correct variogram in 40% of the cases for sample size 50 or above. Cross-validation is able to detect the original function in only 20 % of the cases. With 30% nugget (Fig. 6a, middle panel), the relative rank of the different *gof* criteria is very similar, although the power of AIC, *gof2* and *min* increases to 50 - 60% the probability of detecting the reference variogram. The criterion *gof1* performs poorly, with chances of detecting the reference variogram around 40% for small sample sizes and around 30% for larger sample sizes. The power of the cross-validation criteria *cros1* and *cros2* is also very low. With increasing nugget effect (50%, Fig. 6a, lower panel) the results are very similar, with AIC, *gof2* and *min* performing reasonably well. It is remarkable that the power of *gof1* decreases with increasing nugget variability and sample size.

Regarding log-Gaussian data (Fig. 6b), results obtained for the *gof* criteria are very similar to the normally distributed data described above. Clearly, AIC, *gof2* and *min* are the most suitable methods to detect agreements between estimated and reference variograms, while *gof1* and *gof3* only give poor results with increasing sample size and level of the pre-selected nugget effect.

3.4 Evaluation of adjustment models to correct the estimated model parameters depending on sample size

The adjustment models fitted to the standardised estimates of the spherical variogram model parameter *vs* sample size are summarised in Fig. 7. The asymptotic behaviour of the estimates with increasing sample size is represented very well by three-parameter exponential models, showing low values of RSS. The correction factors for nugget (Fig. 7, a and b) were lower than for the sill parameter (Fig. 7, c to f). The types of models and the estimated parameters of the adjustment models are listed in Table 1.

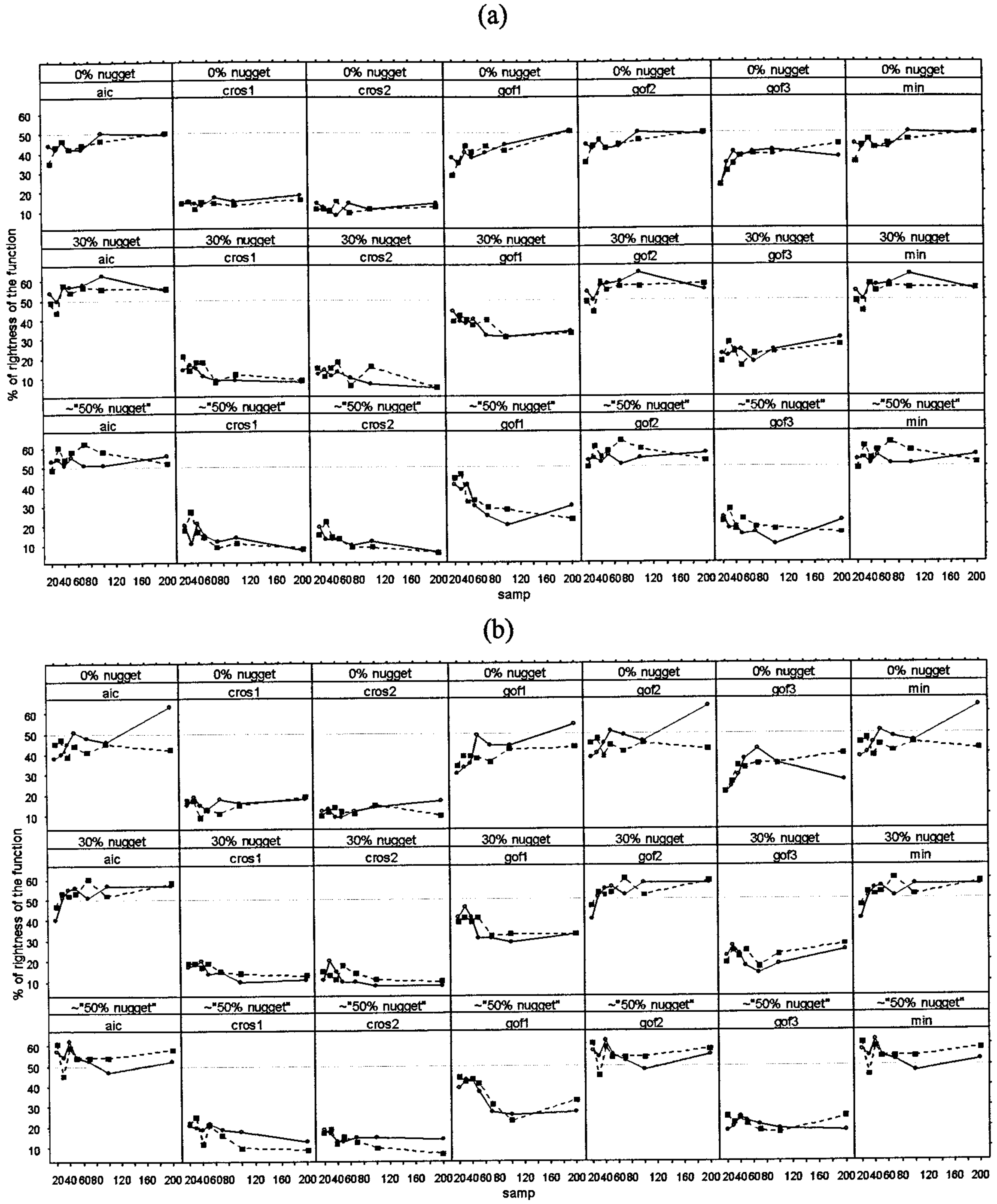


Fig. 6: Percentage of cases in which the diverse "goodness-of-fit" criteria tested were able to detect a spherical model as the best fit as with increasing sample size, with normal data (a) and log-normal data (b). Here estimator types, with (o) for the classical estimator (continuous line) and (□) for the modulus estimator (dashed line) and percentage of relative nugget have been distinguished Cros1 indicates the mean standardised error and cros2 its standard deviation, obtained by cross-validation.

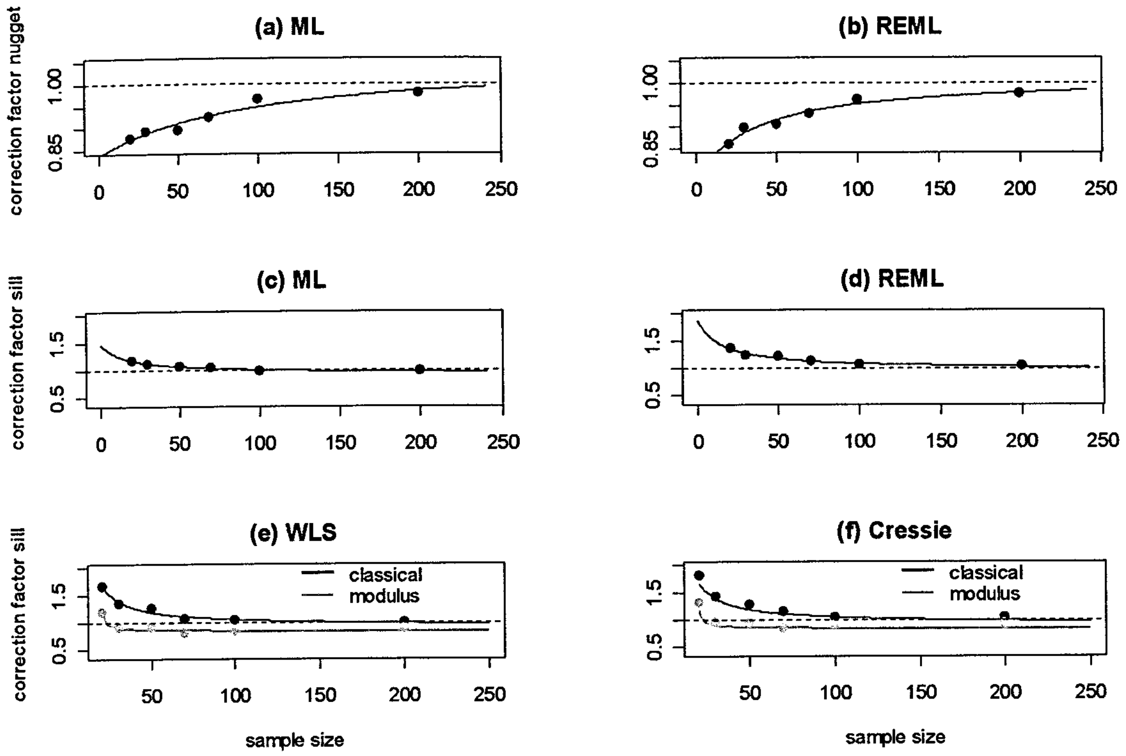


Fig.7: Analysis of relationships between the standardised estimates of the spherical variogram model parameters nugget and sill as a function of sample size, using non-linear exponential models with the estimated parameters a, b, and c. The standardised parameter estimates were derived using, ML (a and c), REML (b and d), WLS (e) and Cressie (f) in the case of log-normally distributed data with a pre-selected relative nugget effect of 50 %. Models employed and estimated parameters in Table 1. See text for more details.

Table 1: Analysis of relationships between the standardised estimates of the spherical variogram model parameters nugget and sill with sample size using non-linear exponential models with the estimated parameters a, b, and c. Factors of influence and levels considered: log-normally distributed data with a relative pre-selected nugget effect of 50%. These models aim to adjust parameter estimates to any sample size > 20. RSS is the value of the residual sum of squares and AIC is the value of Akaike's information criterion.

variogram parameter to adjust	method / estimator	non-linear adjustment model	model parameter			RSS	AIC
			a	b	c		
nugget	ML	$a \cdot e^{(b / \text{sample size} + c)}$	1.06	-20.5	88.07	0.0006	-31.79
nugget	REML	$a \cdot e^{(b / \text{sample size} + c)}$	1.01	-8.20	31.71	0.0004	-35.13
sill	ML	$e^{a+(b / (\text{sample size} + c))}$	-0.07	9.26	20.43	0.0009	-29.46
sill	REML	$e^{a+(b / (\text{sample size} + c))}$	-0.03	13.57	20.60	0.0023	-24.24
sill	$\text{WLS}_{\text{classical}}$	$e^{a+(b / (\text{sample size} + c))}$	-0.07	12.38	1.62	0.0063	-18.16
sill	$\text{WLS}_{\text{modulus}}$	$e^{a+(b / (\text{sample size} + c))}$	-0.16	0.79	-17.62	0.0055	-18.86
sill	$\text{Cressie}_{\text{classical}}$	$e^{a+(b / (\text{sample size} + c))}$	-0.05	12.98	0.50	0.0049	-19.60
sill	$\text{Cressie}_{\text{modulus}}$	$e^{a+(b / (\text{sample size} + c))}$	-0.10	0.52	-18.55	0.0065	-17.90

4 Discussion

This study focused on evaluating the robustness of the most common geostatistical methods used in fisheries applications. Thus only a selection of possible factors (sample size, relative amount of white noise, estimator type, fitting method, data distribution) effecting a sound geostatistical analysis could be assessed here. Of course Gaussian and log-Gaussian data distributions are not the only ones possible in fisheries (Rivoirard *et al.*, 2000; Stefánsson, 1996), but a log-Gaussian distribution represents one possible skewed distribution. Also, a random sampling design constitutes the most simple design possible, in practice other sampling designs like stratified random might be more common, but the complications in estimating the parameters deriving from the sampling design were not the objective of this work and deserve further study (see *e.g.* Kalikhman and Ostrovsky, 1997; Simmonds and Fryer, 1992).

Our simulation study clearly indicates that the Mantel test has a high power to detect spatial structures only for large sample sizes, absence of any nugget variability and normally distributed data. Increasing random variability (*viz.* higher levels of nugget effects) decreases the amount of autocorrelation present in the samples, and consequently, diminishes the coefficient of correlation and the % of significant cases (Fig. 2). It has been previously described that values of the correlation coefficient of the Mantel test need not be large in order to be statistically significant (Legendre and Fortin, 1989). These authors have stressed that the Mantel test statistic involves a linear model, being indicative only for the linear component of the relationship between values from two distance matrices. Hence it tests the null hypotheses "H_0: the variable is not autocorrelated as a gradient", although non-parametric coefficients (e.g. Kendall, Spearman) may also be used. Thus, non-linear spatial relationships cannot be detected by the Mantel test. In this study, the overall underlying covariance function has been defined as a spherical one, which is nearly linear only for small distances. Consequently, the Mantel test will be appropriate only for small distances in non-linear covariance functions.

Furthermore, our results showed that the factors sample size, nugget variability, fitting method and estimator type have an important influence in recovering the reference covariance structure. For normally distributed data, all the methods tested can provide correct estimates of the sill for large sample sizes (100 samples or more), in some cases even for 50 or 70 samples. Our results show that sample size is a very important factor in determining the reliability of variogram parameter estimates. For sample sizes below 50, estimates of the nugget and sill variogram parameter are doubtful for large amounts of nugget variability, except for moderate amounts of nugget variability (30%) and Cressie's fitting method. This is consistent with Legendre (1989), who advised not to perform a spatial autocorreation analysis with fewer than 30 sampling points. Webster (2001) recommended a minimum of 100 sampling points to achieve moderate confidence in the empirical variogram. Since in standard fishery surveys the number of samples are typically lower, geostatistical evaluations are normally carried out at the limit of the reliability of these methods. Thus, the best available tools should be selected, based on the knowledge available for sample distribution.

Comparing the estimator types, our results showed no differences for Gaussian-distributed data between the classical and the robust estimator in both accuracy and precision. Contrary, in the log-Gaussian case, the robust estimator significantly underestimates the nugget and overestimates the range parameter, regardless of any amount of nugget variability and sample size, whereby accurate estimates were detected for the sill parameter. Genton (1998), for example, suggested applying both Matheron`s and the robust estimator and comparing the outcomes. On the other hand, McBratney (1986) pointed out that the robust estimator was devised for the case when even after transformation to normality a variable may be heavier in the tails of its distribution than normal. Thus, in our study the robust estimator did not perform appropriately for log-Gaussian data with increasing nugget variability because it departs importantly from the underlying distribution assumption. There are, however, some reported examples from fisheries studies where the robust estimator had been successfully applied even though the data included extreme values (Maravelias *et al.*, 1996; Sullivan, 1991). In the presence of outliers in skewed distributions, application of the robust estimator might drastically influence the estimation of variogram parameters, in much the same way as the elimination of the outliers from the data set (M. Rufino, unpubl. data). We thus conclude that it is best to consider the results of both estimators, and caution should be taken when there is strong departures of normality in the data distribution.

Our assessment of the *gof* criteria reveals the poor behaviour of the cross-validation procedure in defining the proper variogram model: it yields good results in only 20% of all cases, regarding all sample sizes, levels of the nugget variability, types of estimator and data distributions. This might be explained by the fact that the cross-validation procedure is able to indicate the reference model only when the correct variogram model is supplied. We recommend the application of goodness-of-fit criteria based on the Akaike Information Criterion (AIC), or alternatively, with weights equal to the number of pairs (*gof2*), even for small sample sizes. Other authors have also recommended the Akaike Information Criterion for selecting the best model from several plausible ones (McBratney and Webster, 1986; Webster and Oliver, 2001).

For the sill and nugget, underestimation was detected for any of the methods tested, with increasing levels of nugget variability. Also with increasing nugget variability, more samples are required to increase the accuracy of the estimates of these parameters. This finding is less pronounced in the case of maximum likelihood method for estimating the range, where accuracy is high regardless of sample size. The range parameter of variograms was in general overestimated by all methods studied, with the lowest precision shown by the least square methods, with deviations up to ± 0.05 from the correct value. Further on, precision is slightly higher for maximum likelihood methods when estimating any of the variogram parameters, both for Gaussian and log-Gaussian data. Our results showed that maximum likelihood methods (ML and REML) are robust against deviations of normality, which is an assumption of these methods (Cressie, 1991).

Finally, the correction factors (Fig. 7) were very low for the example of the nugget, which is the parameter that controls smoothness in the kriging procedure. Thus, even if the differences do not appear very large on a contour map of kriging estimates, they can have a large impact on the accuracy of the abundance estimates, so the choice of fitting method is critical (Matheron, 1989).

5 Conclusions

Sample size proved to be a very important factor in determining the reliability of variogram parameter estimation. For sample sizes below 50, estimates of the nugget and sill of variograms are problematic, especially for least square methods. In this case, maximum likelihood methods yield better results, even for log-normally distributed data and especially for high levels of a nugget variability. They generally have higher precision and a higher accuracy in the estimation of the variogram parameters, especially the range. Although the weighted least squares estimator (WLS) introduced by Cressie (1985) is widely adopted in spatial analysis, probably due to its simple form, several authors point to its poor finite sample behaviour (Müller, 1999). Within the family of least square fitting methods, Cressie's method is more reliable than WLS, especially for estimating the sill and nugget, for low number of samples (Cressie, 1991). Thus, given the low number of samples normally occurring in a fishery survey, we suggest that the ML or REML method be employed for estimation of the variogram model parameters. However, the higher the level of nugget variability, the more critically must the estimates be evaluated. The proper selection of models should be based on AIC or a goodness-of-fit criterion giving weights equal to the number of pairs considered. Generally, a geostatistical approach in a fisheries context is often carried out at the border of acceptability from a theoretical point of view; however, the results of this simulation study show that the reliability of a structural analysis can be improved when appropriate tools are employed. Another aspect that must be considered is to correct the estimated variogram parameters derived from a small number of samples by correction factors similar to the ones shown in Fig. 7, in order to obtain more precise parameter estimates. For this purpose, the non-linear models provided in this study might be used to express the relationships between the standardised estimates of the spherical variogram model parameters nugget and sill with sample size (Table 1). However, this approach needs further evaluation and verification with independent data sets before it can be used in routine surveys. Further simulations studies are essential to account for other types of data distribution or sampling designs. In general, we recommend that more attention is devoted to the combination of data distribution and number of samples for selecting the tools for structural variogram analysis. Thus, the appropriate choice of geostatistical tools in the analysis of fisheries data to obtain more accurate and precise abundance indices is essential, taking into account the particular spatial phenomenon under investigation (Matheron, 1989).

6 Acknowledgements

During this work the author MMR was supported by an EC grant (PRAXIS XXI) and VS by the Scholarship Programme of the German Federal Environmental Foundation (No.20002/290).

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KAPITEL 2

Meso-scaled investigation of spatial distribution of the flatfish species dab, *Limanda limanda* (Linnaeus, 1758), within the German Bight: a geostatistical approach*

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Abstract

In the context of planning and building offshore windfarms within the inner German Bight, this study tries to provide a method for evaluation of future long-term monitoring data in order to assess possible effects on fishes. Data collected by the German Small-scale Bottom Trawl Survey (GSBTS) during the summer cruises 1996-2000 in a small area of the inner German Bight were supplied by the German Institute of Sea Fisheries as an example data set for spatial analysis. Geostatistical tools were used to discover characteristics and persistence of spatial structures of two different size classes of the demersal fish species dab, *Limanda limanda* (Linnaeus, 1758), as a measure of natural variability. Spatial autocorrelation was detected in the catch data for both size classes, and spatial structuring was persistent throughout the time of investigation. Both size classes could be characterised by a moderate degree of spatial dependency within the catch rates. Furthermore, larger dab tend to aggregate in patches 3.2 km in diameter, whereas medium-sized dab aggregated in patches with average diameters of 1.1 km. The modelled structures were used to calculate the mean c.p.u.e. of dab within the survey area. This kriged mean was compared with the calculated arithmetic mean. Furthermore, the geostatistical variance of the arithmetic mean was compared to the 'classical' variance (neglecting the spatial structures). The contour plots of biomass index, estimated by kriging based on the models fitted to the mean structures for all years, displayed no locations with persistently increased fish biomass index for either size class throughout the years.

Key Words: dab, geostatistics, *Limanda limanda,* mean semivariogram, ordinary blockkriging, spatial structure

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* *pre-print*: Proceedings of the Second International Symposium on GIS/Spatial analyses in Fishery and Aquatic Sciences (Nishida, T., Kailola, P.J. & Hollingworth, C.E., Eds.), Fishery/Aquatic GIS Research Group 2004, Kawagoe-city, Japan (2004). 249-268.

1 Introduction

The inner part of the German Exclusive Economic Zone (EEZ) is a preferred area for constructing offshore windfarms. One of the questions is how to detect possible effects on fish populations after the windfarms have been put into operation. Classical methods to obtain quantitative information within fish assemblages and to detect possible changes over time are based on bottom trawl surveys, which are carried out under standard survey protocol conditions, including standard fishing gear and sampling strategies.

Stations randomly distributed over an area can yield unbiased estimates of the variable of interest only if the sampling-point observations are independent (Petitgas, 2001). When random sampling is carried out at an appropriate spatial scale, it effectively extinguishes any underlying spatial structure in the distribution of organisms. However, the scale of spatial distribution of the target species is usually unknown, and this factor may result in a bias in the calculation of estimates (Maynou, 1998). The presence of a spatial structure is indicated by spatial autocorrelation between pairs of samples, *viz.* the realisation of a regionalised variable (e.g. biomass of organisms) at one location influences the realisations at neighbouring locations. Thus, when samples are not taken independently of one another and when the population sampled is spatially structured, the computation of any variance requires a model of the spatial correlation in the population (Matheron, 1971). Spatial autocorrelation present in a data set can be analysed and modelled mathematically by geostatistics.

Geostatistics was initially developed for the mining industry to optimise the exploration of natural resources (Clark and Harper, 2001; Isaaks and Srivastava, 1989; Journel and Huijbregts, 1978). In the past 25 yr, applications of this methodology in ecology have increased continuously (Legendre, 1993; Robertson, 1987; Rossi *et al.*, 1992). In fisheries, geostatistics is used to optimise sampling strategies (Petitgas, 1996), to estimate catch data and corresponding variances, taking into account the existence of spatial structures (Conan *et al.*, 1992; Fernandes and Rivoirard, 1999; Maynou, 1998; Warren, 1997), as well as to map the estimated distributions and spatial patterns of organisms (Lembo *et al.*, 1999; Maravelias *et al.*, 1996). Therefore the geostatistical approach was employed to investigate the persistence and changes of spatial patterns with time. Additionally, the computation of unbiased estimates of the mean fish biomass within an area of interest can be achieved by this method.

The German Institute for Sea Fisheries provided for this study catch data from the German Small-scale Bottom Trawl Survey (GSBTS) sampled in an area of about the same size as an offshore windfarm with approximately 200 windmills. The development of the spatial characteristics of the non-target flatfish species dab (*Limanda limanda*), the most common flatfish species in the North Sea, is described. Although this species carries out seasonal migrations between feeding and spawning areas, the spatial distributions of the fish in spring and summer are supposed to be stable (Rijnsdorp *et al.*, 1992). The objective of this study was the application of geostatistical tools for the assessment of spatial structures and the estimation and mapping of a demersal species. The advantages of a spatial analysis as a means of providing information on natural variability and possible effects of windfarms on the fish population were highlighted.

2 Methods

2.1 Survey area and fishing surveys

The data used for this analysis are from an area of the inner German Bight (box A, Figure 1), one of the eleven standard sampling areas of the GSBTS in the North Sea (Ehrich *et al.*, 1998). Sampling took place from 1996 to 2000 during summer. Catch data were assembled aboard the German research vessel "Walther Herwig III". Fishing was carried out under standard IBTS (International Bottom Trawl Survey) protocol using a standard net GOV (Chalut à Grande Ouverture Verticale), with a trawling time of 30 min at a trawling speed of 4 knots (1 knot = 0.514 m s^{-1}). The locations of sampling stations (21 to 24) as well as trawl directions were selected randomly within the area of investigation for each year of the survey. The trawl positions were taken as midpoint of the haul converted to an absolute measure in km (easting and northing) relative to 54°27'N and 6°58'E.

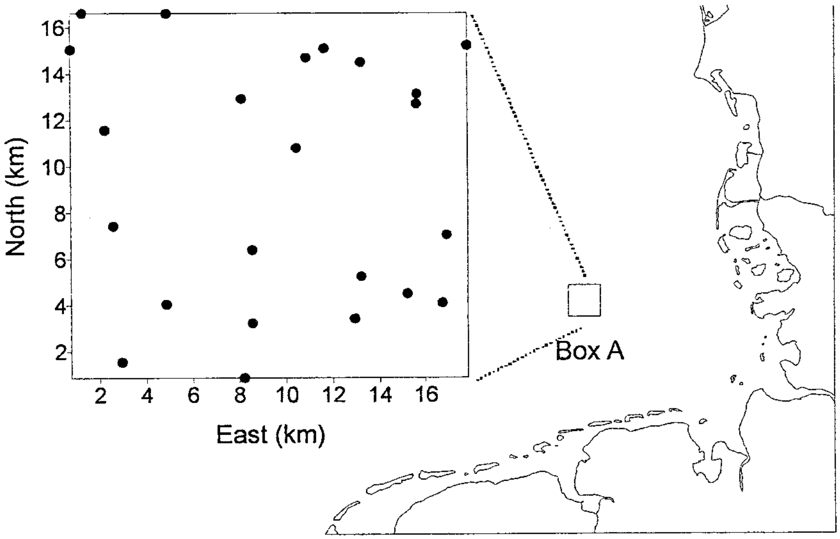

Fig. 1: Survey area "box A" within the German Bight, with locations of the sampling stations in 1996 as an example of the survey design.

2.2 Biological categories considered

In order to explore spatial structures depending on biological categories, such as size (age) of fish (Fernandes and Rivoirard, 1999), the catch data for dab were separated into two size classes: 9.5–19.5 cm (2-7 yr old; referred to as d2) and > 19.5 cm (older than 7 yr; referred to as d3) following Heessen and Daan (1996). The size-class < 9.5 cm was excluded from the analysis as there were too few juveniles in the catches. The group d2 is supposed to be the most important one, because dabs will mature at a length of 13 cm (Rijnsdorp *et al.*, 1992).

2.3 Preparatory data analysis

Numbers per 30 min trawl time within each size class were converted into biomass (kg30min^{-1} trawl time; c.p.u.e.) on the basis of the following length-weight relationship (unpublished data):

$$\text{weight [g]} = a \cdot \text{length [cm]}^b \quad \text{with } a = 0.0074 \text{ and } b = 3.113 \qquad (1)$$

All catch data were tested for normality using the Shapiro-Wilk test (Royston, 1982). In cases of deviation from normality, c.p.u.e.s were log-transformed and the log-transformed data were used for further analysis. Catch data that had to be transformed were d2 and d3 in 1997, d3 in 1998 and d3 in 1999. Further linear and non-parametric regressions with one covariate (Bowman and Azzalini, 1997) (north and east co-ordinates) were carried out to investigate possible trends within the c.p.u.e.s (Kaluzny *et al.*, 1998). Significant linear trends within the catch data with east co-ordinates were detected for d2 in 1997 and 1998 and with north co-ordinates for d2 in 1999. These trends were taken into account for the subsequent spatial analysis.

2.4 Geostatistical analysis

Variography

First an experimental semivariogram was calculated to analyse the spatial structure of dab, followed by fitting of a theoretical variogram model. Using the spatial structure defined, ordinary blockkriging, a linear method of spatial prediction was used to estimate the annual mean c.p.u.e. within box A. For mapping predicted distributions of dab, ordinary pointkriging was employed.

The structure of spatial variability of $Z(x)$ (kg30min^{-1} per size class) was assessed by an experimental covariance function. Experimental semivariograms $\hat{\gamma}(h)$ were used to describe the spatial structure of fish biomass. The semivariogram outlines the spatial correlation of data, measuring the half variability between data points as a function of their distance. In the absence of spatial autocorrelation among samples, the semivariance is equal to the variance of $Z(x)$. A monotonic increase of the semivariance with increasing separation distance (h) of the sampling positions indicates the presence of spatial autocorrelation. When a linear trend was present, c.p.u.e.s were detrended (Kaluzny *et al.*, 1998). Only omnidirectional semivariograms were computed using the classical estimator (Matheron, 1971):

$$\hat{\gamma}(h) = \{1/[2N(h)]\} \sum_{i=1}^{N(h)} [Z(x_i + h) - Z(x_i)]^2 \quad (2)$$

and the robust estimator ("modulus"), which is supposed to be resistant against extreme values, introduced by Cressie and Hawkins (1980):

$$\hat{\gamma}(h) = \left\{ \left[1/[N(h)] \right] \sum_{i=1}^{N(h)} |Z(x_i + h) - Z(x_i)|^{0.5} \right\}^4 \Big/ [0.914 + 0.988/N(h)] \quad (3)$$

where $Z(x_i)$ is the realisation of biomass (c.p.u.e.) of dab for one size class at station x_i, $Z(x_i + h)$ is another realisation separated from x_i by a discrete distance *h* (measured in km) and $N(h)$ is the number of pairs of observations separated by *h*. Furthermore, to improve knowledge of spatial structures, for each size class, average semivariograms (survey years 1996-2000) were computed (Rivoirard *et al.*, 2000). The absolute average semivariogram represents the average of the different individual semivariograms, weighted by the number of pairs at each distance. It was thus assumed that the different spatial distributions can be described by the same ecological process.

In many cases a transformation of the data is recommended, since the structure of the transformed variable often is more regular than that of the untransformed variable (Rivoirard *et al.*, 2000). This would lead to a biased estimate of the raw structure. However, to allow ecologically sound interpretations and to establish the structure of the raw variable, an appropriate back transformation is required after performing the structural analysis. We used the following equation for the log-transformed data (Guiblin *et al.*, 1995):

$$\gamma(h) = \left[m^2 + \mathrm{var}(Z) \right] \left\{ 1 - \exp - \left[\sigma^2 \gamma_L(h) / \mathrm{var}(L) \right] \right\} \tag{4a}$$

with

$$\sigma^2 = \log \left[1 + \mathrm{var}(Z) / m^2 \right] \tag{4b}$$

where m is the mean of $Z(x)$, L is the logarithmic transformation of the variable and $\gamma_L(h)$ is the structure of the transformed variable. A simulation study described in Rivoirard et al. (2000) showed that the use of log-transformation, associated with a back transformation, provides an improved method for estimating variogram parameters and estimation variance. Subsequently, parameters (nugget, sill and range) of spherical and linear models were fitted automatically (Cressie, 1991), to reduce subjectivity and to ensure reproducibility of the fit (Fernandes and Rivoirard, 1999). Following Webster and Oliver (2001), firstly the types of models regarding the general trends of the semivariogram curve (log back semivariograms) were selected, and then models were fitted using a weighted least-squares method with suitable weights. Least-squares methods are based on finding the model which is "visually" close to the semivariogram curve by minimising the sum of squares of the differences between the generic semivariogram estimator and a model (Chilès and Delfiner, 1999). Here a weighted least-squares procedure recommended by Cressie (1991) was employed, where more weight is given to the points near the origin, which is the crucial part in determining the variogram parameters:

$$\sum_h N(h) \left\{ \left[[\hat{\gamma}(h)] / [\gamma(h)] \right] - 1 \right\}^2 \tag{5}$$

where $N(h)$ is the number of pairs used to compute the experimental semivariogram $\hat{\gamma}(h)$ and $\gamma(h)$ is the fitted model (spherical, exponential or linear). In order to assess the goodness-of-fit (*gof*) of the different models, for each fitting procedure an index recommended by Fernandes and Rivoirard (1999) was computed:

$$gof = \left\{ \sum_h \omega(h) \left[\hat{\gamma}(h) - \gamma(h) \right]^2 \right\} / \left\{ \sum_h \omega(h) \left[\hat{\gamma}(h) \right]^2 \right\} \tag{6}$$

where $\omega(h)$ is the number of pairs used to compute the semivariogram, $\hat{\gamma}(h)$ is the experimental semivariogram and $\gamma(h)$ is the fitted model. The closer the *gof* to zero, the better the fit. Furthermore, the strength of spatial dependence (*SpD*) was calculated (Robertson and Freckmann, 1995) as:

$$SpD = (1 - nugget / sill) \cdot 100 \tag{7}$$

This information was used to compare changes in the development of spatial autocorrelation in catch data with time and among size classes. The greater this value (ranging from 0 to 100), the greater the spatial dependence. Low spatial dependency indicates a high sampling and/or analytical error, or a spatial variability occurring at scales smaller than the minimum distance separating small sampling pairs (Robertson and Freckmann, 1995). Sokal and Oden (1978) related the diameter of an aggregation of a species to the modelled range. Therefore the effective range (eR) was compared for each model fitted, in order to detect characteristics and changes of spatial patterns with time. The effective range for spherical models is equal to the estimated range. In addition, the observed data were cross-validated by ordinary kriging, which provides a measurement of the reproduction of the data by the model defined and the kriging procedure. The results of this jack-knifing method are given by standardised errors. If the mean of this standardised error (*Zscore*) is zero and the standard deviation (*SD-Zscore*) approximately 1, then the model and the method employed provide an adequate reproduction of the data (Isaaks and Srivastava, 1989).

Ordinary kriging

Mapping of density surfaces of the predicted dab biomass index was carried out for both size classes with ordinary pointkriging. This method estimates the variable values at unsampled locations using the observed values $Z(X_i)$ in the surrounding neighbourhood as follows (Matheron, 1971):

$$\hat{Z}(X_0) = \sum_{i}^{n} \lambda_i Z(X_i) \qquad (8)$$

where λ_i are charging weights attributed to each $Z(X_i)$ subject to $\sum_i = 1$ in order to guarantee unbiased estimates (Cressie, 1991). The uncertainty of the estimation of ordinary pointkriging was expressed by mapping the kriging variance (Petitgas and Lafont, 1997). Mean catch rate estimates over box A for both size classes $\hat{Z}(X_0)$ of dab were obtained by ordinary blockkriging, a method used as a direct method of biomass assessment in fisheries (Maynou, 1998). The computerised algorithm requires the area to be finely discretised. The discretisation used here is a grid of 35 x 35 blocks, which was found to optimise speed and precision of the computation. Variances were expressed as coefficients of variation of the arithmetic mean (m) and were calculated using the classical estimator, which does not take into account the spatial autocorrelation within the sampled data:

$$CV_{class} = (s^2/n)^{0.5} / m \qquad (9)$$

with s^2 as data variance and n as number of stations. CV_{class} was compared with the geostatistical estimation variance of the arithmetic mean (Matheron, 1971):

$$CV_{geo} = (\sigma_E^2)^{0.5} / m \qquad (10)$$

with σ_E as the global estimation variance (Petitgas and Lafont, 1997), which is influenced by the geographical position of the stations, the shape of the survey area and the model fitted. Computations were done using R (version 1.7.1), a programming environment for data analysis and graphics (http://www.r-project.org/) and R-geo (http://sal.agecon.uiuc.edu /csiss/Rgeo/index.html), spatial data analysis (see also http://www.est.ufpr.br/geoR/).

3 Results

3.1 Spatial population structures

Semivariograms revealed that the two size classes of dab displayed different spatial structures during the time of investigation (Figure 2 - 3). For both size groups of dab, almost all spatial structures, including the mean structures (Figure 3), could be successfully described by spherical and linear models (1997, d2, d3). The parameters nugget, sill and range of the models fitted, the values of goodness-of-fit statistic, the measure of strength of spatial dependency (Equation 7), the effective range, as well as the results of the cross-validation, are compiled in Table 1, indicating valid models throughout the years and size classes.

Models fitted to the semivariograms showed values for the goodness-of-fit statistic (*gof*) close to zero for both size classes, pointing to reliable fitting procedures. For both size classes the effective ranges and values of spatial dependence peaked in 2000 (d2: 8.62, 78.09; d3: 6.94, 77.62; Table 1). On the average, d2 and d3 developed a medium strength of spatial dependency, indicated by the values of SpD (d2: 43.21; d3: 40.74) of the mean structures. Size class d3 tend to aggregate in patches with a diameter of 3.2 km, which is more than double the mean patch diameter of d2 (1.1 km).

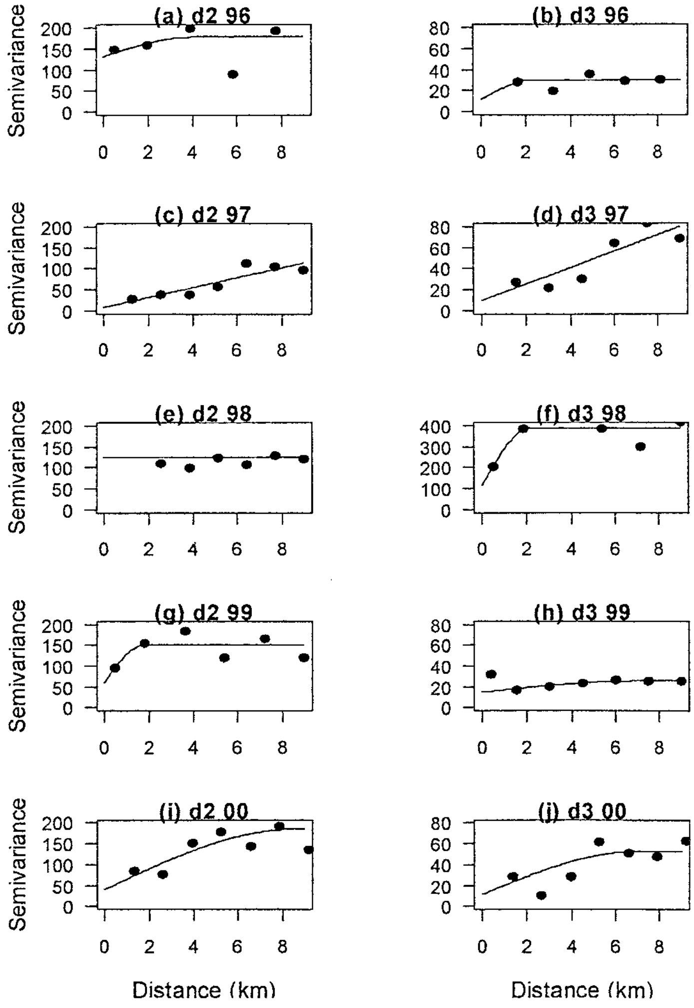

Fig. 2: Experimental semivariograms of c.p.u.e. catch data for dab size class d2 and d3 (1996-1999) with fitted spherical and linear (1997) models. Note that for the structural analysis in 1998 and 2000 of d3 the modulus estimator was used. Note: Figure 2 (f) varies in scale.

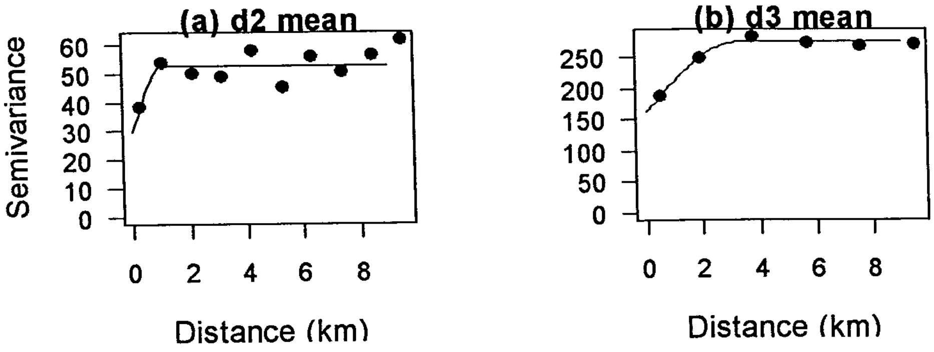

Fig. 3: Mean spatial structures (1996-2000) of dab size class d2 and d3 with fitted spherical models (model parameters in Table 1).

Table 1: Estimated parameters[a] of spherical and linear semivariogram models fitted with a least-squares method to c.p.u.e. data for dab in the German Bight (sampling area box A, Figure 1).

Year	Group	Model	C_0	C	a	Spd	*gof*	*Zscore*	*SD-Zscore*
1996	d2	Sph	132	46	3.9	25.8	0.06	0.00	0.96
1997	d2	Lin	8	12	n.a.	0.0	0.04	n.a.	n.a.
1998	d2	Nug	124	0	0.0	0.0	0.06	n.a.	n.a.
1999	d2	Sph	61	90	1.8	59.5	0.03	0.00	1.14
2000	d2	Sph	41	145	8.6	78.1	0.04	-0.01	1.28
Mean	d2	Sph	30	23	1.1	43.2	0.01	0.00	5.15
1996	d3	Sph	12	19	2.3	61.8	0.05	-0.01	1.09
1997	d3	Lin	10	8	n.a.	0.0	0.04	n.a.	n.a.
1998	d3	Sph	118	271	2.1	69.6	0.02	0.00	2.55
1999	d3	Sph	15	11	7.1	41.7	0.01	0.00	3.65
2000	d3	Sph	12	41	6.9	77.6	0.06	-0.01	1.15
Mean	d3	Sph	162	112	3.2	40.7	0.00	0.00	1.76

[a] Group: size groups d2 and d3; Sph: spherical; Lin: linear; Nug: pure nugget; C_0: nugget; C: sill (for linear models = slope); a: range ; SpD: spatial dependency (Equation 7); *gof*: measure of the goodness-of-fit (Equation 6); *Zscore*: mean standardised error of the crossvalidation; *SD-Zscore*: standard deviation of the standardised error (see Methods section for details)

3.2 Geostatistical estimation of biomass (mean catch in weight)

The biomass index (c.p.u.e., kg30min^{-1}) of d2 varied between 26.5 (1996) and 40.2 (2000), whilst c.p.u.e. of d3 ranged from 9.2 (1996) to 43.0 (1998) (Figure 4a, 4b). The c.p.u.e. of medium-sized dab (d2) showed a slow increase from 1996 to 2000, whereas the biomass index of d3 increased from 1996 to 1998 and decreased in 1999 and 2000 (Figure 4a, 4b). The estimated geostatistical and arithmetic means were in good agreement. With one exception (1996, d3), the geostatistical estimation variance (CV_{geo}) was always smaller than the classical one (CV_{class}) (Figure 4a, 4b). The largest difference between the two coefficients of variation was found in 1997 for both size classes.

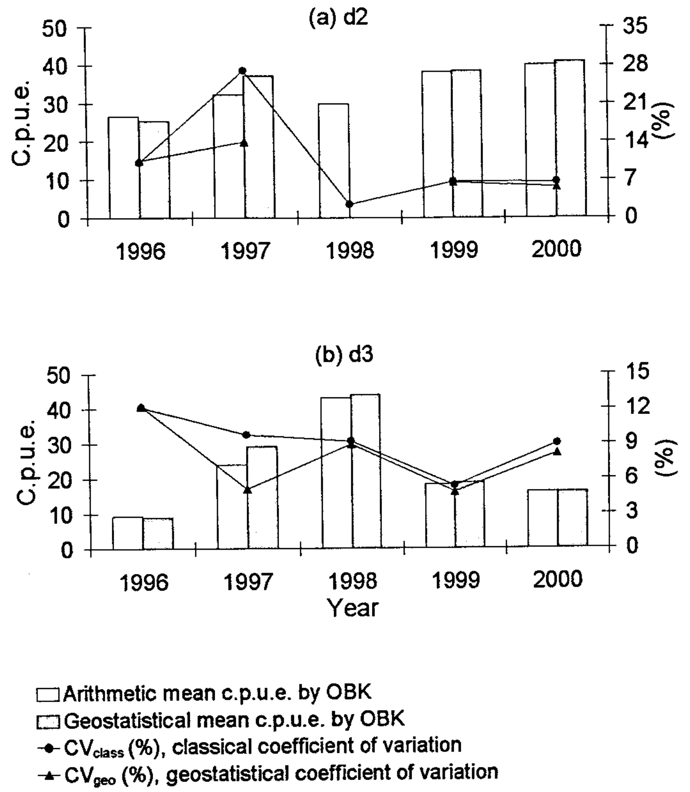

Fig. 4: Arithmetic mean c.p.u.e., geostatistical mean c.p.u.e. of dab size class d2 (above, a) and d3 (below, b), estimated with oridinary blockkriging (OBK), and coefficients of variation CV_{class} (%) and CV_{geo} (%) (Equations 9, 10) of the arithmetic mean c.p.u.e. (see Methods section for details).

3.3 Geostatistical mapping

The patchiness of the distribution of both size classes was different in shape and size for each year. For both size classes, the estimated maps of fish biomass index showed no persistent area, with high density in box A throughout the years (Figure 5, 6). Similarities of the geographical locations of the patch centres between size classes were obtained for 1996, 1997 and 2000. The mapped uncertainties for the kriged biomass index demonstrate that the estimated locations, shapes and sizes of the patches are reliable.

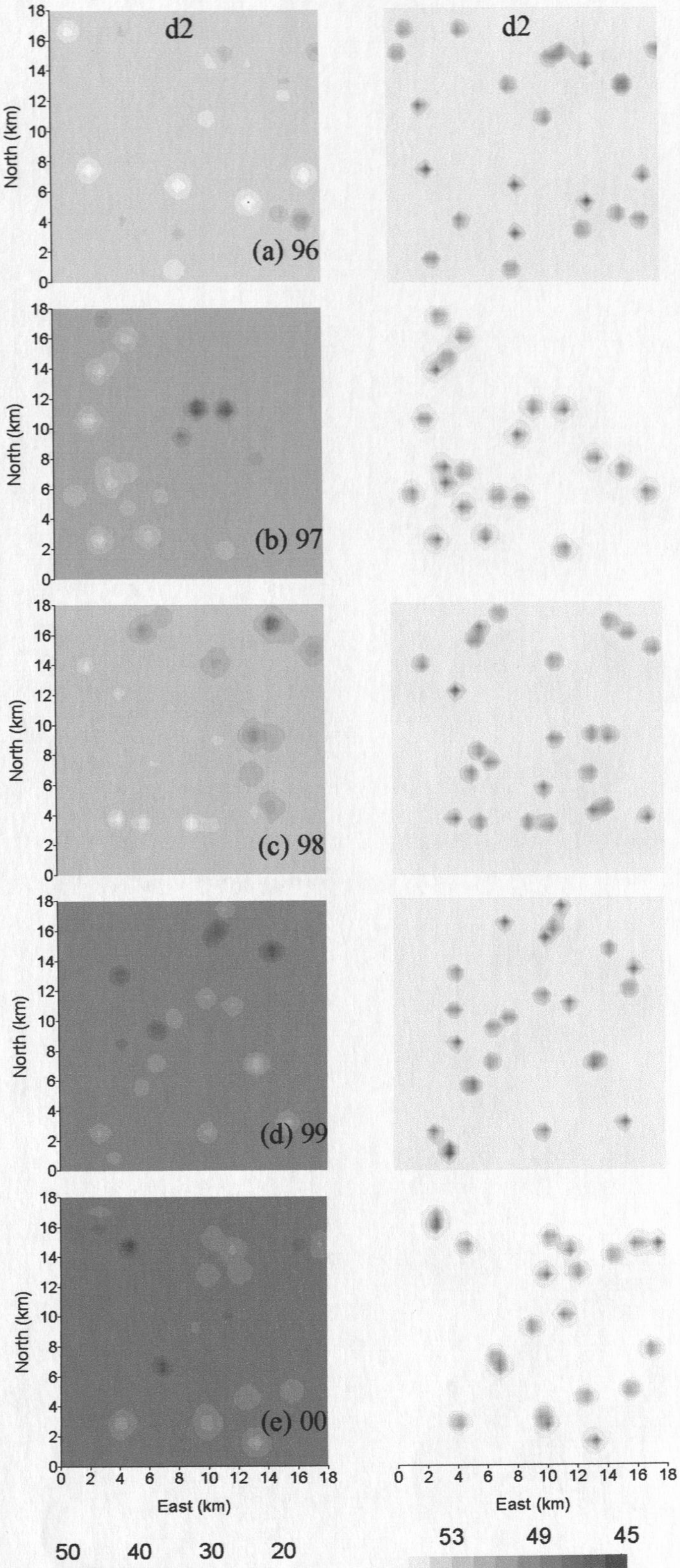

Fig. 5: Density of c.p.u.e. biomass index for dab size class d2 within box A estimated with ordinary pointkriging (left panel) and estimated kriging variance (right panel) for the summer surveys 1996 – 1999 (a-e).

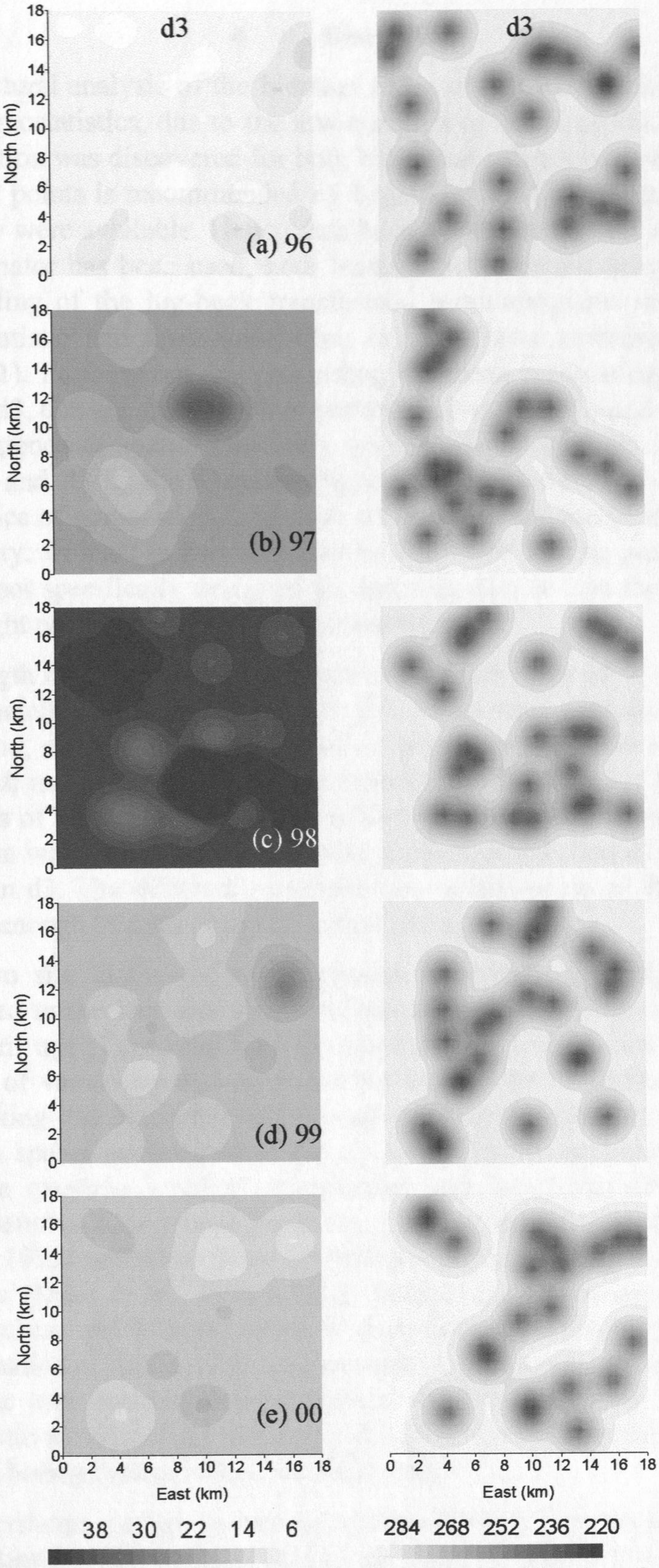

Fig. 6: Density of c.p.u.e. biomass index for dab size class d3 within box A estimated with ordinary pointkriging (left panel) and estimated kriging variance (right panel) for the summer surveys 1996 – 1999 (a-e).

4 Discussion

Although the structural analysis of the biomass index of dab was carried out at the limit for an application of geostatistics, due to the low numbers of sampling stations, the presence of spatial autocorrelation was discovered for both biological categories considered. A minimum of 30-50 sampling points is recommended by Legendre (1993), whereas here only 21 to 24 stations per survey were available. Hence data have been transformed, and also the classical and modulus estimator has been used, both leading to less erratic semivariograms. Finally, due to the modelling of the log-back transformed semivariograms and the results of the goodness-of-fit statistic and cross-validation, one can have confidence in the modelled structures (Table 1). Furthermore, by computing the mean semivariograms of the biomass indices of d2 and d3, derived from summer surveys in box A and based on the survey design applied, the persistence of spatial structures was obvious (Figure 3). Although the spatial structuring of d2 and d3 in the German Bight was only moderate, one has to take into account the presence of spatial autocorrelation when estimating the mean catch rate of dab or assessing variability. At least in part this may be due to the fishing gear used in this survey (GOV), which is not specifically designed for catching dab, so that the population structure of this species might not have been resolved completely.

In 2000, the strength of spatial autocorrelation in the catch rates of d2 and d3 were highest, also the greatest patch diameters (d2: 8.6 km; d3: 7 km) were detected, and throughout the investigation period, size class d3 aggregated in larger patches. This is consistent with the idea that larger fish may tend to form larger associations than smaller fish (Rivoirard *et al.*, 2000). An analysis of the length frequency within one size class showed that, in most cases, a length of 16.5 cm was predominant within the medium-sized class d2 and 19.5 cm was the dominant length in d3. The difference between the modal values of the length frequencies seems to be large enough to cause varying spatial patterns.

Distinguishing two size classes of a fish species in order to investigate different spatial structures is related to the idea that fish distribution depends on the size of the individuals rather than on their age (Fernandes and Rivoirard, 1999; Guiblin and Rivoirard, 1996). A further reduction of variability and an improved assessment of spatial structuring may be obtained when taking into account other biological categories such as sex. Furthermore, an improvement of a spatial analysis when the c.p.u.e. of female and male dab are taken into account raises the question whether reproduction may cause the development of spatial patterns of fish density. This would be likely, because spawning occurs from Jan to Sep (Rijnsdorp *et al.*, 1992) and takes place in well-defined nursery areas situated in the south-eastern North Sea (Daan *et al.*, 1990). Other marine organisms, especially benthic ones, often develop patches, which could result from social behaviour or reproduction (Valiela, 1995). Patch formation of dab may be also caused by sediment composition (Ehrich, 1988), distribution of the prey species (epizoobenthos) and fish behaviour due to reproduction. Additionally, abiotic variables may also induce a spatial pattern, but salinity and temperature were more or less homogeneous within the study area.

Because of the persistence of spatial patterns found for both size classes of dab throughout the time of investigation, the models fitted to the mean structures were used for estimating the density maps (Figure 5, 6). The detected conformance of the locations of the patch centres in 1996, 1997 and 2000 could be explained by reproduction, when biomass indices of two size classes were almost identical with fractions of female and male dab. The variability of the location of high-density spots may be due to the fact that the area of investigation is homogeneous, and probably a preferred feeding site for dab does not exist.

During the time of investigation, the variability of the catch rates of d2 was small, whereas the c.p.u.e. of d3 varied by more than 30 kg30min^{-1}. This may be explained by increased fishing effort in 1999 or a weak recruitment. The geostatistical coefficient of variation in almost all cases showed lower values than the classical one, although differences between the two coefficients were small. The geostatistical variance depends on the model specified, sample locations, shape of investigation area and intensity of sampling (Petitgas, 1996, 2001). Therefore, the low number of sampling stations (21-24) of the surveys may have resulted in increased geostatistical variances.

The main focus of the present study was to develop a strategy to evaluate long-term monitoring data to assess possible effects of offshore windfarms on a fish population within a meso-scaled area. The main advantage of the procedure used was that the detected spatial autocorrelation within the catch data has been taken into account. Furthermore, additional information about the spatial characteristics of the species studied, which may be correlated with population dynamics (Warren, 1997), is provided. The species-specific aggregation within an area is an interesting measure of variability. With this method, the differentiation of natural and experimental variability is possible, after the sampling strategy has been optimised. Then the natural variability within an area may be explored and possible effects of offshore windmills on fish populations can be defined and evaluated, provided that an appropriate reference area is available.

5 Acknowledgements

This work is part of the PhD thesis of V. Stelzenmüller at the Carl von Ossietzky Universität, Oldenburg, Germany, supported by the Scholarship Program of the German Federal Environmental Foundation (Deutsche Bundesstifung Umwelt, Osnabrück; No. 20002/290).

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KAPITEL 3

Improvement of the geostatistical analyses of demersal fish species in the North Sea by additional small-scale catch data (star survey design)

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Abstract

Geostatistical tools have been used to investigate improvements of a spatial analysis and subsequent reduction of uncertainty in estimates of catch per unit effort (cpue) for the dab, *Limanda limanda* and whiting, *Merlangius merlangus* in the North Sea. A standard survey design was modified by additional small-scale sampling, resulting in a star survey design, which reduces small-scale uncertainty. Furthermore, the effects of biological variables such as fish size or sex on spatial analysis were assessed and species-specific characteristics in spatial patterns were analysed. Sampling took place in January 2001, 2002 and 2003 in a meso-scaled area, in the German Bight. All biological categories considered displayed a persistent spatial structuring in the cpue, which was described best by spherical and exponential semivariogram models. Incorporation of the star survey design in 2002 and 2003 reduced the small-scale variability for dab, as indicated by lowered values of nugget effect and an increased resolution of spatial dependency (especially for medium-sized and male dab). For whiting no reduction of the small scale variability could be detected. Moreover, no significant differences were found in the spatial structuring of the biological categories of dab. Spatial distributions and characteristics in spatial patterns of female and male dab were in good agreement, indicating that spawning behaviour might have caused the observed patchiness. Differences in spatial structuring between the size groups of whiting were significant and may be explained by differences in sensitivity to environmental variables. For each of the species uncertainty in biomass estimates was reduced by approximately 50 % in all cases, by adding nearby stations to the conventional sampling scheme, in an inexpensive, timesaving and efficient manner.

Key Words: spatial structuring, semivariogram, whiting, *Merlangius merlangus*, dab, *Limanda limanda*, star survey design, log-back-transformation, ordinary kriging.

submitted to: Scientia Marina

1 Introduction

Classical methods of obtaining quantitative information on fish assemblages and detecting possible changes over time are normally based on large-scale bottom trawl surveys, carried out under a standard survey protocol, mainly concentrated on standard fishing gear and a standard sampling strategy. Unlike a large-scale bottom trawl survey design such as the IBTS in the North Sea (International Bottom Trawl Survey; ICES, 1999), the GSBTS (German Smale-scale Bottom Trawl Survey) monitors species abundance and composition in small areas of 10 by 10 nautical miles (nm) distributed over the entire North Sea (Ehrich *et al.*, 1998) since 1986. Within such areas (boxes), a minimum of 20 hauls selected randomly are normally taken during 3 – 5 days. Because stations are randomly distributed, observations are independent from each other, and mean and variance estimates can be derived directly from the sample values without any assumptions about the spatial distribution of the population (Petitgas, 2001). But in cases where random sampling is not carried out on a specific spatial scale, any underlying spatial structure in the distribution of the organisms can not effectively be extinguished, leading to a bias in the study. It is not possible to detect such a bias *a priori*, since an appropriate scale of the spatial distribution of any species of interest is generally unknown (Maynou, 1998).

Spatial autocorrelations are recognised as typical characteristics of natural populations, but also of other environmental variables (Legendre and Legendre, 1998). Thus, an optimal sampling design is needed as well as a sound spatial analysis of catch data, which takes the ecology and the patchy distribution of fish into account (Francis, 1984). A valid estimate of mean biomass and its variance for autocorrelated populations can be obtained by application of geostatistics, regardless of the survey design (Rivoirard *et al.*, 2000). In fisheries, geostatistics is used to optimise sampling strategies (Petitgas, 1996), to estimate catch data and corresponding variances, taking into account the existence of spatial structures (Conan *et al.*, 1992; Fernandes and Rivoirard, 1999; Maynou, 1998; Warren, 1997), as well as to map estimated distributions and spatial patterns of organisms (Lembo *et al.*, 1999; Maravelias *et al.*, 1996). Spatial structures may depend on the species and the age class considered (Fernandes and Rivoirard, 1999; Maynou *et al.*, 1996; Rivoirard *et al.*, 2000); they can also vary with time of day (Simmonds and Rivoirard, 2000; Wieland and Rivoirard, 2001), and with the sampling period (Freire *et al.*, 1992; Hutchings, 1996; Rueda and Defeo, 2001). The importance of a sound spatial analysis is highlighted by the fact that the collapse of the cod (*Gadus morhua*) in Newfoundland waters was, for example, preceded by a change in the spatial structure of the population (Hutchings, 1996).

The focus of this study was to improve the results of the spatial analysis of demersal fish species by attempting to reduce the geostatistical estimation variance. Thus, catch data for dab and whiting normally taken within the GSBTS in the German Bight (box A) were combined with data taken by a modified sampling scheme (referred to as star survey design), which allows a sound modelling of small scale variability and could eventually enhance estimates of semivariograms, especially near the origin. Such a design was recently introduced into fisheries science in acoustic surveys, where transects crossed at a centre point over an aggregation to improve the estimation of biomass of small aggregations of fish (Doonan *et al.*, 2003). Additional dense sampling stations within a sub-area are also used in geosciences to improve estimations and to obtain more pairs of points at small distance classes of the semivariogram (Isaaks and Srivastava, 1989). Further, Simrad *et al.* (1992) suggested an increase of local density of samples to enhance knowledge of the small-scale variability and better define the variogram at small distance classes, to obtain a more precise estimate of the global variance. Hence, in order to reduce small-scale uncertainty, partial over-sampling within an sub-area was assigned to the existing survey strategy of the GSBTS, since the application of geostatistics is generally not restricted to any survey design. In addition, the effects of biological properties such as fish size or sex on the spatial analysis were examined. So far there has been essentially no sound assessment of the spatial structuring of dab and whiting in this area.

2 Materials and methods

2.1 Survey area and sampling design

The study was undertaken in an area of 10 x 10 nm located in the inner German Bight (box A, Fig. 1), which is one out of eleven standard sampling areas of the German Small-scale Bottom Trawl Survey (GSBTS) in the North Sea (Ehrich *et al.*, 1998), during January 2001, 2002 and 2003, to observe the winter distribution. Catch data were assembled aboard the German research vessel "Walther Herwig III". Fishing was performed under standard IBTS (International Bottom Trawl Survey) protocol using the standard net GOV (Chalut à Grande Ouverture Verticale), with trawling time of 30 min at a trawling speed of 4 knots. The locations of sampling stations as well as the trawl directions were selected randomly for each year of the survey. The trawl positions were taken as midpoints of the hauls converted to an absolute measure in km (easting and northing), relative to 54°27'N and 6°58'E. Additionally, to investigate small-scale variability as well as to improve the analysis of spatial structures of demersal fish, the random sampling scheme was modified in 2002 and 2003. Across one randomly selected station within box A trawling was carried out several times, resulting in a star survey design with 7 additional stations in 2002 and 4 in 2003 (Fig. 1). The largest distance between the midpoints of the station tracks was about 500 m. Fishing was restricted to daylight to avoid the possibility of systematic errors due to this factor.

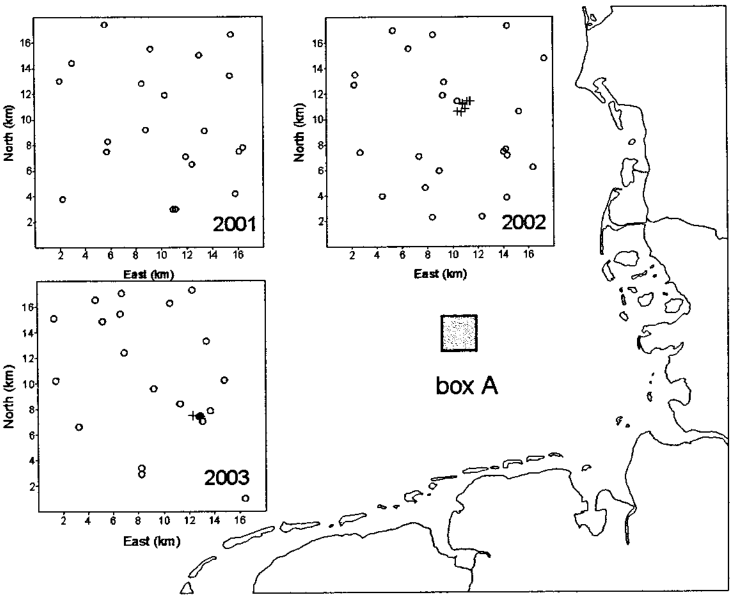

Fig. 1: German Bight with sampling area box A and positions of the trawling midpoints in 2001,2002 and 2003, whereas stations belonging to the "star" are indicated with (+).

2.2 *Biological categories considered*

In order to explore biological factors that might influence the spatial structure of fish populations, the following biological categories (groups) within the catch data were analysed. Spatial patterns can vary with age (Fernandes and Rivoirard, 1999); to correct for this effect catch data for dab and whiting were separated into size groups, representing different age groups. Regarding dab these were < 9.5 cm (excluded from further analysis as there were too few juveniles in the catches), 9.5–19.5 cm (2-7 years old, referred to as d2) and > 19.5 cm (older than 7 years, referred to as d3) (Heessen and Daan, 1996). Due to the length distribution of whiting in the first quarter of the year in box A, the groups considered differed in length in 2001/2002 vs. 2003: < 21 cm vs. ≤ 18.5 cm (0 - 1 years old, referred to as w1) and ≥ 21 cm vs. > 18.5 cm (2 - 4 years old, referred to as w2). Additionally catch data for dab were stratified in two more biological groups, namely in female and male dab, with females referred to as dfe and males as dma.

2.3 *Preparatory data analysis*

Numbers of fish per 30 min trawl time were converted into biomass in kg 30 min^{-1} (catch per unit effort, cpue), on the basis of the length-weight relationships for each species considered. Furthermore, all data sets described above for 2002 and 2003 were analysed in two ways: either including the additional stations at which the star survey was employed (labelled with +) or eliminating those additional sampling stations (labelled with -). All catch data were tested for normality using the Shapiro-Wilk test (Royston. P, 1982). In cases of deviation from normality, cpues were log-transformed and the log-transformed data were used for further analysis. Log transformation of catch data was not necessary for cpues of whiting (w1 and w2 in 2002, w2 in 2003) and dab (d3 and females in 2001). Also linear and non-parametric regressions with one covariate (Bowman and Azzalini, 1997) (north and east co-ordinates) were carried out to investigate possible trends within the cpues (Kaluzny *et al.*, 1998). Significant linear trends within the catch data with north co-ordinates were detected for size class one (w1) and two (w2) of whiting in 2002. Linear trends were significant for medium-sized dab (d2) and males (dma) in 2001, as well as for both size classes of dab (d2, d3) and males (dma) in 2002. These trends were taken into account for the subsequent spatial analysis.

2.4 *Structural analysis*

The spatial structures of fish biomass (distinguished by species, sex and size group) *Z*(*x*) were assessed by experimental semivariograms $\hat{\gamma}(h)$, using the log-transformed cpues, when raw data did not follow a Gaussian distribution. The semivariogram outlines the spatial correlation of data, measuring semivariance between data points as a function of their distance. In the absence of spatial autocorrelation among samples the semivariance is equal to the variance of *Z*(*x*). A monotonic increase of the semivariance with increasing separation distance (*h*) of the sampling position indicates the presence of spatial autocorrelation. When a linear trend was present, cpues were detrended (Kaluzny *et al.*, 1998). Only omnidirectional semivariograms were computed using the classical estimator (Matheron, 1971):

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N_h} [Z(x_i + h) - Z(x_i)]^2 \qquad (1)$$

where $Z(x_i)$ is the realisation of fish biomass (cpue) at station x_i, $Z(x_i+h)$ is another realisation separated from x_i by a discrete distance h (measured in km) and $N(h)$ is the number of pairs of observations separated by h.

In order to improve determination of spatial structures, a inter-annual mean semivariogram can be computed, when a general constancy in the variographic structure between years can be expected (Fernandes and Rivoirard, 1999). Thus, for each variable ($Z(x)$) under study mean variograms (survey years 2001-2003) were computed using all stations sampled (Rivoirard *et al.*, 2000). It was thus assumed that the different spatial distributions can be described by the same ecological process.

In many cases transformation of data is recommended, since the structure of the transformed variable often is more regular than that of the untransformed variable (Rivoirard *et al.*, 2000). This would lead to a biased estimate of the raw structure. However, to allow ecologically sound interpretations and to establish the structure of the raw variable, an appropriate back transformation of the experimental semivariogram is required. We used the following equation for log-transformed data (Guiblin *et al.*, 1995):

$$\gamma(\mathrm{h}) = (\mathrm{m}^2 + \mathrm{var(Z)})\left(1 - \exp - (\sigma^2\gamma_{\mathrm{L}}(\mathrm{h})/\mathrm{var(L)}\right) \qquad \text{with} \quad \sigma^2 = \log\left(1 + \mathrm{var(Z)}/\mathrm{m}^2\right) \tag{2}$$

Where m is the mean of $Z(x)$, var is the variance of $Z(x)$, L is the logarithmic transformation of the variable and $\gamma_L(h)$ is the experimental semivariogram of the transformed variable. A simulation study described in Rivoirard *et al.* (2000) showed that the use of log transformation, associated with a back transformation of the experimental semivariogram, provides an improved method for estimating variogram parameters and estimation variance.

Subsequently, parameters (nugget, sill and range) of spherical, exponential and linear models were fitted semi-automatically (Cressie, 1991), to reduce subjectivity and to ensure reproducibility of the fit (Fernandes and Rivoirard, 1999). Following Webster and Oliver (2001), first the types of models regarding the general trends of the semivariogram curve (backtransformed experimental semivariograms) were selected and then models were fitted using a weighted least-squares method with suitable weights. Least-squares methods are based on finding the model which is “visually” close to the semivariogram curve by minimising the sum of squares of the differences between the generic semivariogram estimator and a model (Chilès and Delfiner, 1999). Here a weighted non-linear least-squares procedure recommended by Cressie (1991) was employed, where more weight is given to the points near the origin, which is the crucial part in determining the semivariogram parameters:

$$\sum_{\mathrm{h}} \mathrm{N(h)}\left\{\frac{\hat{\gamma}(\mathrm{h})}{\gamma(\mathrm{h})} - 1\right\}^2 \tag{3}$$

where $N(h)$ is the number of pairs of points used to compute the empirical semivariogram $\hat{\gamma}(h)$ and $\gamma(h)$ is the fitted model (spherical, exponential or linear).

2.5. Assessing differences in spatial structures

In order to compare the goodness-of-fit (*gof*) of the different models and to select the proper one, for each fitting procedure an index recommended by Fernandes and Rivoirard (1999) was computed:

$$gof = \frac{\sum_{h} N(h)[\hat{\gamma}(h) - \gamma(h)]^2}{\sum_{h} N(h)[\hat{\gamma}(h)]^2} \tag{4}$$

where $\omega(h)$ is the number of pairs used to compute the variogram, $\hat{\gamma}(h)$ is the empirical semivariogram and $\gamma(h)$ is the fitted model. The closer the *gof* to 0, the better the fit. Furthermore, a proportion of model sample variance explained by structural variance was used as a normalised measure of spatial dependence (*SpD*) (Robertson and Freckmann, 1995):

$$SpD = (1 - C_0/[C_0 + C]) \cdot 100 \tag{5}$$

Where C_0 is the estimated nugget parameter and C is the estimated partial sill. This index was used to compare changes in the developed strength of spatial autocorrelation among species, size classes and sex with time and survey design. The greater this value (ranging from 0 to 100), the greater the spatial dependence over the range of separation distances modelled. A low spatial dependence indicates a high sampling or analytical error or that dependence may occur at scales smaller than the average distance separating pairs in the first distance lag of the semivariogram (Robertson and Freckmann, 1995). Sokal and Oden (1978) related the diameter of an aggregation of a species as the modelled range. Therefore the effective range (*eR*) was compared for each model fitted in order to detect characteristics and changes of spatial patterns with time. The effective range for exponential models is three times the estimated range.

In order to measure suitability and power of the modified sampling design, values of the nugget parameter fitted to data without the star survey stations (nug_{-}) were divided by values of the nugget parameters fitted to catch data taking into account the star survey stations: $nug_{-} + 1/nug_{+} + 1$. Ratios larger than one indicate a reduced small-scale variability of the modified sampling scheme (showing a lower nugget effect); conversely, ratios smaller than or equal to one indicate no reduction of small-scale variability due to the star survey. Furthermore, the *gof* values of models fitted to data without star survey stations were divided by the ones derived from modelling including them: gof_{-} / gof_{+}. In analogy to the ratios of the nugget values, values larger than one indicate an improvement of the fitting procedure due to the modified sampling scheme, otherwise (≤ 1) the modelling procedure (describing spatial structures) was not improved by oversampling a sub-area. The higher the absolute values of these ratios, the greater the reduction of small-scale variability or improvement of the fitting procedure, respectively. To detect significant differences between the biological categories distinguished, ANOVA (assuming normal distribution) or Kruskal-Wallis tests (not assuming normal distribution) (Zar, 1999), were carried out with the indicators described above (*gof*, *SpD*, *eR*), derived from models fitted to the cpue of 2001, 2002 and 2003 (including the star survey). The null hypothesis was tested, namely that the location parameters of the distribution of the observed values (*gof*, *SpD*, *eR*) are the same in each group (species, size group and sex). The alternative is that they differ in at least one comparison (when p-values are < 0.05). Thus, it was tested whether any of the the factors species, size group or sex has a significant influence on the observed spatial indicators.

2.6 *Mapping density surfaces and biomass estimations*

Mapping of density surfaces of the predicted biomass of dab (d2, d3, dfe and dms) and whiting (w1 and w2) was carried out with ordinary point kriging using a global neighbourhood (Matheron, 1971). This method estimates the variable values at unsampled locations using the observed values in the surrounding neighbourhood. The models fitted to the annual (backtransformed) semivariograms were used for mapping, but in cases were no structure was detected, models fitted to the mean structures were used for computing the density maps (Fernandes and Rivoirard, 1999).

Biomass estimates for each variable under study were obtained by ordinary block kriging (using the models fitted to the annual semivariograms), a method used as a direct method of biomass assessment in fisheries (Maynou, 1998). The computerised algorithm requires the area to be finely discretised, the discretisation used here is a grid of 0.5 x 0.5 blocks, which was found to optimise precision of the computation. Variances were expressed as coefficients of variation of the arithmetic mean (*m*) and were calculated using the classical estimator, which does not take into account the spatial autocorrelation within the sampled data:

$$CV_{cl} = \sqrt{\frac{s^2}{n}} / m \qquad (6)$$

where s^2 is data variance and n is number of stations. CV_{cl} was compared with the geostatistical estimation variance of the arithmetic mean (Matheron, 1971):

$$CV_{geo} = \sqrt{\sigma_E^{\;2}} / m \qquad (7)$$

where σ_E^2 is the estimate of the estimation variance, obtained from the variogram model (Petitgas, 2001), which is influenced by the geographical position of the stations, the shape of the survey area and the model fitted. Furthermore, the relative estimation error (survey precision) was computed for the classical and geostatistical approach:

$$sp_{cl} = (s^2/n)/m \qquad (8)$$

$$sp_{geo} = \sigma_E^{\;2}/m \qquad (9)$$

where s^2 is the variance, n the number of stations, m the arithmetic mean and $\sigma_E^{\;2}$ is the estimate of the estimation variance, obtained from the variogram model .

3 Results

3.1 *Structural analysis*

The semivariograms clearly showed a spatial structure within the sampling area for the two species investigated regarding all size and sex groups, with the exception of the groups d2, dma and dfe for dab in 2001 and w2 for whiting in 2002 (Figs. 2-4). Parameters of all fitted exponential, spherical and linear models, values of spatial dependency (*SpD*), effective ranges (*eR*), goodness-of-fit statistics (*gof*) and calculated ratios of indicators without and with consideration of the star survey design are presented in Table 1. For both size groups of dab as well as for males and females almost all spatial structures, including the mean structures (Fig. 5), can be successfully described by spherical and exponential models (Figs. 2-5).

Table 1: Estimated parameters of spherical, exponential and linear semivariogram models fitted with a least-squares method to cpue data for dab and whiting in the German Bight (sampling area box A, Fig. 1).

Year	Star survey design	Spec	Group	Model	C_0	C	*SpD*	a	*gof*	$\frac{nug_{-}+1}{nug_{+}+1}$	$\frac{gof_{-}}{gof_{+}}$
							eq (5)		eq (4)		
2001	-	Ll	d2	nug	836	0	0.0	0.0	0.048	n.a.	n.a.
2001	-	Ll	d3	lin	34	1	0.0	n.a.	0.052	n.a.	n.a.
2001	-	Ll	dma	nug	854	0	0.0	0.0	0.090	n.a.	n.a.
2001	-	Ll	dfe	nug	58	0	0.0	0.0	0.101	n.a.	n.a.
2002	-	Ll	d2	lin	3723	154	4.0	n.a.	0.028	n.a.	n.a.
2002	+	Ll	d2	lin	1962	211	0.0	n.a.	0.005	1.9	5.3
2002	-	Ll	d3	sph	4827	68	1.4	3.1	0.030	n.a.	n.a.
2002	+	Ll	d3	sph	11	42	79.4	3.7	0.033	410.9	0.9
2002	-	Ll	dma	nug	4638	0	0.0	0.0	0.026	n.a.	n.a.
2002	+	Ll	dma	exp	144	3292	95.8	0.8	0.008	32.0	3.3
2002	-	Ll	dfe	sph	0	2468	100.0	1.5	0.044	n.a.	n.a.
2002	+	Ll	dfe	sph	685	1131	62.3	2.9	0.003	0.0	16.1
2003	-	Ll	d2	lin	18	2442	0.0	n.a.	0.005	n.a.	n.a.
2003	+	Ll	d2	exp	0	30	100.0	1.3	0.006	19.3	0.8
2003	-	Ll	d3	exp	0	17	100.0	0.5	0.019	n.a.	n.a.
2003	+	Ll	d3	sph	6	11	66.0	3.2	0.017	0.2	1.1
2003	-	Ll	dma	lin	13	3	0.0	n.a.	0.005	n.a.	n.a.
2003	+	Ll	dma	exp	0	27	100.0	2.1	0.010	14.3	0.5
2003	-	Ll	dfe	sph	1	23	94.7	1.7	0.009	n.a.	n.a.
2003	+	Ll	dfe	sph	8	15	65.8	3.0	0.009	0.3	1.0
mean	+	Ll	d2	exp	492	3185	86.6	0.9	0.005	n.a.	n.a.
mean	+	Ll	d3	sph	12	29	70.1	2.9	0.007	n.a.	n.a.
mean	+	Ll	dma	sph	431	2680	86.1	2.3	0.003	n.a.	n.a.
mean	+	Ll	dfe	exp	313	620	66.4	0.7	0.006	n.a.	n.a.

Table 1 (continued)

Year	Star survey design	Spec	Group	Model	C_0	C	*SpD*	a	*gof*	$\frac{nug_- + 1}{nug_+ + 1}$	$\frac{gof_-}{gof_+}$
							eq (5)		eq (4)		
2001	-	Mm	w1	sph	0	5	100.0	2.3	0.024	n.a.	n.a.
2001	-	Mm	w2	sph	0	0.2	74.7	3.9	0.016	n.a.	n.a.
2002	-	Mm	w1	sph	0	294	100.0	1.5	0.062	n.a.	n.a.
2002	+	Mm	w1	sph	0	412	100.0	2.6	0.111	1.0	0.6
2002	-	Mm	w2	sph	0	9	100.0	1.4	0.085	n.a.	n.a.
2002	+	Mm	w2	nug	8	0	0.0	0.0	0.021	0.1	4.1
2003	-	Mm	w1	sph	0	7	100.0	1.7	0.009	n.a.	n.a.
2003	+	Mm	w1	sph	0	6	100.0	2.7	0.021	1.0	0.4
2003	-	Mm	w2	sph	0	1	100.0	4.4	0.006	n.a.	n.a.
2003	+	Mm	w2	sph	1	1	56.8	4.8	0.004	0.6	1.4
mean	+	Mm	w1	exp	23	623	96.5	1.0	0.008	n.a.	n.a.
mean	+	Mm	w2	exp	7	9	56.3	1.2	0.000	n.a.	n.a.

notes

Ll: *Limanda limanda* (with size groups d2 and d3 and males, dma and females, dfe); Mm: *Merlangius merlangus* (with size groups w1 and w2); sph: spherical; exp: exponential; lin: linear; nug: pure nugget; C_0: nugget; C: sill (for linear models = slope); a: range (for exponential model effective range, *eR* =3a); *SpD*: spatial dependency (eq 5); *gof*: measure of the goodness-of-fit (eq 4); $nug_- +1/nug_+ +1$: ratios of nugget values without (-) and with (+) consideration of the star survey stations; gof_-/gof_+: ratios of goodness-of-fit values without (-) and with (+) consideration of the star survey stations; n.a.: not applicable (see Methods section for details).

Regarding dab, effective ranges of the models fitted to the mean semivariograms only differ slightly between size groups and sex (yielding 2.2 – 2.9 km). The same is true for the indicator of spatial dependencies (*SpD*), yielding 86.6 and 86.1 for medium-sized (d2) and male dab (dma) and 70.1 and 66.4 for size group d3 and females (dfe). However, the parametric and non-parametric statistical tests applied showed no significant differences of the observed indicators (*gof*, *SpD*, *eR*, see Table 1) between the biological categories distinguished (d2, d3, dma and dfe). For either size group of whiting, the spherical model adequately describes the spatial structures (Fig. 4, with the sole exception of f; Table 1), whilst the mean structures were described best by exponential models (Fig. 5, a-b; Table 1). On the average (*viz.* regarding mean variograms), the effective range is greater for size group w2 than for w1 (3.0 vs. 3.7), whereas the value for spatial dependence (*SpD*) is much smaller for w2 than for w1 (96.5 vs. 56.3). Non-parametric test statistics indicate significant differences in the values of spatial dependency (χ^2 = 4.35, df= 1, p-value = 0.036) and goodness-of-fit (χ^2 = 3.85, df= 1, p-value = 0.049) of small and medium-sized whiting. Thus, spatial structuring of fish density is more pronounced for small whiting, while models fit better to experimental semivariograms of medium-sized whiting. Comparing mean values of

SpD for dab and whiting, spatial dependency in cpues are rather similar for w1 and for d2 (96.5 and 86.6) and the differences are not statistically significant.

The ideal theoretical model variogram types are altered for dma in 2002 as well as d2, d3 and dma in 2003, when stations employing the star survey design are included in the analysis (Table 1). In most cases, model types without specifying a sill changed to those with a sill. The ideal model type for whiting (w2 in 2002) changed from one displaying spatial structuring to a pure nugget effect. The nugget ratios without and with consideration of the star survey design indicate a reduction of small-scale variability for dab in more than 50 % of all cases (Table 1, five of eight cases), whilst for whiting no reduction was achieved by the modified sampling design. Where small-scale variability was reduced, spatial dependencies within the catch data increase. Ratios of the *gof* values without and with consideration of the star survey design show a clear improvement of the fitting procedure in 50 % of all cases for dab and whiting (Table 1).

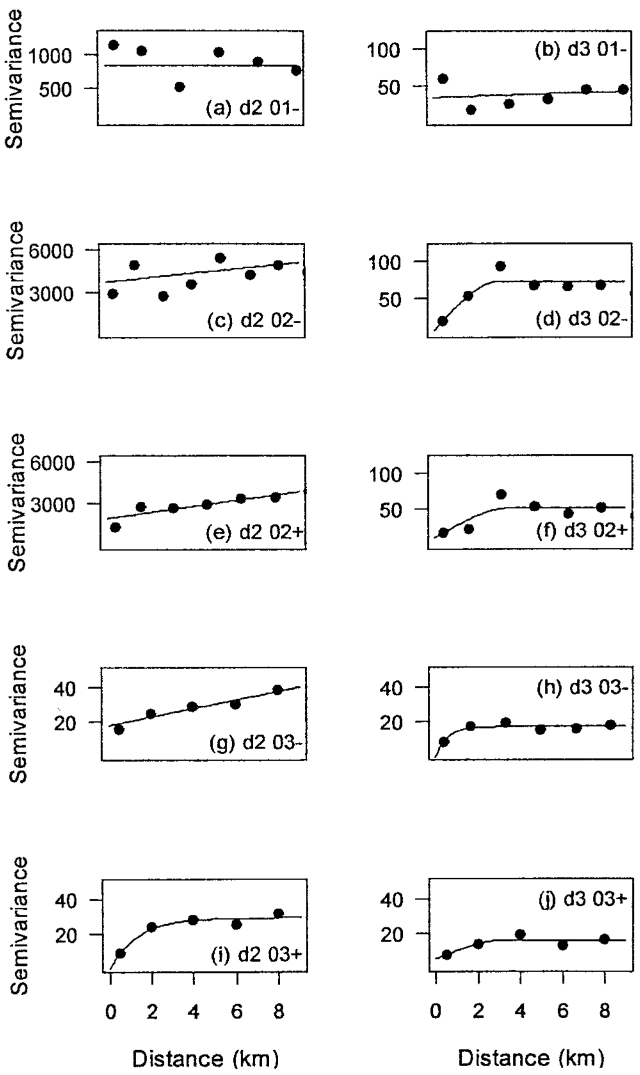

Fig. 2: Empirical (log-back transformed) semivariograms for two size groups of dab (d2, d3) during survey years 2001 (01), 2002 (02) and 2003 (03), without (-) and with (+) consideration of the star survey design; spherical, exponential and linear models fitted by a least-squares.

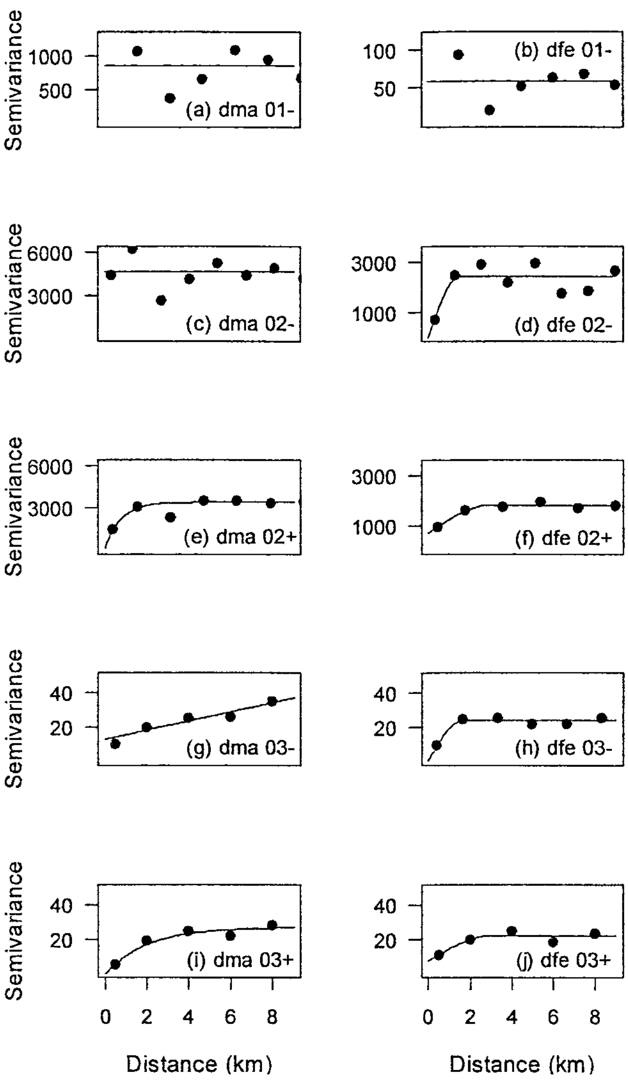

Fig. 3: Empirical (log-back transformed) semivariograms for male and female dabs (dma, dfe) during survey years 2001 (01), 2002 (02) and 2003 (03), without (-) and with (+) consideration of the star survey design; spherical, exponential and linear models fitted by a least-squares.

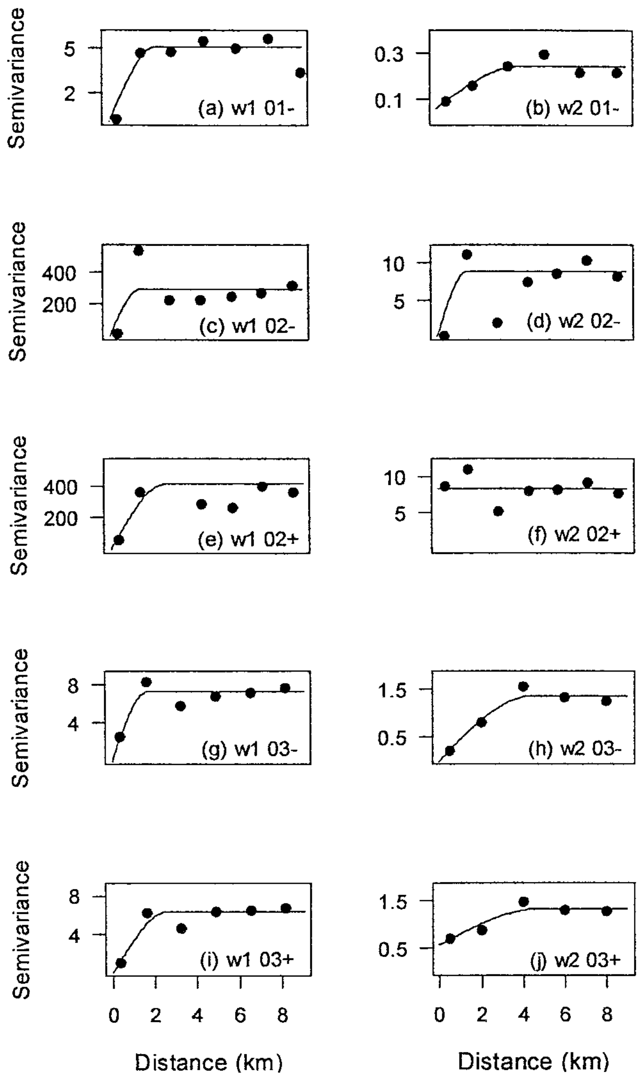

Fig. 4: Empirical semivariograms (log-back transformed semivariograms) for two size groups of whiting (w1, w2) during survey years 2001 (01), 2002 (02) and 2003 (03), without (-) and with (+) consideration of the star survey design; spherical, exponential and linear models fitted by a least-squares.

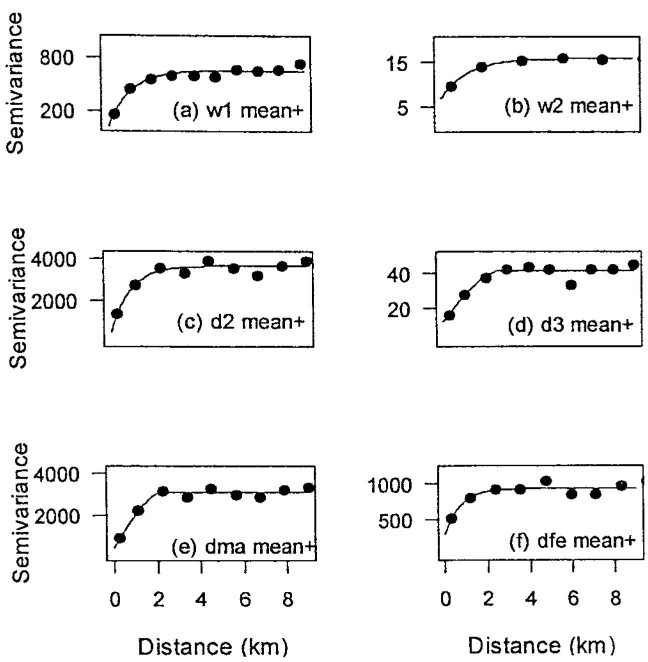

Fig. 5 : Empirical (log-back transformed) semivariograms of mean structures for each of the biological categories considered (d2, d3, dma, dfe , w1, w2) during survey years 2001 (01), 2002 (02) and 2003 (03) with (+) consideration of the star survey design; spherical, exponential and linear models fitted by a least-squares.

3.3 Mapping density surfaces and biomass estimations

Results of the kriging procedure based on the structural analysis clearly showed that patchy distributions of dab and whiting were different in shape and size for each of the categories: year and size or sex group (Figs. 6-8). Moreover, the distribution patterns of dab and whiting indicate no persistent high-density areas within box A in January throughout the years, although the patterns were different in each survey year.

Regarding dab, positions and shapes of high-density spots of size groups d2 and d3 were in good agreement in each year (Fig. 6). The spatial distributions of females and males were in good agreement in every survey year (Fig. 7). Comparing the density maps for dab of the various size and sex groups in 2003, the estimated distribution patterns were very similar for d2 and dma as well as for d3 and dfe. Centres of estimated high-biomass patches of small and medium-sized whiting (w1 and w2) were similarly located in 2001 and 2002 (Fig. 8, a-d), whereas in 2003 varying spatial distributions can be discerned in each of the two size-groups (Fig. 8, e-f).

The catch data for dab and whiting showed a high variability of arithmetic and estimated geostatistical means between years, but both were in good agreement within each year (Table 2). Comparing the estimates of the mean cpue between the data sets without and with consideration of the star survey design for dab and whiting, differences were marginal, except for w1 in 2002, where the mean cpues with and without the star survey vary by 7.2 kg 30 min^{-1}. In general, mean cpues of dab and whiting peaked in 2002.

In almost all cases, geostatistical variances of mean cpue for dab and whiting were clearly smaller than the classical ones. When comparing the absolute values of the coefficients of variation for the analysis with and without star survey design, the uncertainty of the estimated mean cpue was reduced in 50 % of all cases for dab and whiting due to the modified sampling scheme. When the relative estimation errors for dab (sp_{cl} and sp_{geo}, see Table 2) were compared, values of sp_{geo} were lower than sp_{cl} in all cases. More specifically, values of the classical survey precision are reduced in all cases when considering the star survey design. This was also true for the geostatistical survey precision, with the exception of d2 and dma in 2003. For whiting, the geostatistical survey precision was always smaller than the classical one (except for wl(+) in 2003, see Table 2) and classical relative estimation errors were lowered when the star survey design was employed. In contrast, the modified sampling scheme caused the geostatistical survey precisions to be lowered only for wl in 2003.

Table 2: Comparison of classical and geostatistical assessment of biomass indicators for dab and whiting in the German Bight (sampling area box A, Fig. 1).

Year	Star survey design	N	Spec	Group	Arithmetic mean cpue (kg 30min^{-1})	Kriged mean cpue (kg 30min^{-1})	CV_{cl} (%)	CV_{geo} (%)	sp_{cl} (%)	sp_{geo} (%)
							eq (6)	eq (7)	eq (8)	eq (9)
2001	-	21	Ll	d2	68.4	69.0	15.3	9.2	159	58
2001	-	21	Ll	d3	14.5	14.8	9.4	8.7	11	12
2001	-	21	Ll	dma	63.9	64.6	15.7	10.0.	158	64
2001	-	21	Ll	dfe	19.5	19.6	8.7	8.6.	15	14
2002	-	23	Ll	d2	88.3	87.5	15.3	15.1	393	197
2002	+	30	Ll	d2	81.3	85.2	14.8	11.0	257	104
2002	-	23	Ll	d3	15.6	16.3	11.5	10.3	42	18
2002	+	30	Ll	d3	15.5	16.4	11.9	7.8	26	13
2002	-	23	Ll	dma	65.8	68.6	25.7	21.6.	434	307.
2002	+	30	Ll	dma	60.5	63.	19.7	18.0	282	216
2002	-	23	Ll	dfe	36.9	39.1	29.4	26.7	296	294
2002	+	30	Ll	dfe	35.4	38.7	28.8	20.8	184	182
2003	-	21	Ll	d2	8.3	8.6	17.0	12.8	35	15
2003	+	25	Ll	d2	7.9	8.4	19.1	14.4	27	18
2003	-	21	Ll	d3	6.2	6.3	15.0	14.7	25	14
2003	+	25	Ll	d3	5.8	6.3	19.7	13.3	19	12
2003	-	21	Ll	dma	7.1	7.6	19.0	13.3	34	14
2003	+	25	Ll	dma	6.8	7.2	22.3	15.9	26	20
2003	-	21	Ll	dfe	7.3	7.5	16.0	14.5	29	16
2003	+	25	Ll	dfe	6.8	7.6	19.5	13.2	23	14

Table 2 (continued)

Year	Star survey design	N	Spec	Group	Arithmetic mean cpue (kg 30min^{-1})	Kriged mean cpue (kg 30min^{-1})	CV_{cl} (%)	CV_{geo} (%)	sp_{cl} (%)	sp_{geo} (%)
							eq (6)	eq (7)	eq (8)	eq (9)
2001	-	21	Mm	wl	5. 6	5.7	9.0	8.6	4	4
2001	-	21	Mm	w2	0.8	0.7	11.2	11.2	1	< 1
2002	-	23	Mm	wl	41.2	42.7	9.1	8.4	160	32
2002	+	30	Mm	wl	33.9	43.2	15.9	9.1	131	46
2002	-	23	Mm	w2	2.9	2.9	22.5	21.3	18	13
2002	+	30	Mm	w2	2.3	2.6	35.8	24.5.	15	14
2003	-	21	Mm	wl	13.3	13.2	4.8	4.5	3	3
2003	+	25	Mm	wl	13.3	13.3	5.9	4.2	2	2
2003	-	21	Mm	w2	8.3	8.1	3.4	2.9	6	< 1
2003	+	25	Mm	w2	8.5	8.0	4.1	3.3	5	< 1

notes

N: number of samples; CV_{cl}: classical variance of the arithmetic mean; CV_{geo}: geostatistical variance of the arithmetic mean; sp_{cl}: classical relative estimation errors; sp_{geo}: geostatistical relative estimation errors (see Methods section for details); otherwise as in Table 1.

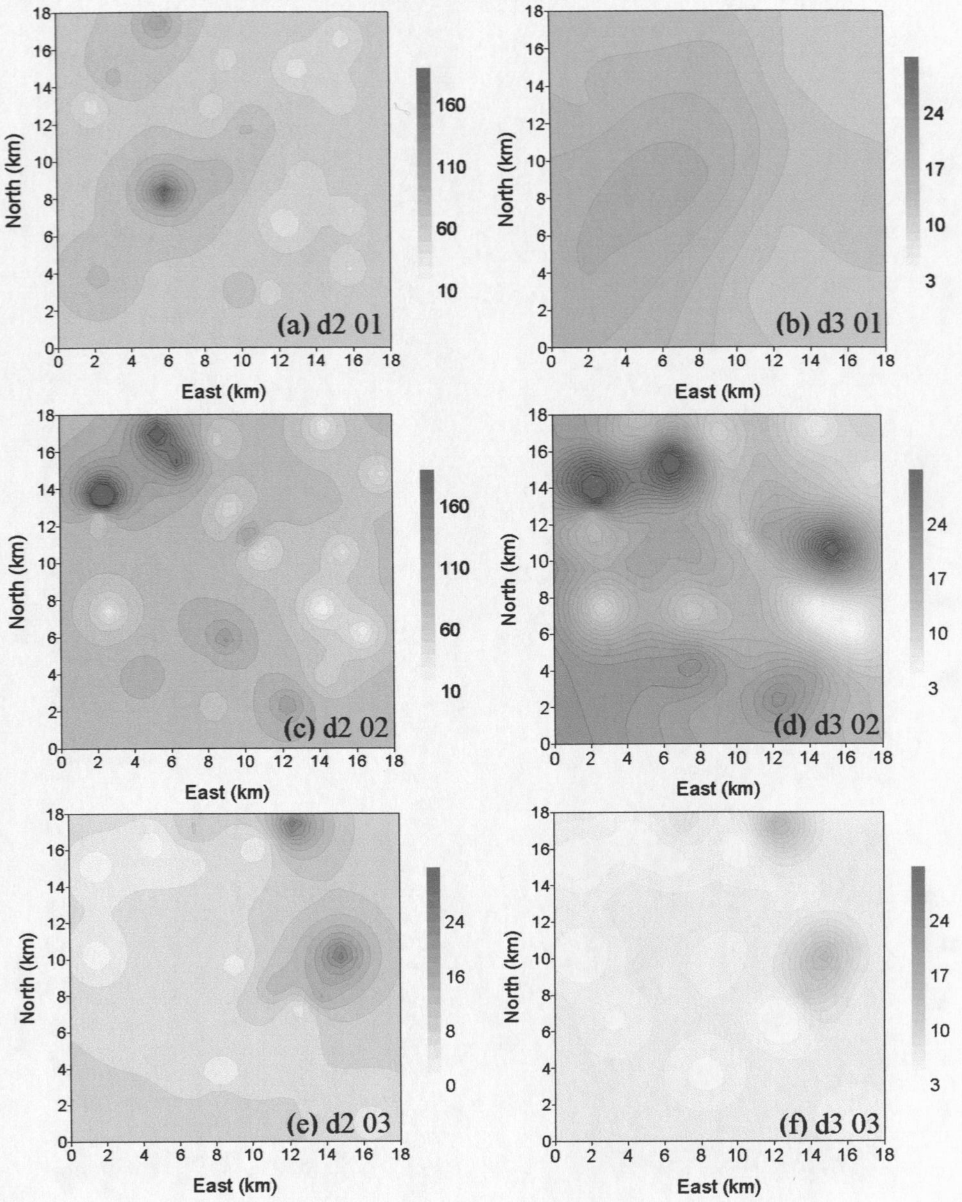

Fig. 6: Density of dab biomass (cpue, kg 30min^{-1}) for size group d2 (a, c, e) and d3 (b, d, f) during cruises 2001 – 2003 (with star survey design) within box A. Estimations with ordinary kriging based on models fitted to annual structures. For d2 in 2001 and 2002 the model fitted to the mean semivariogram was used for mapping. Note that the estimated kriging variance (not shown) was highest at the borders of the investigation area.

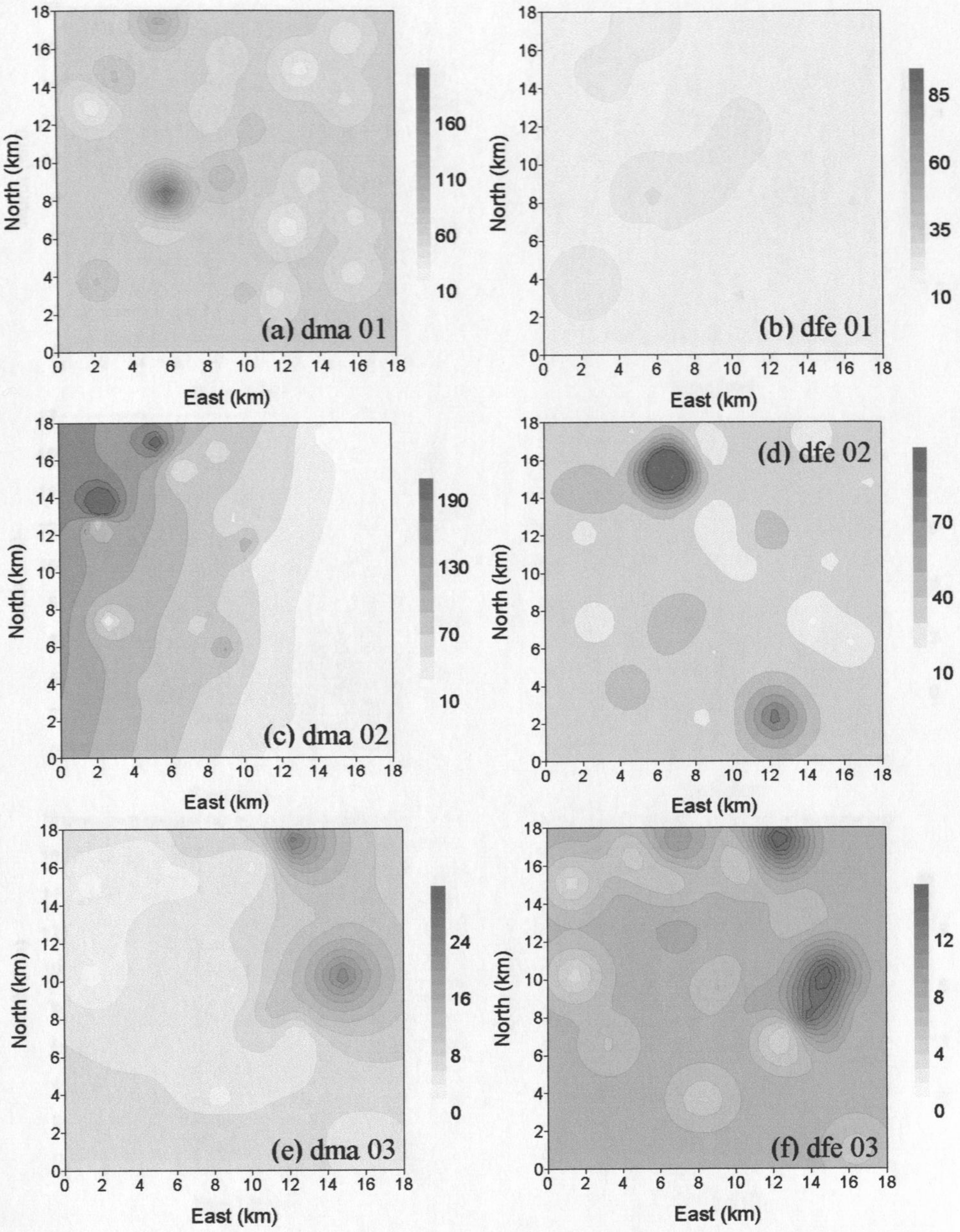

Fig. 7: Density of dab biomass (cpue, kg 30min^{-1}) for males, dma (a, c, e) and females, dfe (b, d, f) during cruises 2001 – 2003 (with star survey design) within box A. Estimations with ordinary kriging based on models fitted to annual structures. For dfe and dma in 2001 the model fitted to the mean semivariogram was used for mapping. Note that the estimated kriging variance (not shown) was highest at the borders of the investigation area.

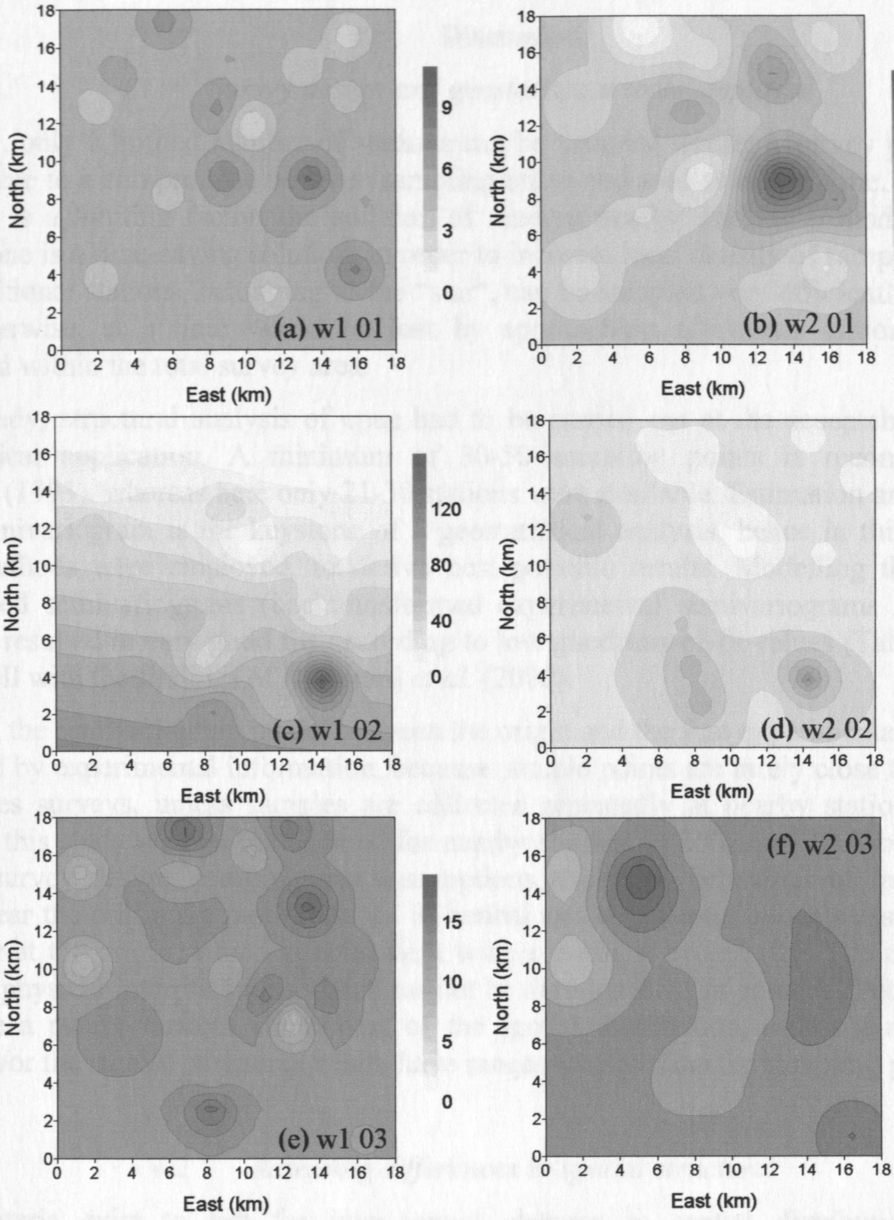

Fig. 8: Density of whiting biomass (cpue, kg 30min^{-1}) for size group w1 (a, c, e) and w2 (b, d, f) during cruises 2001 – 2003 (with star survey design) within box A. Estimations with ordinary kriging based on models fitted to annual structures. For w2 in 2002 the model fitted to the mean semivariogram was used for mapping. Note that the estimated kriging variance (not shown) was highest at the borders of the investigation area.

4 Discussion

4.1 Survey design and geostatistical tools employed

Generally, only a limited number of stations can be sampled during a survey period of the GSBTS, due to a compromise between sampling effort and available ship time. As available ship time is a limiting factor, the addition of random nearby stations around a randomly selected one is a time-saving solution, in order to increase local density of sampling stations. Thus additional stations, belonging to the "star", can be sampled very efficiently within one day. Otherwise, ship time would be lost by approaching additional stations randomly distributed within the total survey area.

In this study, structural analysis of cpue had to be carried out at the acceptable limit of a geostatistical application. A minimum of 30-50 sampling points is recommended by Legendre (1993), whereas here only 21-30 stations were available. Estimation and modelling of the semivariogram is the keystone of a geostatistical analysis, hence in this study only robust methods were employed, to derive best possible results. Modelling the log-back-transformed semivariograms (backtransformed experimental semivariograms of log data) generally resulted in very good fits according to low goodness-of-fit values (Table 1), which agrees well with the findings of Rivoirard *et al.* (2000).

However, the semivariogram model between the origin and the first experimental point is not controlled by experimental information, because sample points are rarely close to each other in fisheries surveys, unless samples are collected repeatedly at nearby stations (Petitgas, 2001). In this study we met the demand for nearby stations in 2002 and 2003 by employing the star survey design, ensuring that assumptions about the behaviour of the variogram models near the origin are more reliable. Spherical and exponential models assume a linear behaviour at the origin, which is coincident with a medium irregularity. The nugget effect has three physical interpretations which cannot be distinguished in practice (Petitgas, 1996). These are a purely random component of the spatial distribution, and/or a measurement error, and/or the sum of structures which have ranges smaller than the sampling grid.

4.2 Assessing differences in spatial structures

Three criteria exist to test for inter-annual changes in spatial distributions: density histograms, density maps and variograms (Petitgas, 2001). We used the annual spatial structures (variograms) as well as the density maps to assess differences in spatial distribution of cpue between years. Homogenous oceanographic conditions in this area (S. Ehrich, unpublished data) support the assumption of stationarity. Consequently, annually varying locations of randomly selected sampling stations and placement of the additional star survey stations are appropriate to make unbiased temporal comparisons of spatial patterns.

When the data for dab in 2002 and 2003 included the star survey design, model types changed in 50 % of the cases compared to the analysis without this scheme. With the star survey design, models with a sill were fitted more often than a pure nugget or linear models (Table 1), indicating that the spatial resolution for dab was really improved by this procedure. On the other hand, a simple increase of the number of stations alone (additional random samples) can also improve the modelling procedure (Webster and Oliver, 2001) making it is impossible to rule out the role the star survey design in the detected improvement. Nevertheless, the main goal of this study was to reduce the nugget variability, which requires partly over-sampling of a sub-area to provide densely located sampling stations and is clearly favouring the star survey design in addition to the saving of ship time as mentioned above.

The calculated ratios of the nugget values without and with consideration of the star survey design showed values smaller than one for dfe in 2002, d3 and dfe in 2003 (Table 1), indicating no reduction of small-scale uncertainty. From these results we can infer that the level of resolution of small-scale structures was increased for males, in contrast to females, due to partly oversampling a sub-area. This fact points to a structuring of size group d3 and females (dfe) at a smaller scale or to white noise being more important for these biological categories. Possible reasons for an increased white-noise component are differences in fish behaviour, which would likely be to influence catchability, or in spawning behaviour. In 50 % of all cases, the gof values of the models for dab were lowered when considering the star survey design (Table 1) and improvements of the fitting procedure occurred in each of the biological categories considered.

In general, no significant differences between the biological categories of dab were detected. Regarding these results, spatial structuring of female, male, d2 and d3 were in good agreement. This might be due to the fact that cpues of the different groups were in good agreement (Table 2, Fig. 6 - 7, e-f). However, size group d2 could be on average characterised by patches 2.6 km in diameter, where cpues were strongly autocorrelated, and size group d3 by patches 2.9 km in diameter, where the spatial autocorrelation was only moderate compared to d2. Furthermore, male dab (dma) during January, on the average, formed patches 2.3 km in diameter and cpues were strongly autocorrelated, whilst females formed patches 2.2 km in diameter and cpues showed only moderate spatial autocorrelations compared to males. Computing the inter-annual mean semivariogram improves the determination of spatial structures (Petitgas, 2001), as the low number of data points can cause high fluctuations of the yearly semivariograms. Hence derived characteristics of spatial structuring of the biological categories considered can be interpreted as "category-specific" for the time of the year and area investigated.

Conversely, the modified sampling scheme did not result in an improvement of the analysis of spatial structures of whiting: the values of the nugget effect did not decrease and consequently, the values of spatial dependency did not increase for 2002 and 2003 when the star survey design was taken into account (see nugget ratios in Table 1). Moreover, the small-scale variability in those years increased, especially for whiting of size group 2, and in one case the model type changed from a spherical to a pure nugget model. Furthermore, our results show a significant difference in spatial dependency ($\chi^2 = 4.35$, df= 1, p-value = 0.036), between the two size groups of whiting with small whiting (w1) showing a much stronger spatial dependency than size group w2.

On the average, small whiting (w1) could be characterised by patches 3.8 km in diameter and size group w2 by patches 6.3 km in diameter (Table 1). Fish caught within size group 1 (age group 0-1) are not expected to be sexually mature, thus the spatial structures obtained cannot be associated with spawning. Although the differences among observed modelling results for dab and whiting were not significant, patchiness seemed to be more pronounced for small whiting (w1) than for medium-sized dab (d2). Likewise, effective ranges for whiting were, on the average, larger than effective ranges for dab. These differences in spatial structuring between species and among biological categories may be caused, among other things, by a greater mobility near the bottom, which is to be expected for whiting compared to dab.

4.3 *Assessing spatial distributions of fish biomass*

Due to a study carried out by Stelzenmüller et al. (in press), where a constancy of variographic structure was found for dab within box A in summer and the assumption of temporal stationarity, we used models fitted to the mean semivariograms of dab and whiting to estimate the density maps in cases, where no spatial structure was obvious (d2, dfe, dma in 2001, w2 in 2002 and for d2 in 2002, because of negative values received by ordinary point kriging) according to results of Fernandes and Rivoirard (1999).

However it was reported that small dab (10 to 15 cm) prefer water temperatures no lower than 2.5 °C (Rijnsdorp et al., 1992). Thus, environmental variables probably induce spatial structuring of medium-sized dab (d2) but not so for d3. On the other hand, size group d2 most likely also included fish which were sexually mature (11 to 14 cm, 2 to 3 yr of age); therefore patchy distributions were probably influenced by fish behaviour. Dab and whiting are high-fecundity serial spawners (Daan et al., 1990). Some of the serial spawners form dense spawning shoals and it is likely that several males may contribute to fertilisation of a given batch of eggs (Daan et al., 1990). Thus, the fact that the estimated density surfaces for female and male dab appear visually more similar than the density maps of the two size groups (Fig. 6, Fig. 7) could probably be explained by the above described spawning process. Thus, spatial structuring of dab during January in the German Bight might have been influenced by spawning behaviour rather than by other factors such as seawater temperature, salinity or distribution of prey. Likewise, the similar effective ranges (eR), interpreted as average patch diameters, for the mean structures of female and male dab point to the development of a patchy distribution due to fish behaviour (spawning).

The estimated density maps showed similar distributions of high biomass patches for small and medium-sized whiting (w1 and w2, Fig. 8). Daan *et al.* (1990) noted subtle differences between distributions of juvenile and adult whiting. Furthermore, the winter distribution of 1-year-old whiting coincided with shallow, cold and less saline waters, whilst the 2-year-old fish were found in deeper waters. This sensitivity of small whiting to temperature and salinity may explain the differences in the characteristics of spatial distribution patterns between the two size groups of whiting in that study. This agrees well with the fact that within species, different age groups may behave differently in relation to the physical environment (Daan *et al.*, 1990). Zheng (2001) showed that spatial patterns of whiting abundance in winter were related to age, depth and sea-surface temperature. Although size group w2 in this study most probably included sexually mature fish and spawning normally occurs during January in the German Bight, spatial structures for whiting seemed to be induced by other factors such as temperature or salinity, because of the strong patchiness detected in cpues of small whiting and the similarities in locations of high-density spots for the two size groups. Consequently, the distribution of small whiting is likely to be dependent on the distributions of the adults. Further differences may be explained by the fact that larger fish probably tend to form larger associations than smaller fish (Rivoirard *et al.*, 2000).

4.4 *Biomass estimates*

Due to the facts that values of the geostatistical variances were lower than the classical ones in most of the cases analysed and that a clear spatial structuring of cpues for dab and whiting could be detected, a spatial analysis of the catch data sampled within a meso-scaled area is essential to obtain unbiased estimates of fish biomass in the area. Improvements in the absolute values of the coefficients of variation as well as reduction of uncertainty of the estimated mean fish biomass for dab and whiting could be attributed to the modified sampling scheme employing the star survey design.

The geostatistical variance depends on the model specified, sample location, shape of investigation area and intensity of sampling (Petitgas, 1996, 2001). In case of dab, the geostatistical estimation variances were much lower than the classical ones during 2002 and 2003, when considering the star survey design. Without this design, differences between CV_{cl} and CV_{geo} were much smaller (see Table 2). For whiting, the two variances (with and without the star survey design) only differ slightly, with the sole exception of w1 in 2002. Therefore, species-specific differences in reduction of uncertainty of abundance estimates are obvious. Furthermore, the relative estimation errors (sp_{cl} and sp_{geo}, Table 2) indicate that the star survey design improved the abundance estimates. The geostatistical survey precision was largely reduced for dab with star survey design, in contrast to whiting, where the star survey resulted in an improvement of the survey precision only once, regardless whether this could have happened also due to a simple increase in number of samples (see above). From the results obtained in this study we can thus infer, that the stronger spatial dependency is developed within cpue of fish, the more appropriate is the incorporation of a small-scale star survey design.

In conclusion, the biological categories of dab and whiting studied here displayed persistent spatial structures within the area of investigation and time of the year. Category-specific characteristics derived from a spatial analysis, such as the explored differences in spatial dependency between male and female dab or various size or age groups of whiting, must be known in order to assess the variability of fish biomass in space and time within an area. To investigate the role of fish behaviour (spawning) or other environmental variables on the spatial distribution of fish, more biological categories as well as a spatial analysis of sea water temperature and salinity should be taken into account in future studies. However, employing a star survey design has proven to be an inexpensive, time-saving and effective procedure, depending on the species or biological category studied, when explicitly a minimised small-scale variability and unbiased estimates of fish biomass are the goal of interest.

5 Acknowledgement

The present study was based on data provided by the Institute of Sea Fisheries, Hamburg (thanks to Ingo Wilhelms, who kindly compiled the catch data from the database). It is part of the PhD thesis of V. Stelzenmüller at the Carl von Ossietzky Universität, Oldenburg, Germany, supported by the Scholarship Program of the German Federal Environmental Foundation (Deutsche Bundesstifung Umwelt, Osnabrück; No. 20002/290).

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KAPITEL 4

Effects of survey scale and water depth on the assessment of spatial distribution patterns of selected fish in the northern North Sea showing different levels of aggregation

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Abstract

Geostatistics was employed to investigate spatial structuring of herring, cod, dab, haddock and whiting at different spatial scales in the northern North Sea. Additionally, a structural analysis of the maximum water depth was carried out to assess habitat associations of fish. Linear, spherical, exponential and Gaussian models were fitted to the semivariograms, showing clear spatial autocorrelations. At the smaller scale, spatial structuring was weak for haddock, herring and dab, increasing at the greater spatial scale, with the exception of whiting. Mean catch rates, estimated classically and geostatistically, were in good agreement. Corresponding variances were clearly reduced at both spatial scales, when accounting for spatial distribution of the fish. At the greater survey scale a high level of habitat association was detected for haddock and whiting, while a poor habitat association was found for cod, dab and herring. The smaller scale seems to be the threshold at which spatial structuring of cpue could have marked influence on estimation error. Thus, survey scale is important when analysing spatial patterns and estimating mean biomass indices, and a sound analysis of relations in spatial structuring of fish and habitat conditions is essential to derive more precise estimates.

Key Words: spatial analysis, universal kriging, variogram models, cod, dab, haddock, herring whiting, habitat associations

submitted to : Marine Ecology Progress Series

1 Introduction

Classical methods of monitoring the abundance of fish stocks and detecting possible changes over time are normally based on large-scale bottom trawl surveys. These are carried out under a standard survey protocol, e.g. using standard fishing gear and a standard sampling strategy. A large-scale bottom trawl survey strategy such as the IBTS in the North Sea (International Bottom Trawl Survey Group 1999) involves one or two samples in each ICES statistical rectangle, the spatial unit of investigation in the North Sea. This design allows the estimation of regional mean fish abundance. In contrast, the German Small-scale Bottom Trawl Survey (GSBTS) aims to monitor species abundance and composition on a more local scale, involving extensive sampling within a few days in small areas of 10 by 10 nautical miles (nm). Such areas are distributed over the entire North Sea (Ehrich et al. 1998).

In general, local heterogeneity in the spatial distribution of fish cannot be detected by large scale surveys. Nevertheless, local and meso-scale aggregation patterns of fish contribute significantly to the error variance of global abundance estimates (Petitgas 2001). Thus, locally increased sampling effort is required in order to reduce this variability. The sampling intensity required is clearly related to the spatial patterns of fish populations under study. Thus, in cases where random sampling is not carried out on a specific spatial scale, any underlying spatial structure in the distribution of the organisms can produce bias in the study. It is not possible to detect such a bias a priori, since an appropriate scale of the spatial distribution of any species of interest is generally unknown (Maynou 1998).

A sound analysis of spatial patterns in fish distribution can be done by geostatistical methods. In fisheries, geostatistics is used to optimise sampling strategies (Petitgas 1996), to estimate catch data and corresponding variances, taking into account the existence of spatial structures (Conan et al. 1992, Warren 1997, Maynou 1998, Fernandes & Rivoirard 1999), as well as to map estimated distributions and spatial patterns of organisms (Maravelias et al. 1996, Lembo et al. 1999). Such spatial patterns depend on the species and age class considered (Maynou et al. 1996, Fernandes & Rivoirard 1999, Rivoirard et al. 2000, Stelzenmüller et al. 2004); they can also vary with time of day (Rivoirard et al. 2000, Wieland & Rivoirard 2001), and with the sampling period (Freire et al. 1992, Hutchings 1996, Rueda & Defeo 2001).

Aggregations in the distribution of fish in space can be caused by physical, chemical and biological factors which control the activity of fish, such as feeding, predator avoidance, migration, reproduction and habitat selection (Simrad et al. 1992). In fact most animals and plants in aquatic and terrestrial environments are aggregated (Methven et al. 2003). Numerous studies have been carried out to assess associations between environmental factors, such as temperature, salinity or bottom depth, and fish distribution by employing various methods. For example, spatial relationships between whiting and measures of environmental conditions on large spatial scales were studied applying Generalised Additive Models (GAM) in combination with GIS (geographic information system) (Zheng 2002) and a test for associations between environmental conditions and distribution of ground fish species was developed (Perry 1994), in which the null hypothesis of random relationships between fish catch and habitat variables was tested using the empirical cumulative distribution function of environmental variables compared to the same distribution weighted by the catch (Páramo & Roa 2003).

This study focuses on the assessment of spatial patterns for herring (*Clupea harengus*), cod (*Gadus morhua*), whiting (*Merlangius merlangus*), haddock (*Melanogrammus aeglelfinus*) and dab (*Limanda limanda*) in the northern North Sea, analysed at two different spatial scales, and their effects on biomass estimates. The species analysed belong to the ten dominant ones (in weight) in this area (Daan et al. 1990). They are of special interest in this study, since differences in their aggregation behaviour and in the location of their distribution centres in the North Sea can be assumed. Thus, our area of investigation is located in the centre of the distributions of adult whiting and haddock, while the main distribution areas of dab and cod are more southern and northern, respectively (Daan et al. 1990, Heessen & Daan 1996). The spatial evaluation of herring catch data derived from a bottom trawl survey using a GOV is of particular interest, since herring abundance indices of the IBTS 1st quarter surveys are the basis of herring stock assessment (Simmonds & Rivoirard 2000).

For this analysis a unique data set was used, elaborated by the Institute of Sea Fisheries, Hamburg in the year 1986. Within the scope of a comparative fishing experiment, 127 standard hauls were sampled in an area of 15 by 16 nm in the northern North Sea (Ehrich 1991), including one of the current standard monitoring areas of the GSBTS (box D) in its north-western part. To address scale effects by application of geostatistical tools, this data set is promising due to the great number of sampling stations, which is exceptional in fisheries science. We also performed spatial analysis of the habitat with respect to variations in water depth, which can be regarded as an indicator of other environmental variables that might influence specific fish aggregation patterns, in order to further reduce bias in the abundance estimates.

2 Material and Methods

2.1 Survey area, sampling and data

Data were collected during a comparative fishing experiment in June 1986 within an area of 15 by 16 nm in the northern part of the North Sea (57°43.5′N-57°58.5′N; 0°34′W-1°04′W) using the German research vessels "Walther Herwig II" and "Anton Dohrn". In total, 127 hauls were taken, each at randomly selected stations and towing directions (for details of the experimental set up see Ehrich 1991), using the standard net GOV (Chalut à Grande Ouverture Verticale) trawled for 30 min at a speed of 4 knots. In subsequent analysis the space from which these 127 samples were derived is referred to as "total area". From 1986 on, a smaller area of 10 by 10 nm was investigated within the GSBTS in the North Sea (Ehrich et al. 1998) which is situated in the north-western part of the investigation area mentioned above. For spatial analysis of samples taken in the 1986 survey from this smaller area (59 stations), the area is called "box D" (57°48′N-57°58′N; 0°44W′-1°04′W) (Fig.1). Additionally, the maximum catch depth (max. depth) was recorded, in the spatial analysis referred to as "depth". Trawl positions were taken as midpoints of the hauls converted to an absolute measure in km (easting and northing), relative to 57°43.5′N and 1°04′W for data of the "total area" and relative to 57°48′N and 1°04′W for data belonging to "box D".

2.2 Preparatory data analysis

Biomass indices of herring (*Clupea harengus*), cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), whiting (*Merlangius merlangus*), and dab (*Limanda limanda*) are expressed as total catch in kg per 30 minutes trawl time (cpue). Differences in cpue caused by either ship involved in this survey were assumed to be negligible (Ehrich 1991). Unfortunately only incomplete information is available regarding length and sex, thus no biological categories were considered. All catch data were tested for normality using the Shapiro-Wilk test (Royston. P 1982). As a result we employed a log-transformation (in presence of "zero-catches" a small numerical constant was added), while depth data were not transformed. Linear and non-parametric regressions of data with one covariate (Bowman & Azzalini 1997) (north, east co-ordinates and depth) were carried out to detect possible trends (Kaluzny et al. 1998).

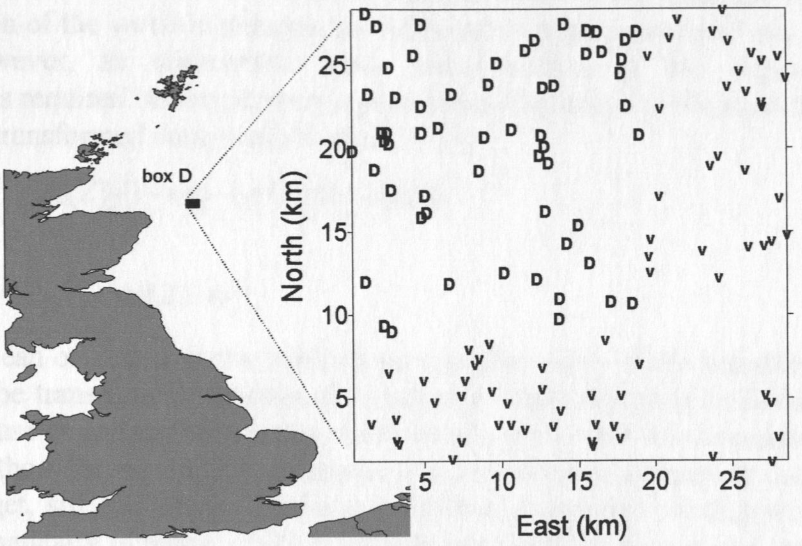

Fig. 1: Spatial distribution (post plot) of sampling stations within the area of investigation. (+) sampling stations belonging to the area referred as "total area". (D) sampling stations situated in the area "box D", belonging to the eleven standard monitoring areas of the GSBTS.

2.3 *Structural analysis*

The structure of spatial variability of $Z(x)$ (log-transformed cpue for each fish species and "depth") was assessed by an experimental covariance function. Experimental semivariograms $\hat{\gamma}(h)$ were used to describe the spatial structure of fish biomass and depth, respectively. The semivariogram outlines the spatial correlation of data measuring the half variability between data points as a function of their distance. In the absence of spatial autocorrelation among samples the semi variance is equal to the variance of $Z(x)$. When a significant linear trend was encountered, data were detrended (Kaluzny et al. 1998). Omnidirectional semivariograms as well as directional semivariograms were computed using the robust "modulus"estimator, which is supposed to be resistant against extreme values (Cressie (1980):

$$\hat{\gamma}(h) = \left\{ \frac{1}{N(h)} \sum_{x_i-(x_i+i)\sim h} \left|Z(x_i+h)-Z(x_i)\right|^{\frac{1}{2}} \right\}^4 \Bigg/ (0.914+(0.988/N(h))) \qquad (1)$$

where $Z(x_i)$ is the realisation of the variable under study (biomass and depth) at station x_i, $Z(x_i+h)$ is another realisation separated from x by a discrete distance h (measured in km) and $N(h)$ is the number of pairs of observations separated by h. Spatial structuring of the distributions of herring, cod, whiting, haddock, dab and depth were assessed within the "total area" (127 stations) and "box D" (59 stations). Directional semivariograms (for whiting and haddock from “total area” with axis = 70°/160°, for dab from “total area” with axis = 130°/30°) were corrected by an anisotropy factor (0.3 for whiting ; 0.2 for haddock and dab) due to the detected presence of a geometric anisotropy (Kaluzny et al. 1998).

Experimental semivariograms often show fluctuations preventing a straightforward interpretation. Thus, Rivoirard (1997) suggested that a relative structure be computed in which the experimental semivariogram is standardised by the sample variance, or that the log-transformed variable be used with a back transformation of the analysed structure. The log-transformation of the variable reduces the influence of high values and was employed in this study. However, an appropriate back transformation of the experimental log semivariograms is required before performing the structural analysis. We used the following equation for log-transformed data (Guiblin et al. 1995):

$$\gamma(h) = (m^2 + \mathrm{var}(Z))\left(1 - \exp - (\sigma^2 \gamma_L(h) / \mathrm{var}(L)\right)$$

$$\text{with} \quad \sigma^2 = \log\left(1 + \mathrm{var}(Z)/m^2\right) \tag{2}$$

where m is the mean of $Z(x)$, L is the logarithmic transformation of the variable and $\gamma_L(h)$ is the structure of the transformed variable. A simulation study described in Rivoirard (2000) showed that the use of log transformation, associated with a back transformation, provides an improved method for estimating variogram parameters and estimation variance. Thus parameters (nugget, sill and range) of linear, spherical, Gaussian and exponential models were fitted automatically (Cressie 1991) to experimental semivariograms of catch data and depth measured in the “total area” and within “box D”.

To reduce subjectivity and to ensure reproducibility of the fit, a weighted least squares procedure recommended by Cressie (1991) was employed, where more weight is given to the points near the origin, which is the crucial part in determining the variogram parameters. In order to assess the goodness-of- fit (*gof*) of the different models, for each fitting procedure an index recommended by Fernandes (1999) was computed:

$$gof = \frac{\sum_h N(h)[\hat{\gamma}(h) - \gamma(h)]^2}{\sum_h N(h)[\hat{\gamma}(h)]^2} \tag{3}$$

where $N(h)$ is the number of pairs used to compute the semivariogram, $\hat{\gamma}(h)$ is the experimental semivariogram and $\gamma(h)$ is the fitted model. The closer the *gof* to 0, the better the fit.

2.4 *Assessing spatial structuring at different scales and water depth*

In order to assess effects of the spatial scale on spatial structuring of fish distribution (“total area” *vs.* “box D”), the strength of spatial dependence (*SpD*) was calculated for each model (Robertson & Freckmann 1995):

$$SpD = (1 - C_0 / (C_0 + C) \cdot 100 \tag{4}$$

where C_0 is the nugget parameter and C the sill of the modelled covariance function. The greater this value (ranging from 0 to 100), the greater the level of spatial dependence. Additionally the value of the relative nugget (C_0/C_0+C) was calculated to compare the fraction of variability explained by spatial structuring of catch data and the level of developed spatial structuring at different survey scales. Sokal (1978) related the diameter of an aggregation of a species to the modelled range. Therefore the practical range (*pR*) was computed for each model in order to detect characteristics of possible habitat associations (relations of spatial patterns of fish to depth). The effective range for spherical models is equal to the estimated range, the effective range of an exponential model being $3 \cdot a$ and that for a Gaussian model $\sqrt{3} \cdot a$.

2.5 Mapping density surfaces and biomass estimations

Mapping of density surfaces of the predicted cpues of herring, cod, whiting, haddock and dab as well as the maximum depth was carried out with ordinary kriging and universal kriging (kriging in the presence of a drift when a linear trend was detected). For punctate estimates of variable values at unsampled locations, the estimator given by Webster (2001) was employed:

$$\hat{Z}(X_o) = \sum_{k=0}^{K}\sum_{i=0}^{N} a_k \lambda_i f_k(X_i) \qquad (5)$$

where λ_i are charging weights attributed to each $Z(X_i)$, f_k represents the drift by a set of functions, $f_k(x)$, $k = 0,1,...K$, of our choice (here simple polynomials of the order 1) and a_k are the unknown coefficients. To apply this interpolation method a grid was drawn on the area investigated with a mesh size of 0.5 km. The uncertainty of the estimation of ordinary and universal kriging was expressed by computing the square root of the kriging variance (kriging error).

Mean cpue estimates for each fish species regarding the "total area" $\hat{Z}(X_0)$ and regarding only "box D" were obtained by ordinary and universal blockkriging (with a drift equal to the east co-ordinates) (Isaaks & Srivastava 1989). Blockkriging is used as a direct method of biomass assessment in fisheries (Maynou 1998). The computerised algorithm requires the area to be finely discretised; the discretisation used here is a grid of 2 x 2 blocks, which was found to optimise the precision of the computations.

When an appropriate spatial model is fitted, then the mean cpue estimated by kriging is expected to be similar to the sample mean (Isaaks & Srivastava 1989). Furthermore, in order to compare the variability of the estimates at different spatial scales, coefficients of variation of the arithmetic mean (*m*) and the mean cpue estimated by blockkriging (m_{BK}) were calculated. A classical estimator

$$CV_{class} = s \,/\, m \; (\%) \qquad (6)$$

where *s* is the standard deviation, and the geostatistical estimator

$$CV_{geo} = ke \text{ (squared root of mean kriging error) } / \, m_{BK} \; (\%) \qquad (7)$$

where spatial structuring of data and number of samples were taken into account, were also calculated.

3 Results

3.1 Preparatory data analysis

Regarding catch data from the "total area" significant linear trends ($\alpha = 0.05$) with east co-ordinates and depth were detected for whiting (log-cpue = 4.84 - 0.109 east, $R^2 = 40.7$ %, $p < 0.001$; log-cpue = 10.9 - 0.07 depth, $R^2 = 18.0$ %, $p < 0.001$), haddock (log-cpue = 5.58 - 0.03 east, $R^2 = 18.9$ %, $p < 0.001$; log-cpue = 8.06 - 0.028 depth, $R^2 = 15.2$ %, $p < 0.001$), and dab (log (0.01 + cpue) = 1.5-0.12 east, $R^2 = 36.5$ %, $p < 0.001$; log (0.01 + cpue) = 3.92 - 0.04 depth, $R^2 = 3$ %, $p = 0.028$), but for cod only with depth (log (0.01 + cpue) = 6.75 - 0.04 depth, $R^2 = 4.7$ %, $p = 0.008$).

Regarding catch data from "box D" a significant linear trend with east co-ordinates was discovered for herring, whiting and dab (herring: log(1+cpue) = 4.1 - 0.08 east, $R^2 = 5.61$ %, $p = 0.038$; whiting: log-cpue = 5.1 - 0.1 east, $R^2 = 34.0$ %, $p < 0.001$; dab: log (0.01 + cpue) = 1.21 - 0.09 east, $R^2 = 18.2$ %, $p < 0.001$) and with depth for whiting (log-cpue = -9.65 + 0.09 depth, $R^2 = 19.8$ %, $p < 0.001$). These detected linear trends were taken into account for the subsequent structural analysis.

3.2 Structural analysis

Regardless of the spatial scale, robust experimental semivariograms computed for herring, cod, whiting, haddock, dab and depth show a clear spatial autocorrelation (Fig.2 and 3). In any case, classical model types such as linear, spherical, exponential and Gaussian models were appropriate. Parameters of the fitted models, values of the indicator of spatial dependence (*SpD*), "goodness – of – fit" values (*gof*), the value of the relative nugget (*rel.* C_o) and the practical range (*pR*) are listed in Table 1.Spatial structures were analysed to maximum distance of 18.5 km where the "total area" was concerned and of 8.5 km for "box D". All models fitted show a "goodness – of – fit" value around zero, which indicates that differences among the experimental semivariograms and models are small. The lowest value of the *gof* was obtained for the spherical model regarding herring in box D (Table 1). Model types changed in all cases between both survey scales, with one exception (whiting). For herring, haddock, dab and depth the model type changed from linear regarding "box D" to a model with a sill regarding the "total area". Thus only whiting and cod cpue of box D were described by models having a sill.

At the greater spatial scale spatial dependence among catch data decreases in the following order: haddock ($SpD_{\text{total area}} = 94.3$), dab ($SpD_{\text{total area}} = 75.4$), whiting ($SpD_{\text{total area}} = 62.9$), cod ($SpD_{\text{total area}} = 53.7$) and herring ($SpD_{\text{total area}} = 40.7$). A high spatial dependence is also obvious for the catch depth ($SpD_{\text{total area}} = 93.0$). When comparing values of the relative nugget at both spatial scales, a reduction of the relative nugget at the greater scale is detected for cod (19.3 %), whereas an increase of 11.7 % is observed for whiting. Considering the "total area", the greatest practical range is visible for dab (17.8 km) and the smallest for herring (2.8 km). Whiting (11.4 km), haddock (7.8 km), cod (6 km) and the maximum catch depth (11 km) display intermediate values. Conversely, considering "box D" patch diameters do not differ between whiting (5.4 km) and cod (4.5 km) (Table 1). Thus, patchiness is most developed for cod at smaller survey scales, while within the "total area" herring showed the highest level of patchiness.

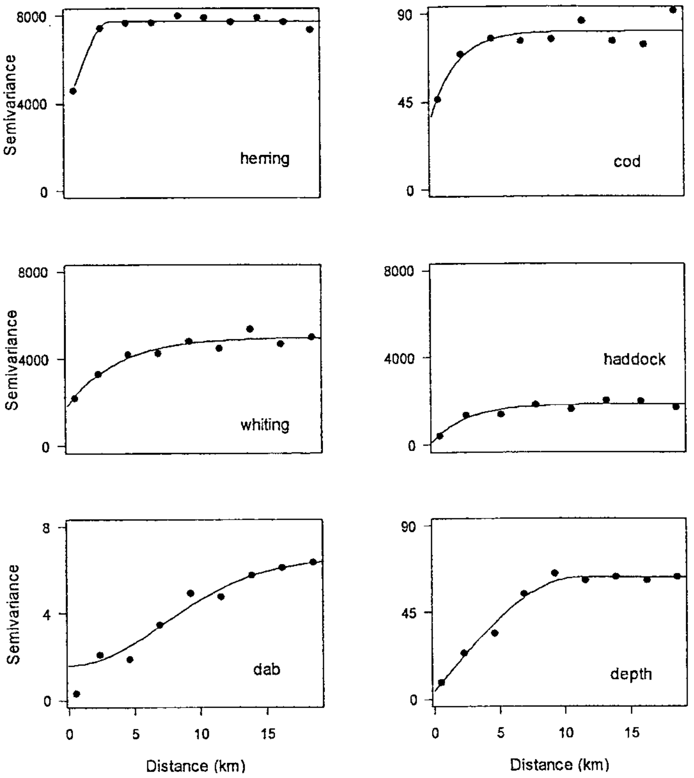

Fig. 2: Experimental robust semivariograms of cpue of herring, cod, whiting, haddock, dab and measure of maximum depth sampled within the total area with spherical, exponential and Gaussian models, fitted by a least-squares method.

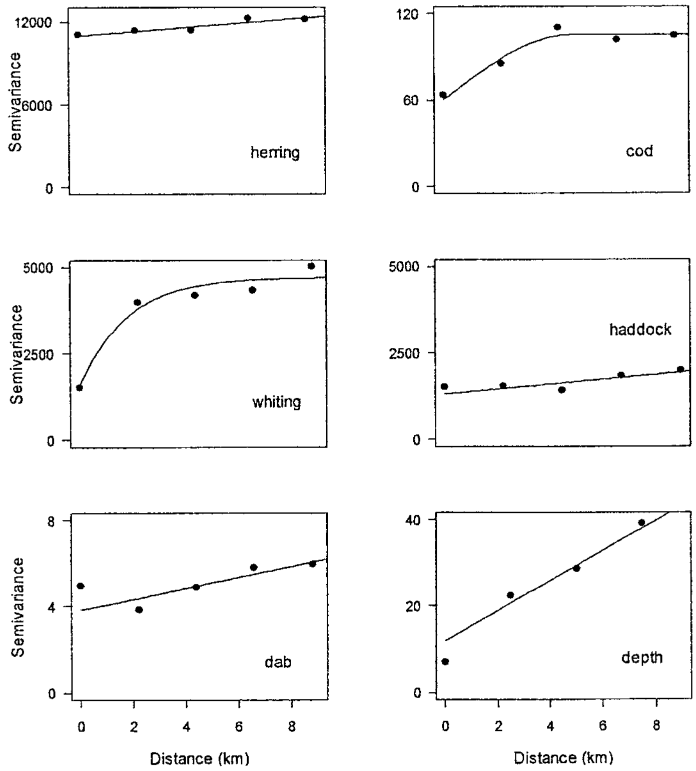

Fig. 3: Experimental robust semivariograms of cpue of herring, cod, whiting, haddock, dab and measure of maximum depth sampled in the area referred as “box D” with linear, spherical and exponential models, fitted by a least-squares method.

Table 1: Estimated parameters nugget (C_0), partial sill (C) , slope and range (a) of the linear (lin), exponential (exp), spherical (sph) and Gaussian (gauss) models fitted to the cpue derived from the "total area" (total) and to cpue derived from "box D" (box D). Also the practical range (*pR*), value of the relative nugget (rel. C_0), strength of the spatial dependency (*SpD*) and the values of the "goodness - of - fit" statistic (*gof*) are listed.

variable	area	model	C_0	C/slope	a	pR	rel. C_0 (%)	SpD	gof
herring	total	sph	4593.8	3147.8	2.8	2.8	59.3	40.7	0.0005
herring	box D	lin	10954.9	150.5	n.a.	n.a.	n.a.	n.a.	0.0003
cod	total	exp	37.6	43.6	2.0	6.0	46.3	53.7	0.0050
cod	box D	sph	60.4	44.8	4.5	4.5	57.4	42.6	0.0014
whiting	total	exp	1847.4	3138.0	3.8	11.4	37.1	62.9	0.0032
whiting	box D	exp	1562.4	3145.8	1.8	5.4	33.2	66.8	0.0042
haddock	total	exp	106.4	1773.5	2.6	7.7	5.7	94.3	0.0082
haddock	box D	lin	1313.3	69.1	n.a.	n.a.	n.a.	n.a.	0.0050
dab	total	gauss	1.6	4.9	10.3	17.8	24.6	75.4	0.0050
dab	box D	lin	3.8	0.3	n.a.	n.a.	n.a.	n.a.	0.0035
mx depth	total	sph	4.4	58.8	11.0	11.0	7.0	93.0	0.0019
mx depth	box D	lin	12.1	3.5	n.a.	n.a.	n.a.	n.a.	0.0021

3.3 *Mapping density surfaces and abundance estimates*

The density maps derived from the kriging procedure and the corresponding kriging errors are presented in Figures 4 and 5. It can be seen that herring and cod are distributed in clearly defined patches within the "total area", while whiting and haddock display more overlapping spatial distributions with highest biomass densities in the western part of the investigation area. In contrast, dab is aggregated in one big patch also located in the western part of the area. Regarding the maximum catch depth, we find a gradient running from northwest to southeast throughout the area. In any case, the estimated uncertainties (Fig. 5) are highest at the border of the investigation area.

Regardless of the spatial scale, haddock is the most abundant species investigated, followed by whiting and herring, while cod and dab show lower abundance (Table 2). The mean catches expressed as the arithmetic means (m) are in good agreement with mean catches calculated by blockkriging (m_{BK}). The geostatistical variances (CV_{geo}) of mean cpue for herring, cod, whiting, haddock and dab are clearly smaller in all cases than the classical ones (CV_{class}). Generally, mean cpues calculated for "box D" are higher than those for the "total area".

Table 2: Estimates of the mean cpue of herring, cod, whiting, haddock and dab (m = arithmetic mean, m_{BK} = geostatistical mean) caught within the "total area" (total) and in "box D" (box D). Variability of the estimates is expressed as standard deviation (s), kriging error (ke = square root of the mean kriging variance), as well as the classical (CV_{class} (%)) and geostatistcial (CV_{geo} (%)) coefficients of variation.

specie	area	m	m_{BK}	s	ke	CV_{class}	CV_{geo}
herring	total	72.3	72.1	90.6	36.9	125.2	51.2
herring	box D	83.7	82.2	111.7	44.7	133.4	54.4
cod	total	16.0	15.6	14.0	4.3	87.0	27.4
cod	box D	17.7	16.1	14.5	5.4	82.2	33.5
whiting	total	63.3	62.8	81.7	33.2	129.1	52.8
whiting	box D	94.8	124.0	92.7	42.0	97.8	33.8
haddock	total	199.3	193.3	104.7	21.3	52.5	11.0
haddock	box D	229.9	216.1	103.6	24.3	45.1	11.3
dab	total	1.9	1.8	2.4	1.0	122.4	53.2
dab	box D	2.5	3.3	2.8	1.4	112.0	43.0

Scale effects are less pronounced for the abundance estimates of cod, herring and dab, where differences in the mean cpue and the corresponding measure of variability are low (Table 2). Conversely, for haddock the scale effect is high due to the great reduction of the mean cpue when considering the "total area" and due to the marginal increase of the variability of the estimates. For whiting differences in the mean catches at both survey scales are highest, with values from "box D" being twice as high as those for the "total area", associated with a slight decrease of the corresponding variability at the greater spatial scale (Table 2).

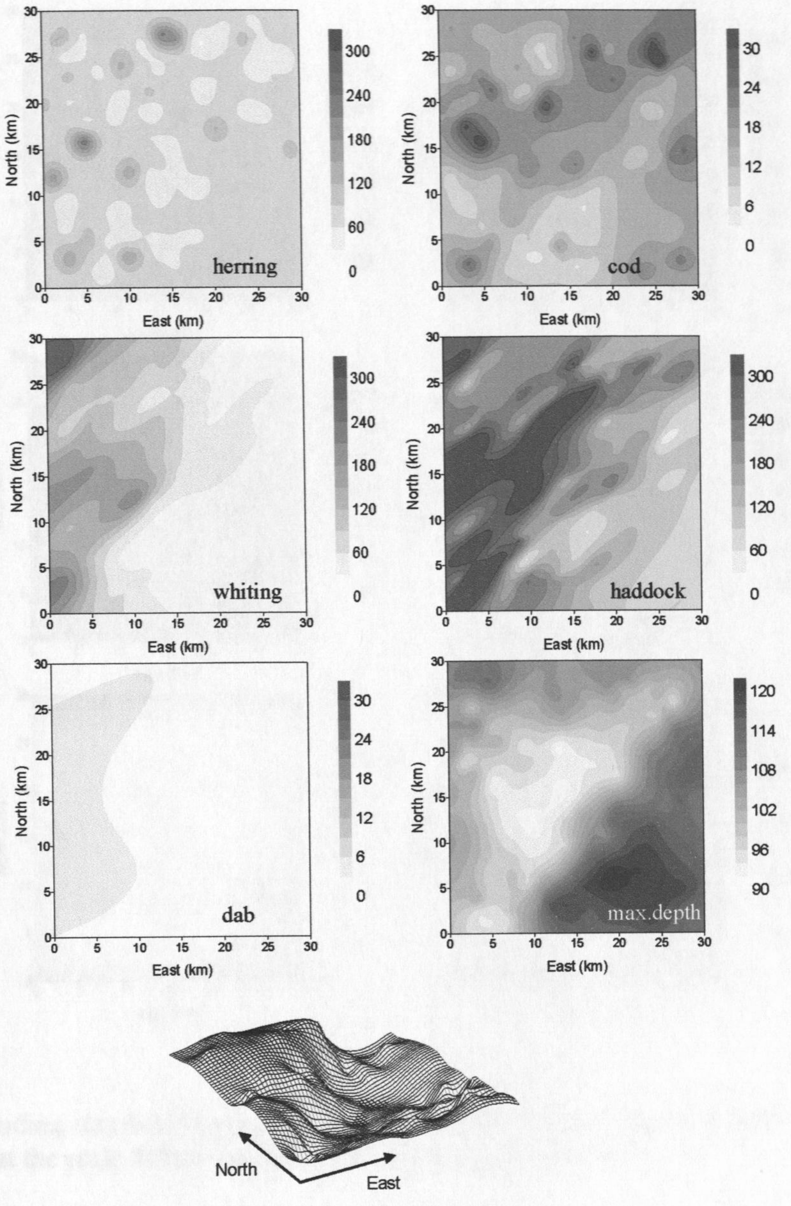

Fig.4: Density maps of herring, cod, whiting, haddock, dab as well as the maximum depth within the total area, estimated with (universal) point kriging. Note that the scale differs due to the varying abundance.

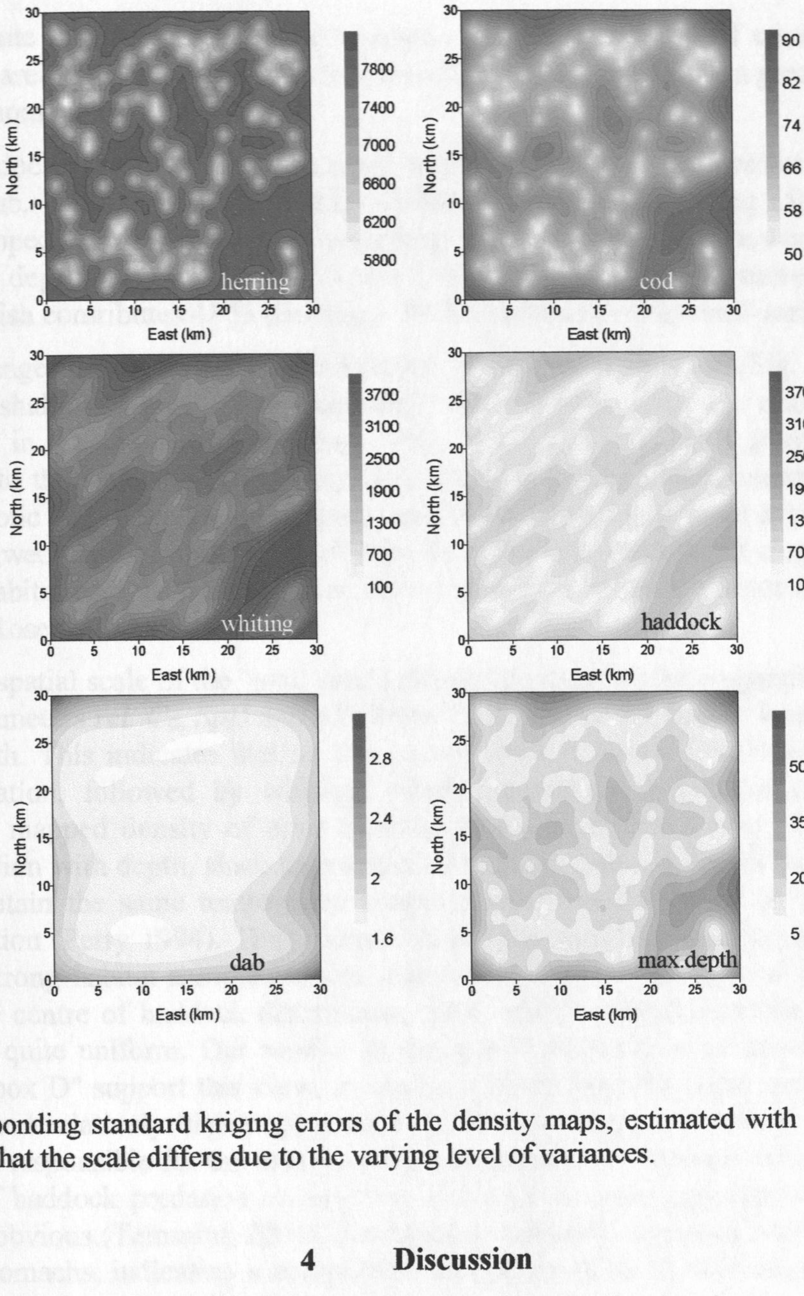

Fig.5: Corresponding standard kriging errors of the density maps, estimated with (universal) point kriging. Note that the scale differs due to the varying level of variances.

4 Discussion

At both scales investigated, spatial structuring of cpue at varying levels was observed (Table 1). Thus, a sound spatial analysis proved to be necessary to obtain unbiased estimates of mean cpues and to assess spatial patterns in fish distributions. The keystone of a geostatistical analysis is the estimation and modelling of the semivariogram and due to the fact that fisheries data are often skewed, in this study only robust methods were employed. Furthermore, the great number of sampling stations at the spatial scale of the "total area" and modelling the log-back-transformed semivariograms generally resulted in very good fits according to low goodness-of-fit indicators (Table 1), demonstrating the validity of this spatial analysis.

The choice of the variogram model corresponds to a physical interpretation of the spatial process from the data sampled (Petitgas 1996). In our study, linear, spherical and exponential models could be fitted in almost all cases, assuming a linear behaviour near the origin, which is coincident with a medium irregularity. Bulit (2003) associated a spherical function with a system in which patches were more structured, whereas exponential functions indicate that patches have fuzzy edges. Spatial structuring of cpue data for dab from the "total area" was described best by a Gaussian model, indicating a great regularity of the spatial phenomenon (Petitgas 1996).

Cpues for haddock were spatially structured more obviously at the greater survey scale, followed by dab, whiting, cod and herring (Table 1). Spatial structuring (*SpD*) was more strongly developed for the "total area" regarding cod, while whiting showed an increased level of spatial dependency in "box D" (Table 1, Fig. 6). At the greater survey scale spatial structuring of fish contributes 41 % (herring) - 94 % (haddock) of the total variability.

Only small changes of water depth were detected in the area of "box D" (Fig. 4), which thus represents the shallowest part of the "total area" (90 – 96 m), while the maximum bottom depth is found in the south-eastern corner of the "total area". A depth gradient runs from north-western to the south-eastern corner. Here changes in depth were assumed to indicate changes in abiotic (e.g. temperature, salinity) and biotic factors (e.g. food availability). Thus similarities between spatial structuring of cpue biomass index and depth can be interpreted as a general habitat association. However, fish distribution patterns are not controlled by a single factor (Rose et al. 1994).

At the greater spatial scale of the "total area", displaying a greater heterogeneity of the water depth, the parameters *rel.* C_0, *SpD* and *pR* (Table 1) calculated for haddock are most closely related to depth. This indicates that on this survey scale haddock developed the strongest habitat association, followed by whiting, which aggregated in patches of 11.4 km in diameter. The mapped density of cpue biomass index for haddock (Fig. 4) confirms the strong association with depth, since high cpues of haddock coincided with the lowest depth. Haddock maintain the same temperature range in winter and summer by changing their depth distribution (Perry 1994). Thus thermal conditions might have marginal influence on the detected strong habitat association. But due to the fact that the area of investigation is situated in the centre of haddock distribution, catch ability is high and fish distribution is thought to be quite uniform. Our results on the spatial distribution of corresponding cpue values from "box D" support this view, as can be inferred from the weak spatial structuring (liner model and relatively high nugget value). Thus, homogenous habitat conditions are most probably responsible for the nearly random distribution of haddock within "box D". In an analysis of haddock predation on sand eel in box D, a weak aggregation behaviour of haddock was obvious (Temming 2004). Stomachs of haddock contained more sand eel than did whiting stomachs, indicating a competitive advantage of the benthivorous haddock due to a more effective hunting method.

Similarly, whiting too was distributed in coincidence with depth (Fig. 4), showing high-density patches in the area of least water depth. Furthermore, a spatial overlapping of high cpues of whiting and haddock is obvious. This implies that whiting and haddock favour analogous habitat conditions. In winter and spring the spatial pattern of the sea surface temperature has a strong influence on the spatial distribution of whiting in the northern North Sea, whereas such a relationship is absent in summer (Zheng 2002). This may be due to a stratification of the water body during summertime, because whiting can be regarded as demersal. In our study, the inferred habitat association of whiting indicates that temperature could have had some influence on the formation of spatial patterns, since this fish prefers colder waters at greater depths. However, the fact that whiting also developed a mean level of spatial structuring in "box D", in contrast to haddock, contradicts this conclusion. An alternate explanation is that the spatial depth-dependent distribution of available food (e.g. sand eels) might have influenced the distribution of haddock and whiting. In box D the local population of adult whiting was almost exclusively feeding on sand eels Mergardt (1997) and a highly aggregative behaviour of whiting within box D, with highest fish concentrations in the south-western part of the area, has been described (Temming 2004). These results and our data support the hypothesis that in the study periods a patchy distribution of sand eels might have determined the aggregation behaviour of whiting in this area.

Our results show that cod developed a weak habitat association at the greater spatial scale of the "total area", indicated by great differences in the estimated parameters *pR* and *SpD* in comparison to the ones estimated for water depth (Table 1). Positive relationships of the spatial distribution of cod to thermal conditions in cold northern waters, negative relationships in warm waters and an absence of relationship in intermediate waters were reported (Planque 1998); however, cod was not consistently associated with particular depths either in spring or in summer (Perry 1994). Hence, the patchy distribution of cod in our study was probably triggered by biotic rather than abiotic habitat factors. Although habitat association of cod was weak, most patches were formed in the shallower part of the "total area" (Fig. 4). Consequently, spatial structuring of cod cpue biomass index remains at the same level in "box D", corroborating the idea that prey distribution might have triggered the patchy distribution in this area.

The greatest practical range was found for dab at the greater spatial scale of the total area. Whereas spatial structuring was strongly developed ($SpD_{\text{total area}} = 75.4$), patchiness was low, because dab aggregated in a single patch with a diameter of 18 km. Kriged dab biomass was highest in a homogenous region, where changes in depth were marginal (Fig. 4), indicating only a weak relation of dab distribution with habitat conditions. We assume that aggregation of this fish was more closely related to biotic factors like food availability or social behaviour. Furthermore, the centre of dab distribution is located in the southern North Sea, so that the low level of patchiness might also be caused by the low fish abundance in our study area. In contrast, patchy distributions of medium-sized and great dab were observed in the German Bight, were dab is the most abundant species (Stelzenmüller et al. 2004).

The lowest level of spatial structuring and no habitat association were observed for herring at the greater spatial scale. Patchiness was most clearly indicated by the low patch diameter of 2.8 km, whereas most of the patches were located in the western part where water depth is least. At the smaller spatial scale almost no spatial structuring was detected, indicating an almost random distribution of herring within box D. It was suggested that patch formation of herring depends on topography and substrate of the seabed, water temperature, salinity, water depth and food availability (Maravelias et al. 1996).

Regardless of the survey scale, haddock was the most abundant species both within "box D" and the "total area", followed by whiting and herring. Generally, high kriged abundance in this area is most likely due to the fact that haddock tends to concentrate around the Orkney and Shetland Islands for feeding (Zheng et al. 2002) and that our the investigation area is situated close to the feeding grounds. Also the centre of high whiting abundance is reported to be in the northern North Sea (Zheng et al. 2001), explaining the high mean biomass index in this study.

Mean cpue biomass indices for all species investigated at both survey scales were obtained by ordinary and universal blockkriging with a drift in relation to the east co-ordinates. When employing the trend component, kriged estimates with minimised variability were received. Classical and geostatistical estimates of mean biomass were in good agreement in almost all cases, but a great reduction of corresponding variability was detected (Table 2), demonstrating a considerable spatial phenomenon: At both survey scales the classical coefficient of variation indicated higher variability than the geostatistical coefficient of variation (Table 2). The greatest absolute reduction of variability, when calculating the geostatistical variance, was detected for whiting and herring within the "total area" and for herring within "box D". With the sole exception of herring, the absolute reduction of variability by geostatistical estimations was higher at the greater survey scale of the "total area". The greatest difference in mean biomass index between the survey scales was found for whiting and haddock, while this was quite stable for herring, cod and dab.

Our findings support the assumption of strong habitat association of whiting and haddock, because mean kriged cpue biomass indices clearly increased within the area of box D, where habitat conditions were inferred to be homogeneous. Conversely, for cod and dab the spatial aggregation modelled in this study is not strongly associated with habitat conditions. Thus differences in mean kriged abundance at both survey scales are marginal regarding these species.

5 Conclusions

Although the differences in the spatial dimension at both survey scales investigated were rather small, the degree of development of spatial structuring of fish density differed clearly in any case. Hence, at small scale ("box D") spatial structuring of cpue biomass indices were almost negligible for haddock, herring and dab, where variability is mainly due to random effects and/or microvariability. Conversely, cod and whiting were the only species from "box D" in which almost half of the total kriged variability is due to spatial structuring.

It is important to note that "box D" has a lower spatial dimension than does the total area and that the spatial structuring of cpue biomass indices could have a strong influence on the kriged estimation error under such circumstances. This view is supported by the fact that differences between the modelling results for both scales were most pronounced for those fish species in which a strong habitat association was detected by our spatial analysis. Therefore, a more intensive sampling is recommended to capture most of the sample variability and to reduce the nugget variability, even at the smaller scale, especially for those species for which a clear distribution trend can be expected. This agrees with a simulation study (Petitgas 2001), where allocating more sampling to the experimental design after detecting a trend resulted in a lowered bias and a better precision of kriged abundance estimates. Our results show that considering fish aggregation patterns for biomass estimates by applying geostatistics can lead to an enormous reduction of the estimation error, even at smaller scales.

Furthermore, habitat associations inferred in this study were more pronounced with increasing survey scale, indicating that for some species a great proportion of variability, calculated from large-scale survey designs (like IBTS), could be due to species-specific aggregation patterns, resulting in more precise estimates.

The location of the area of investigation compared to the distribution centres of the species might have played an important role when analysing the spatial distribution of the fish and interpreting possible factors, which give reason for patch formations. Thus, our results should be considered in the design for monitoring programs, for example in the context of the construction of offshore windmills or the installation of Marine Protected Areas, since an accurate assessment of spatial distribution patterns of target species within different areas at different times requires an exact knowledge of the level of habitat association and species-specific distribution patterns.

In summary, the survey scale is important when analysing spatial patterns and estimating mean biomass indices. In the future more effort should be invested in sound analysis of relations in spatial structuring of fish spatial distribution and habitat conditions, so as to detect small-, meso- and large-scale trends in distribution patterns and to derive more precise estimates.

6 Acknowledgements

This work is part of the PhD thesis of V. S. at the Carl von Ossietzky Universität, Oldenburg, Germany, supported by the Scholarship Program of the German Federal Environmental Foundation (Deutsche Bundesstifung Umwelt, Osnabrück; No. 20002/290).

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KAPITEL 5

Assessing impact of fishing gear type on the analysis of spatial distribution of the dab (*Limanda limanda*) within the German Bight

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Abstract

This study focuses on the impact of fishing gear type on analysing spatial patterns of three size classes (age groups) of *Limanda limanda* (dab) in the German Bight, employing geostatistics. During a comparison fishing experiment in December 2001 within a 10 x 10 nautical miles sized monitoring area, the gear efficiencies of a 7m-beam trawl and an otter trawl for different size groups of dabs were investigated. A structural analysis, carried out for each size group of dab and type of gear, showed a presence of spatial autocorrelation in the catch data in any case. The restricted maximum likelihood estimation method (REML) was used to estimate parameters of spherical and Gaussian models. An increased gear efficiency of the 7m-beam trawl was detected for small and medium sized dab, while gear efficiency was similar but lower for large dab. Results show that separate spatial analysis for three size classes (age groups) of dab were essential to avoid interaction of spatial information and to decrease variability. Further, the use of an efficient sampling gear leads to an improved resolution of spatial structuring, but does not result necessarily a reduction of nugget variability. In cases of high abundance and similar gear efficiency, ecological parameters derived from a spatial analysis are also in good agreement. We conclude that both abundance and gear efficiency are affecting a robust spatial analysis. Thus, satisfying results cannot be obtained, when one gear is used for several target species, unless the gear efficiency and/or species abundance is high. Therefore, to achieve reliable results of a structural analysis and an accurate spatial assessment of fisheries data, we recommend considering the combination of the abundance of the target species (biological group) and efficiency of the sampling gear.

Key Words: dab, gear efficiency, REML, spatial distribution pattern, variogram

submitted to: Fisheries Research

1 Introduction

Conflicting interests in management plans for the North Sea and especially for the German Bight such as plans for the implementation of Marine Protected Areas (MPA) vs. plans for the operation of offshore windmills requires growing attention and precaution. The latter produced contradicting discussions about their impact on the marine life. These conflicting interests call for long term monitoring programs assessing the impact and influence of MPAs and wind parks on the marine environment in the North Sea, in particular regarding possible changes in the spatial distributions of various species, including fish, within distinct areas. Such impact assessments are cost-effective and the proper choice of an experimental design is very crucial for this procedure.

Regarding a simple random sampling design, such as normally implemented for the identification of MPAs or for monitoring windmill construction sites, observations are assumed to be independent from each other, and mean and variance estimates can be derived directly from the sample values without any assumptions about the spatial distribution of the population (Petitgas 2001). But in cases where random sampling is not carried out on a specific spatial scale, any underlying spatial structure in the distribution of the organisms can eventually lead to a bias in the study. It is, however, not possible to detect such a bias a priori, since an appropriate scale of the spatial distribution of any species of interest is generally unknown (Maynou 1998). Furthermore, classical abundance estimates could mask a population decline, as fishing might have been performed on an aggregated population and catch rates could be locally high (Hilborn and Walters 1992). For example, the stock decrease of Atlantic cod (*Gadus morhua*) in the waters of Newfoundland was not associated with a clear signal in the cpue-data (Hutchings 1996) but with a change in the distribution pattern. A sound analysis of spatial structuring of fish can be achieved by geostatistical methods. In fisheries, geostatistics is used to optimise sampling strategies (Petitgas 1996), to estimate catch data and corresponding variances, taking into account the existence of spatial structures (Conan et al. 1992; Warren 1997; Maynou 1998; Fernandes and Rivoirard 1999), as well as to map estimated distributions and spatial patterns of organisms (Maravelias et al. 1996; Lembo et al. 1999). Spatial structures depend on the species and the age class considered (Maynou et al. 1996; Fernandes and Rivoirard 1999; Rivoirard et al. 2000; Stelzenmüller et al. 2004a) they can also vary with time of day (Rivoirard et al. 2000; Wieland and Rivoirard 2001), and with the sampling period (Freire et al. 1992; Hutchings 1996; Rueda and Defeo 2001). Further geostatistical methods were used to estimate probabilities to catch more than a certain amount of fish in order to define Marine Protected Areas (Stelzenmüller et al. 2004b).

Quite often environmental impact studies rely on data obtained from different fishing gears, assuming that no bias will be introduced by this fact. Although some information is available, indicating that selectivity and vulnerability of the target species differ between different types of fishing gear (Gunderson 1993), an exploration of possible effects of two different standard gears on a spatial analysis of catch data is still missing. As a consequence, this study focuses on the assessment of the impact of different fishing gears on the analysis of spatial structuring of catch data for the dab, *Limanda limanda*, employing geostatistics. This flat fish is a common and abundant species in the German Bight (Rijnsdorp et al. 1992). A comparative fishing experiment was carried out in December 2001 in the German Bight within box A, one of the standard monitoring areas of the German small-scale bottom trawl survey (GSBTS) (Ehrich et al. 1998). Randomly distributed stations were sampled by a 7m-beam trawl and an otter trawl from the German research cutter “Solea”. Since in a previous study it has been shown that different biological categories might have different spatial patterns (Stelzenmüller et al. 2004a), we distinguished three size classes (age groups) of dab. Our results provide essential information which might help to optimise monitoring strategies, e.g. in the context of establishing offshore wind parks.

2 Material and Methods

2.1 Survey area and experimental set up

The study was undertaken in an area of 10 x 10 nautical miles (nm) located in the inner German Bight (box A, Fig. 1), which is one of the standard sampling areas of the German Small-scale Bottom Trawl Survey (GSBTS) in the North Sea (Ehrich et al. 1998), during December 2001 (Fig. 1). Catch data were assembled aboard the German research cutter "Solea". Two different survey standard gears were used to compare their catch efficiency and their ability to detect spatial patterns of fish biomass indices. The first net was the so-called cod trawl. This otter trawl has an opening height of 3.5m and a horizontal opening between the wingend tips of about 23m. The net is provided with a rubber disc roller gear. The codend is equipped with a fine mesh liner (20mm). The second net was a 7m-beam trawl. It is characterised by a 7m beam, 5 tickler chains and an overall net length of ca 21m. The normal 80mm codend is also fitted with a 20mm mesh liner.

In total 49 stations were sampled during daylight, 25 stations with the 7m-beam trawl (referred to as n1) and at 24 stations with a cod trawl (referred to as n2). Each day the gear has changed to avoid the effect of changing environmental conditions during the period. The locations of sampling and trawl directions were selected randomly. The trawling time was 30 min. at a trawling speed of 3.5 knots. The trawl positions were taken as midpoints of the hauls converted to an absolute measure in km (easting and northing), relative to 54°27′N and 6°58′E.

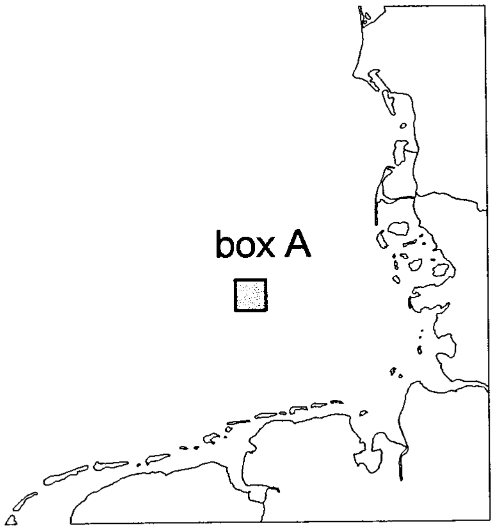

Fig. 1: Location of the investigation area box A within the German Bight.

2.2 *Biological categories considered*

Spatial patterns can vary with age (Fernandes and Rivoirard 1999). To correct for this effect all catch data for dab (*Limanda limanda*) were separated into three size groups, representing different age groups. Regarding dab these were < 9.5 cm (0-2 years old, referred to as d1), 9.5–19.5 cm (2-7 years old, referred to as d2) and > 19.5 cm (older than 7 years, referred to as d3) (Heessen and Daan 1996). Taking into account these categories will help to reduce the random errors in the spatial models.

2.3 *Preparatory data analysis*

Numbers of fish per 30 min trawl time were converted into biomass in kg 30 min^{-1} (catch per unit effort, cpue) on the basis of the length-weight relationships for each biological group considered. Due to the differences between the swept area of the fishing gear employed, data were standardized to biomass per 10 000 m^2 (kg ha^{-1}) to ensure comparability. Therefore the swept area of each haul was calculated by multiplying the towed distance over ground (satellite positions) by the effective width of the gear (n1 = 7 m, n2 = 23 m). A box-and-whisker plot (Tukey 1977) was computed to explore the presence of extreme sample data. Data were defined as outliers when the values were greater in magnitude than 99 % of all sample data. Furthermore, large values of the sample data were scrutinised by creating post plots, where cpue biomass indices were plotted proportional to the highest sample value at each sampling station. A nonparametric one-way Analysis of Variance (Kruskal-Wallis rank sum test) (Hollander and Wolfe 1973) was performed for each biological group to test if cpues of both nets employed (n1 and n2) differ significantly.

2.4 *Structural analysis*

For this study the structure of spatial variability of $Z(x)$ (cpue of each biological group separated by the factor "gear" and total catch d2) was assessed by an experimental covariance function. Experimental semivariograms $\hat{\gamma}(h)$ were used to describe the spatial structure of fish biomass. The semivariogram outlines the spatial correlation of data measuring the half variability between data points as a function of their distance. In the absence of spatial autocorrelation among samples the semivariance is equal to the variance of $Z(x)$. Omnidirectional semivariograms were computed using the classical (Matheron 1971) and the robust "modulus" estimator, which is supposed to be resistant against extreme values (Cressie (1991):

$$\hat{\gamma}(h) = \left\{ \frac{1}{N(h)} \sum_{x_i-(x_i+i)\sim h} \left| Z(x_i+h) - Z(x_i) \right|^{\frac{1}{2}} \right\}^4 \Big/ (0.914 + (0.988/N(h)) \qquad (1)$$

where $Z(x_i)$ is the realisation of the variable of study (biomass) at station x_i, $Z(x_i+h)$ is another realisation separated from x by a discrete distance h (measured in km) and $N(h)$ is the number of pairs of observations separated by h.

Extreme values, which are common in sample data derived from a winter survey may spoil the structural analysis (Rivoirard et al. 2000), therefore the effect of extreme values on the latter was assessed. Webster (2001) recommend to perform a structural analysis with and without these outliers, if they cannot be regarded as measurement errors, to assess the effect on the experimental semivariances. Thus the structural analysis of d3 (all catch data), n2 d2 and n2 d3 were carried out by removing temporally the most extreme value from the sample data.

Parameters of Gaussian and spherical models were fitted using a generic estimation method, namely the restricted maximum likelihood (REML) parameter estimation (Cressie 1991), which does not require the computation of experimental semivariograms. The basic idea behind maximum likelihood is to find the values of the parameters for which the observed data are most likely (Diggle 2002). In general, maximum likelihood estimators should be preferred compared to least squares because maximum likelihood is based on careful consideration of how "errors" arise and are distributed, whereas least-squares estimators for most non linear problems are essentially *ad hoc* (Hilborn and Walters 1992). Further REML has proven to generate robust estimates even for a small number of samples and a skewed sample distribution (Rufino et al. submitted).

Additionally, Akaike's information criterion (*AIC*) was computed as a measure of the "goodness-of-fit" to select the most suitable model (Akaike 1973). The model associated with the lowest *AIC* should be chosen (Webster and Oliver 2001). Sokal (1978) related the diameter of an aggregation of a species to the modelled range in the semivariogram. Therefore the practical range (*pR*) was compared for each model fitted in order to detect difference of spatial patterns with sampling gear. The practical range for spherical models is equal to the estimated range and for the Gaussian model equal to *sqrt*(3) *a*. In addition, the observed data were cross-validated by ordinary kriging, which provides a measurement of the reproduction of the data by the model defined and the kriging procedure. The results of this jack-knifing method are given by standardised errors. If the mean of this standardised error (*Zscore*) is zero and the standard deviation (*SD-Zscore*) approximately 1, then the model and the method employed provide an adequate reproduction of the data (Isaaks and Srivastava 1989).

2.5 Density maps

Mapping of density surfaces of the predicted cpue biomass index for dab (d1, d2, d3 derived with n1) was carried out with ordinary point kriging, based on the models fitted using all sample data. This interpolation method estimates the variable values at unsampled locations using the observed values $Z(X_i)$ in the surrounding neighbourhood (Matheron 1971):

$$\hat{z}(X_o) = \sum_{i}^{n} \lambda_i z(X_i) \tag{3}$$

where λ_i are charging weights attributed to each $Z(X_i)$ subject to $\Sigma_i = 1$ in order to guarantee unbiased estimates (Cressie 1991). The uncertainty of the estimation of ordinary pointkriging was expressed by mapping the corresponding kriging variance (Isaaks and Srivastava 1989).

2.6 Estimation of cpue biomass indices

Mean cpue estimates within the area of investigation for all biological groups distinguished $\hat{z}(X_0)$ were obtained by universal block kriging (Isaaks and Srivastava 1989). Block kriging is used as a direct method of biomass assessment in fisheries (Maynou 1998). The computerised algorithm requires the area to be finely discretised; the discretisation used here was a grid of 1 x 1 blocks, which was found to optimise precision of the computation.

When the model fitted is appropriate than the mean cpue estimated by kriging is expected to be similar to the sample mean (Isaaks and Srivastava 1989). Furthermore in order to compare variability of the estimates coefficients of variation of the arithmetic mean (m) and the mean cpue estimated by blockkriging (m_{BK}) were calculated using the classical estimator

$$CV_{class} = s \,/\, m \ [\%] \tag{4}$$

were s is the standard deviation and the geostatistical estimator

$$CV_{geo} = ke \text{ (squared root of mean kriging error)} \,/\, m_{BK} \ [\%] \tag{5}$$

were spatial structuring of data and number of samples were taken into account. For the block kriging procedure all data were used.

3 Results

3.1 *Preparatory data analysis*

Since small dab (d1) were only caught with the 7m beam trawl (n1), possible influence of the fishing gear on spatial structuring could not be compared for the smallest size class. Results of the nonparametric ANOVA show, that the cpue biomass index for d3 does not differ significantly ($\alpha = 0.05$) with gear ($\chi^2 = 2.96$, $p = 0.085$, $df = 1$), in contrast to d2 ($\chi^2 = 25.8$, $p < 0.001$, $df = 1$).

The post plots presented in Figure 2 show that highest dab biomass was detected in the centre of the investigation area, independently from fishing gear used and size class of dab considered. For the smallest size class (d1) high abundance was also detected in the north-eastern corner of the area. For d3 the 7m-beam trawl produced highest cpue values again in the centre, but also in the north-western and eastern parts of box A. These values were considered to be correct and to be part of the sample data.

3.2 *Structural analysis*

Small dab displayed a weak level of spatial structuring of cpue (Fig. 3 a). A spherical model was fitted (Table 1) with a mean patch diameter of 4.9 km and a relative nugget of 59.4 %, indicating that almost 60 % of the total variability are not caused by the spatial component. Experimental semivariograms of cpue biomass index for medium sized dab (Fig. 3 b, e) show a high level of spatial structuring. In both cases, Gaussian models gave the best fit to the data (details of the model parameters can be found in Table 1). The practical range of medium sized dab was estimated to be between 6 and 6.4 km. In all cases the highest level of spatial structuring was detected for large sized dab, indicated by values of the relative nugget of 0 %. Cpue biomass index for d3 was described best by spherical models, regardless of the gear used (Fig. 3 c, f). Catch data of large dab (d3) were analysed using a spherical variogram model. A difference between the estimated patch diameters of d3 is obvious (d3: 1.8, n1 d3: 1.7, n2 d3: 2.7; Table 1). Results of the cross-validation show, that the fitted models and the kriging method give a fair description of the data (Table 1).

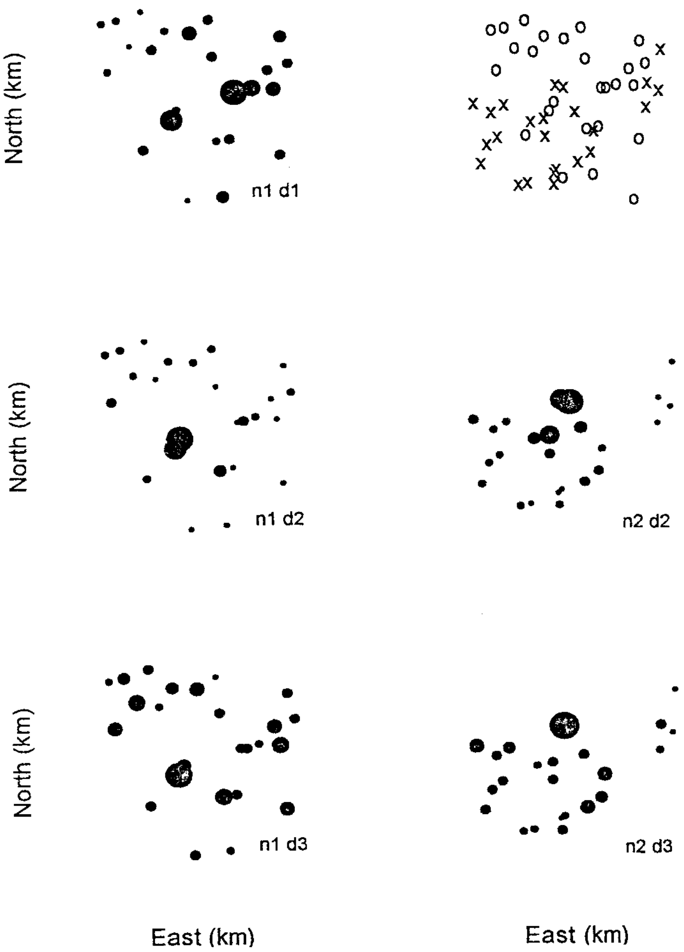

Fig. 2: Spatial distributions (post plots) of sampling stations within box A. With (o) stations sampled with the 7m-beam trawl and (x) stations sampled with the cod trawl. Proportional to the highest cpue a relative measure of abundance at sample locations are provided for the three size classes of dab (d1, d2, d3) and both sampling gears (n1, n2). See material and method section for more details.

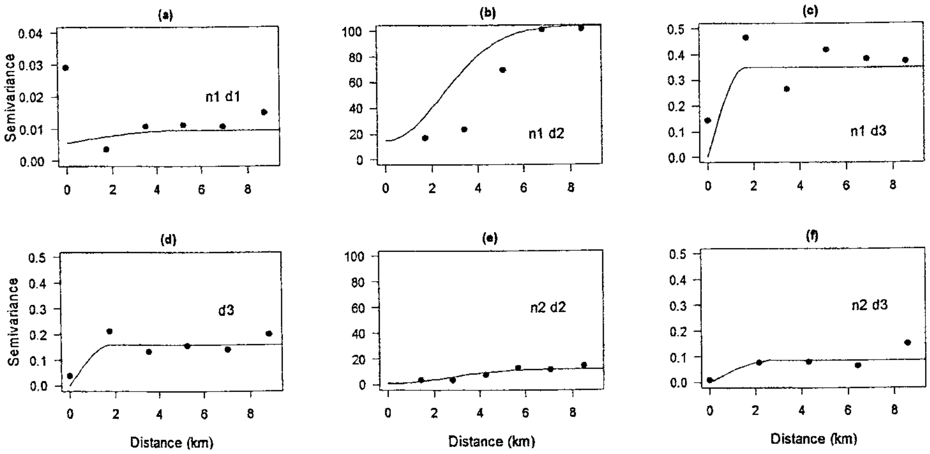

Fig. 3: Experimental semivariograms of small (a), medium (b,e) and large sized dab (c,f) collected with from both nets (n1, n2) and summarised cpue of d3 (d) with Gaussian and spherical models fitted with the restricted maximum likelihood method. See material and method section for more details.

Table 1: Estimated parameters nugget (C_0), partial sill (C) and range (a) of the exponential (exp), spherical (sph) gaussian (gau) models and pure nugget (nug) fitted to the cpue of all biological categories of dab considered. Also the practical range (pR), value of the relative nugget (rel. C_0), the values of the "goodness-of-fit" measure (AIC) and the results of the cross-validation (*Zscore, SD-Zscore*) are listed.

group	*model*	C_0	C	a	pR	*rel.* C_0 *(%)*	*AIC*	*Zscore*	*SD-Zscore*
n1d1	sph	0.01	0.00	4.90	4.90	59.38	-36.90	-0.01	1.00
n1d2	gau	14.97	88.98	3.48	6.03	14.40	137.40	-0.05	0.89
n2d2	gau*	0.93	11.46	3.67	6.36	7.48	106.10	0.02	1.07
n1d3	sph	0.00	0.35	1.65	1.65	0.00	50.04	0.00	1.02
n2d3	sph*	0.00	0.09	2.74	2.74	0.00	13.93	0.04	0.95
d3	sph*	0.00	0.16	1.81	1.81	0.00	51.59	0.01	0.98

* models were fitted to catch data with removed outliers; with n1: 7m-beam trawl, n2: otter trawl, d1: dab of < 9.5 cm (0-2 years old), d2: dab of 9.5–19.5 cm (2-7 years old) and d3: dab of > 19.5 cm (older than 7 years)

3.3 Density maps and cpue biomass indices

The density maps obtained by the kriging procedure and the corresponding kriging errors are presented in Figure 4. Results show that the smallest size class developed mainly two communicating patches located in the centre of box A (Fig. 4, n1 d1), while medium sized dab were distributed in one dominating patch also in the centre of the box. Patchiness was developed most for the largest size class, patches of highest biomass were detected in the centre and in the northern part of the area. Thus, spatial distributions of the three size classes were in good agreement. In any case, kriging errors were highest in the southern part of the box A (Fig. 4, right panel).

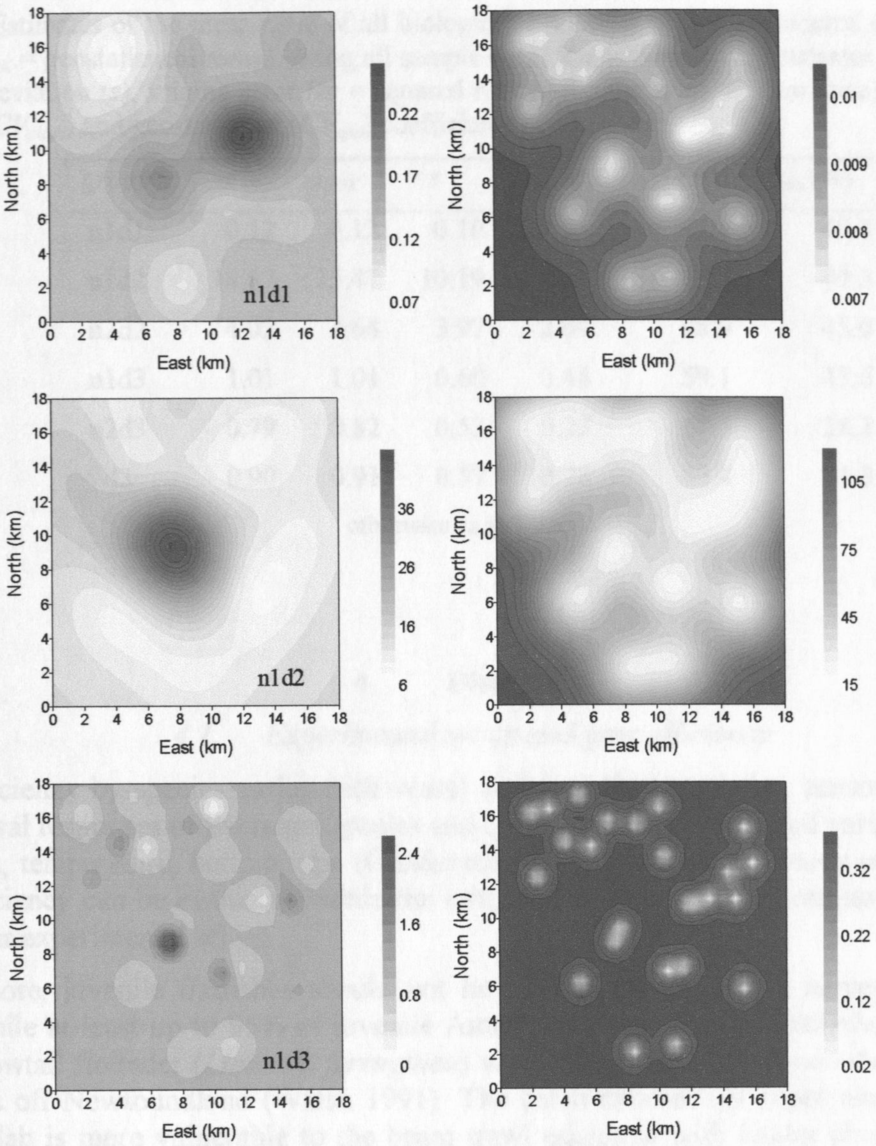

Fig. 4: Density maps of biomass indices for three size classes of dab (d1, d2, d3), derived with ordinary point kriging using catch data of the 7m-beam trawl (left panel) with corresponding kriging variance (right panel). Note the scales differs due to the varying level of abundance and variance.

In general, the most abundant group was the medium sized dab, regarding the 7m-beam trawl yielding a mean cpue of 15.5 kg ha^{-1}. With the cod trawl a mean biomass index of 4.6 kg ha^{-1} was obtained (see Table 2). With the 7m-beam trawl we found a mean cpue biomass index for d1 of 0.12. kg ha^{-1}. Large dab were the second abundant group with total mean catch of 0.91 kg ha^{-1}. Differences in the mean catch of d3 were small between the two sampling gears (n1d3: 1.01 kg ha^{-1}, n2d3: 0.82 kg ha^{-1}). The geostatistically estimated mean cpues were in all cases in good agreement with the arithmetic means (Table 2), but in general, a great reduction of the estimation variance was achieved when taking spatial structuring into account (CV_{class} *vs.* CV_{geo}, Table 2).

Table 2: Estimates of the mean cpue of all biological categories of dab considered (m = arithmetic mean, m_{OBK} = geostatistical mean), using all sample data. Variability of the estimates is expressed as standard deviation (s), kriging error (ke = squared root of the mean kriging variance), as well as the classical (CV_{class}) and geostatistcial (CV_{geo}) coefficients of variation.

group	m	m_{OBK}	s	ke	CV_{class} (%)	CV_{geo} (%)
n1d1	0.12	0.12	0.10	0.05	82.5	45.4
n1d2	14.87	15.47	10.19	6.24	68.5	40.3
n2d2	4.02	4.64	3.97	2.09	98.9	45.0
n1d3	1.01	1.01	0.60	0.44	59.1	43.6
n2d3	0.79	0.82	0.53	0.23	67.5	28.1
d3	0.90	0.91	0.57	0.28	63.4	31.3

otherwise as in Table 1

4 Discussion

4.1 Experimental set up and gear efficiency

Gear efficiency by species varies with vessel and gear characteristics, sensory capabilities, behavioural responses of the target species and a variety of environmental variables like light condition, temperature, bottom type (Gunderson 1993). Thus, in this study only the overall gear efficiency can be evaluated, while the influence of single factors can not be elucidated within our experimental set up.

Furthermore, juvenile flatfishes should not be targets for otter trawl surveys (Gunderson 1993) while at least up to 95% of juvenile American plaice (*Hippoglossoides platessoides*) and yellowtail flounder (*Limanda ferruginea*) were not be detected by an otter trawl survey in waters off Newfoundland (Walsh 1991). The catch data in this paper also show that in general dab is more vulnerable to the beam trawl equipped with tickler chains than to the otter trawl equipped with a rubber disc ground rope. This is well known for a flatfish like dab but it is also shown that the differences decrease with increasing fish length.

This study is not focused on the presentation and explanation of differences in catch rates. It focuses on the spatial analysis of dab distribution, based on catch data of two different gears providing at least representative catches for dab of medium and large sizes. Due to the fact, that the size of the study area resembles a possible construction site of offshore windmills a spatial analysis of catch data is of special interest, especially since adequate information of the variability in fish distribution pattern in space and time, depending on sampling gear, is lacking.

4.3 Structural analysis

Although structural analyses were carried out at the limit for an application of geostatistics, due to the low numbers of sampling stations, the presence of spatial autocorrelation was discovered for all categories considered. Generally, a minimum of 30-50 sampling points is recommended (Legendre 1993), whereas in this study only 24 (cod trawl) and 25 (7m-beam trawl) stations per sampling gear were available. Hence robust geostatistical tools were used and the influence of extreme values on the semivariograms was assessed. Finally, results of the goodness-of-fit statistic and cross-validation show that the modelled structures give a fair description of the data (Table 1).

Our results show a presence of spatial autocorrelation in cpue, regardless of the biological group and sampling gear, whereby the lowest level of spatial structuring was observed for small dab. The estimated patch diameter for d1 is 4.9 km, smaller than those of medium sized dab (6.0 - 6.4 km). This is consistent with the idea that larger fish may tend to form larger associations compared to smaller fish (Rivoirard et al. 2000). In this study, Gaussian models were found to represent best the spatial structuring of d2, regardless of the gear used, indicating a great regularity of the spatial phenomenon (Petitgas 1996). Such continuous behaviour at small distances between sample points could be attributed to the geographically dense distribution of the stations (Fig. 2). The good agreement of the Gaussian models fitted for both types of gear (n1 and n2), although gear efficiency differs, indicate that the detected spatial patterns might be a general characteristics of these size groups of dab, at least in winter time. Conversely, in summer a spherical models described best the detected persistent spatial structures for medium and large sized dab in box A (Stelzenmüller 2004a). In this study, however, sampling was done with another gear and ship (*viz.* a GOV, Chalut à Grande Ouverture Verticale, aboard the German research vessel "Walther Herwig III").

Our results show, that calculated average patch diameters only differ marginally for d2 (6.0 – 6.4 nm). On the other hand this agreement in the range parameter of the variogram models is probably due to an increased biomass of this biological group. This idea is supported by a reported breakdown in the spatial structure of the Atlantic cod (*Gadus morhua*) in the North Western Atlantic. It coincides with a decline in their abundance (Warren 1997; Bowman and Azzalini 1997). Occurring differences in the values of the relative nugget are probably attributed to differences in the gear efficiency. Thus, the low biomass of small sized dab might have caused the weak spatial structuring of this biological group.

The good agreement of cpues of d3 for both fishing gear gave support to perform a structural analysis of large sized dab regarding all 49 sampling locations. The resulting practical ranges are different from those obtained for both gears alone (Table 1). We infer that either the low abundance of this biological group and/or the generally reduced gear efficiency of both gears for large sized dab might have affected the structural analysis. The nugget variability has three physical interpretations, which cannot be distinguished in practice 1) purely random component of the spatial distribution, 2) measurement error and 3) a sum of structures which have ranges smaller than the sampling mesh grid (Petitgas 1996). Our results show, that the efficiency of the sampling gear has an influence on the modelled nugget variability and relative nugget respectively, whereby gear efficiency can be assigned as a "measurement error".

4.4 *Spatial distribution patterns of biomass indices*

Mapped spatial distributions of fish biomass indices show that all biological categories were most abundant in the centre of the area, while the corresponding distribution patterns differed clearly among the size (age) groups investigated. An intermediate level of patchiness was found for small sized dab, a low level for medium and the strongest level for large sized dab, indicating that underlying causes for the patch formation might differ for the distinguished size classes. Possible reasons include the distribution of prey species (such as epizoobenthos) and/or different fish behaviour due to reproduction (Valiela 1995). Additionally, abiotic variables may also induce a spatial pattern, but salinity and temperature were more or less homogeneous within the study area and information on other variables is not available. In any case, application of geostatistics resulted in a reduction of the variability of mean catch estimates, since geostatistical coefficients of variations always showed lower values than the classical ones. Furthermore, our results show that medium sized dab were the most abundant biological group followed by large and small sized dab. Possible reasons for the relatively low abundance of small dab might be due to a low recruitment in the previous years and/or to the selectivity of the gears. The fishing mortality is a good reason for the relative low abundance of large dab.

5 Conclusions

Our results indicate that a spatial analysis of fishery data may be greatly improved when considering different biological categories such as size (age) groups because interaction of different spatial information is avoided and the variability of the estimates much lower. Furthermore, in cases of high detected biomass indices and similar gear efficiencies, we inferred likewise similar ecological parameters from this spatial analysis, e.g. range parameters of the variogram models. Thus, when fish abundance is high, possible effects of gear efficiency on the structural analysis are assumed to be of minor importance. Conversely, the lower the fish abundance the more efficient must be the sampling gear to ensure accurate spatial assessments (Fig. 5). Hence we assume, that abundance and gear efficiency are both affecting a robust spatial analysis. Employment of an efficient sampling gear on the other hand does not imply necessarily low nugget variability (n1d2 *vs.* n2d2). Although the nugget effect has a marked influence on the geostatistical estimation variance, a reduction of nugget variability should not be the main indicator for a satisfying structural analysis.

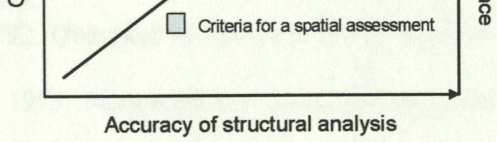

Fig. 5: Qualitative relationship between gear efficiency, accuracy of a structural analysis, species abundance and effect of gear efficiency on structural analysis of catch data of a given target species. The grey shaded box indicates the necessary qualitative criteria for a satisfying spatial assessment.

Furthermore, utilisation of an efficient sampling gear resulted in an improved resolution of the spatial patterns. Assuming that in a standard survey a given sampling gear will not have the best efficiency for all target species and/or biological groups of interest, we cannot expect optimal results from a structural analysis in any case. In Figure 5 the optimal qualitative criteria for a spatial assessment of catch data derived from this study are compiled (shaded box). Hence, to achieve reasonable results of a structural analysis and a satisfying accuracy and validity of a spatial assessment of fisheries data, we recommend considering the combination of the abundance of the target species and the efficiency of the sampling gear when interpreting the results.

6 Acknowledgements

We thank Dr. U. Damm (Institut für Seefischerei, Hamburg) for carrying out the comparison fishing experiment. This work is part of the PhD thesis of V. Stelzenmüller at the Carl von Ossietzky Universität, Oldenburg, Germany, supported by the Scholarship Program of the German Federal Environmental Foundation (Deutsche Bundesstifung Umwelt, Osnabrück; No. 20002/290).

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KAPITEL 6

Spatial analysis of twaite shad, *Alosa fallax* (LACEPÈDE, 1803), in the Southern North Sea: Application of non-linear geostatistics as a tool to search for Special Areas of Conservation*

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Abstract

This study aims to evaluate the suitability of non-linear geostatistics and indicator kriging (IK) as a tool in environmental impact assessment and nature conservation, in particular to search for potential Special Areas of Conservation (SAC) for the endangered fish species twaite shad, *Alosa fallax* (LACEPÈDE, 1803) within the German Exclusive Economical Zone (EEZ) of the North Sea. To analyse the spatial distribution of this fish species, data on standardised biomass index (catch per unit effort, c.p.u.e., kg x 30 min^{-1}) from 1996 to 2001 were used, regarding the third and fourth quarters of each year, respectively. Thereby we assume that the spatial distribution can be described as a time-invariant process. This assumption is supported by information on annual sampling effort, allocation of hauls and spatial distribution of the positive catches. All indicator variograms obtained for different c.p.u.e. cut-off values displayed distinct spatial structures, clearly indicating that the indicator variables were spatially autocorrelated. Gaussian models were fitted by least-squares methods and were evaluated with a goodness-of-fit statistic. Subsequently, IK was employed to estimate the probability of exceeding the c.p.u.e. cut-off values for the twaite shad in the investigation area. These were highest in the Weser- and Elbe-estuary, probably because of migrations of twaite shad to and from estuaries at the time of investigation due to spawning, while within the German EEZ of the North Sea no such areas with increased probabilities could be discerned. Thus, although available data did not allow to identify and implement any SAC in the German EEZ, the methods employed here can be regarded as a promising management tool in biological conservation issues.

Key Words: *Alosa fallax*, indicator kriging, nature conservation, spatial analysis

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**pre-print*: International Review of Hydrobiology. (2004). 89, 337-351

1 Introduction

Within the European Union, the national Exclusive Economical Zones (EEZ) are of increasing importance for environmental studies due to continuing anthropogenic impacts, such as the planning and building of offshore wind farms, and the demand to implement conservation areas. Any such study requires sound scientific knowledge and the use of the best available tools like explicit spatial analyses, e.g. application of geostatistical methods, to account for spatial autocorrelations in environmental data (GOOVAERTS, 1997; LEGENDRE, 1993; ROSSI et al., 1992; WEBSTER and OLIVER, 2001). Further the application of spatial statistical techniques in conservation and ecological research has the potential to provide new insights and ideas that might otherwise remain undiscovered (CARROLL and PEARSON, 2000). In particular, the European Union is in the process of developing a European network of protection areas, called NATURA 2000, according to the Directive 92/43/EC on the Conservation of Natural Habitats and of Wild Flora and Fauna ("Habitat Directive"). The Natura 2000 network consists of Special Areas of Conservation (SACs) and Special Protection Areas (SPAs) designated under the Birds Directive.

Thus, the focus of this study is to evaluate a methodology of spatial analysis which could serve to search for and eventually identify potential protected areas within the German Exclusive Economical Zone (EEZ) of the North Sea for the Annex II fish species twaite shad, *Alosa fallax* (LACEPÈDE, 1803). The spatial distribution of twaite shad within the EEZ and the adjacent coastal areas was investigated for the time interval between 1996 and 2001.

Twaite shad is an anadromous species, which normally lives in the sea but enters the rivers for spawning. Spawning takes place in spring, usually between April and June. The eggs are released into the water column and sink into the interstices between coarse gravel substrates. After hatching, the fry develops and slowly drifts downstream. In the third and fourth quarters of the year the fish move back to the coastal waters (see http://www.fishbase.org/ for details). Population declines in many parts of Europe have been attributed to pollution, overfishing and migratory route obstructions (WHITEHEAD, 1985). The twaite shad is found along the western coastline of Europe, from southern Norway to Morocco and along the eastern Mediterranean, but has declined substantially throughout Europe (RESHETNIKOV et al., 1997).

The present analysis is based on catch data for twaite shad provided by the Institute of Sea Fisheries in Hamburg. We employ a geostatistical analysis of the catch data, which takes into account the natural aggregation of the fish and results in an unbiased spatial estimation of distribution patterns (CONAN et al., 1992; MAYNOU, 1998).

In fisheries geostatistics is used to optimise sampling strategies (PETITGAS, 1996), to estimate catch data and corresponding variances, taking into account the existence of spatial structures (CONAN et al., 1992; FERNANDES and RIVOIRARD, 1999; MAYNOU, 1998; RIVOIRARD et al., 2000; WARREN, 1997), as well as to map the estimated distributions and spatial patterns of organisms (LEMBO et al., 1999; MARAVELIAS et al., 1996). Due to the skewed distribution of our data, caused by the rarity of catches of this species and a great proportion of "0-catches", a non-linear geostatistics approach, namely indicator kriging (JOURNEL, 1983), was applied to evaluate the spatial distribution of twaite shad within the German Exclusive Economical Zone (EEZ) of the North Sea. This is an example to illustrate that indicator kriging is a potentially useful tool in nature conservation issues as well as in environmental impact assessment.

2 Materials and Methods

2.1 Data

Catch data for twaite shad (*Alosa fallax*) from 1996 to 2001, sampled in the third and fourth quarters of each year within the German Exclusive Economic Zone (EEZ) and the adjacent coastal zones, were taken from the database of the Institute of Sea Fisheries, Hamburg (Fig. 1). The database includes data from several standard monitoring surveys of the Institute of Sea Fisheries, thus data used were derived from surveys not designed to assess the abundance of twaite shad. This time period was selected because it also includes the end of the spawning season of this anadromous fish species. Available data did not allow to consider further biological categories (groups) in order to explore biological factors eventually influencing the spatial structure of fish populations. Only standardised catch data, expressed as catch per unit effort (biomass index , c.p.u.e., kg x 30 min^{-1}), were taken into account. Data were obtained under standard IBTS (International Bottom Trawl Survey) protocol conditions aboard the German research vessels "Walther Herwig" and"Walther Herwig III", involving the standard net GOV (Chalut à Grande Ouverture Verticale) or aboard the German research cutter "Solea", using the standard codnet. No significant differences in catch efficiency were found between the two kinds of equipment (S. Adlerstein and S. Ehrich, unpublished data). The trawl positions were obtained as midpoints of the hauls, converted into an absolute distance in km (easting and northing) relative to 53°20'N and 3.0°E (outside the EEZ).

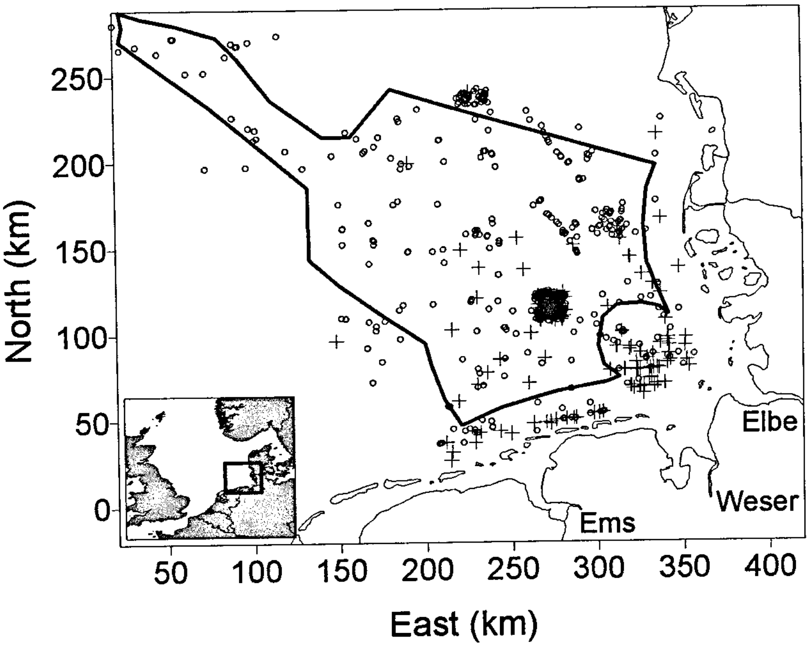

Fig.1: The Exclusive Economical Zone (EEZ) and adjacent coastal areas with the spatial distribution (post plot) of sampling stations for twaite shad, *Alosa fallax* . (+) sampling stations with a minimum of one caught twaite shad, (O) 0-catches. Data (1996 – 2001) provided by the Institute of Sea Fisheries, Hamburg.

2.2 Preparatory data analysis

The c.p.u.e. data for twaite shad at the spatial positions of the sampling stations were summarised as a post plot to assess the overall distribution of the positive catches. Further to assess the annual allocation of hauls with spatial distribution of the positive catches as well as to test the assumption of a time-invariant process (see below) post plots were computed (RIVOIRARD et al., 2000). Furthermore, a frequency distribution of c.p.u.e. classes was computed as well as the average wet weight (kg) of any twaite shad caught. The average weight of a caught twaite shad was calculated by considering all the standardised data (described above) available for 1986-2001 in the data base of the Institute of Sea Fisheries, Hamburg. Finally, to assess the distance between sampling locations, the "nearest neighbour distribution" was computed (CLARK and HARPER, 2001).

2.3 Geostatistical data analysis using indicator kriging

General considerations

Highly skewed data and the prevailing 0-catches of twaite shad gave reason to apply a non-parametric geostatistical method, namely indicator kriging (IK). JOURNEL (1983) proposed this new methodology based on a prior transformation of the continuous variable $z(x)$ to an indicator variable $i(x, z_c)$, thus opening an interesting means of non-linear estimation of spatial distributions. The method of IK has been widely accepted for application to natural resources and also for analysis of categorical data (BIERKENS and BURROUGH, 1993). From catch data $z(x)$ (biomass index, c.p.u.e., kg x 30 min^{-1}) indicator variables $i(x, z_c)$ were created by scoring them 1 if $z(x)$ is more than or equal to a specified threshold or cut-off, z_c, and 0 otherwise:

$$i(x;z_c)=\begin{cases} 1 & if\ z(x)\geq z_c \\ 0 & otherwise \end{cases} \tag{1}$$

If $z(x)$ is a realisation of a random process, $Z(x)$, then $i(x, z_c)$ may be regarded as the realisation of the indicator random function, $\Omega[Z(x) \geq z_c]$ (WEBSTER and OLIVER, 2001). Ordinary kriging of $i(x_i;z_c)$ gives the estimated probability that the value is above the cut-off value at point x_i. However, GOOVAERTS (1997) recommended selection of threshold values (z_c) for the structural analysis according to ecologically relevant information — for example, critical values in ecology or environmental standards in ecotoxicology (ISAAKS and SRIVASTAVA, 1989). It is furthermore advisable to select a series of thresholds within the range of values of ecological importance, instead of just one single cut-off.

The most frequently used method of IK is median IK, based on a single structure of spatial variability or semivariogram. This structure is derived from the median cut-off value and is used to estimate the indicator set obtained from the cut-off values (CHICA-OLMO and LUQUE-ESPINAR, 2002). It is assumed that the different indicator semivariograms are equal in their shapes and underlying proportional covariances, and consequently the weights of the kriging systems are the same for all cut-offs (DEUTSCH and JOURNAL, 1993). In this analysis several indicator semivariograms were computed before to determine whether they can all be described by a common model. However varying nugget effects and differences in the development of spatial continuity at different thresholds, as occurred in this study, require a structural analysis for each indicator semivariogram considered (ISAAKS and SRIVASTAVA, 1989).

Structural analysis

For each cut-off (z_c) a variographic analysis was performed to obtain the indicator semivariograms. An indicator random function has a semivariogram which is analogous to the semivariogram of a continuous variable (MATHERON, 1971; PANNATIER, 1996). The expected semivariances were estimated from the indicator data (WEBSTER and OLIVER, 2001):

$$\hat{\gamma}^{\Omega}_{z_c}(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} \left\{ i(x_i; z_c) - i(x_i + h; z_c) \right\}^2 \tag{2}$$

where $m(h)$ is the number of pairs at the distance (h) and $i(x_i;z_c)$ is the realisation of the indicator random function. Annual experimental indicator semivariograms for the c.p.u.e. cut-offs of 0, 0.07, 0.21, 0.35, 0.49 and 0.7 kg x 30 min^{-1} were investigated separately. These cut-off values were determined by considering the average weight of caught twaite shad and the c.p.u.e. frequency distribution. Considering that cut-off values represent multiples of the mean weight of caught twaite shad, estimated probabilities could be interpreted as the probabilities to catch minimum 1, more than 1, 3, 5, 7 and 10 „mean“ twaite shads.

Omnidirectional and directional indicator semivariograms were computed because anisotropy was detected, suggesting that indicator variables were more continuous in the eastern direction. Since theoretical semivariograms used for kriging are based on isotropic models (ISAAKS and SRIVASTAVA, 1989), directional indicator semivariograms were corrected, due to the presence of a geometrical anisotropy (CRESSIE, 1991), by the ratio of the major axis (East/West) to the minor axis (South/North) of the search ellipse (PANNATIER, 1996), yielding a value of 2.2. Assuming that the spatial distributions of the species studied at any time can be described by the same time-invariant process (RIVOIRARD et al., 2000), the annual directional experimental indicator variograms (1996-2001) were subsequently averaged for each cut off value.

From available theoretical semivariogram functions, Gaussian models were fitted to the indicator semivariograms. This model type represents phenomena which are continuous or similar at short distances (PETITGAS, 1996) and, most importantly, gives a fair description of the data. The following equation was employed (PANNATIER, 1996):

$$\begin{aligned} &\gamma(0) = 0 \\ &\gamma(h) = C_0 + C\left\{1 - e^{\left(-\frac{h^2}{a^2}\right)}\right\} \quad when \quad h > 0 \end{aligned} \tag{3}$$

where γ is the semivariogram, h the distance between two points of interest, a the range of influence of the semivariogram, C the sill of the Gaussian component and C_0 the nugget effect. The modelled range can be related to the diameter of the patch size in an aggregated species (SOKAL and ODEN, 1978). The practical range in the Gaussian model (*viz.* the actual patch size) is given as $\sqrt{3} \cdot a$. The parameters of the Gaussian models were estimated by non-linear least squares methods (CRESSIE, 1991; ZIMMERMAN and ZIMMERMAN, 1991).

A goodness-of-fit statistic was used to assess the estimated models and to select those showing the lowest values for the modified Cressie statistics, MCS (CLARK and HARPER, 2001), adapted to IK:

$$MCS = \frac{1}{\sum_h M_h} \sum_h M_h \left(\frac{\hat{\gamma}^{\Omega}_{z_c}(h) - \gamma(h)}{\gamma(h)} \right)^2 \qquad (4)$$

where M_h are the number of pairs at distance h, $\hat{\gamma}^{\Omega}_{z_c}(h)$ is the indicator semivariance at distance h and $\gamma(h)$ is the model value at distance h. Subsequently, a cross-validation procedure was employed to evaluate the appropriateness of the indicator semivariograms (CLARK and HARPER, 2001). A good representation of the data by the model estimates derived from IK can be assumed if the cross-validation procedure yields a mean of the standardised error around 0 and its standard deviation around 1 (ISAAKS and SRIVASTAVA, 1989).

Estimation of the spatial pattern by indicator kriging

To apply IK, a grid was drawn on the investigated area with a mesh size of 2 km. To avoid border effects due to the shape of the polygon and due to the locations of the sampling stations, this grid differs from the the EEZ in shape, since the northernmost parts of the German EEZ were omitted. On the other hand, the coastal areas, not belonging to the EEZ, were considered in this study due to the ecology of the twaite shad. At each grid point the annual probability of catching more than the selected c.p.u.e. cut-off was estimated using the corresponding mean Gaussian semivariogram models (*viz.* the averaged annual semivariograms), yielding values between 0 and 1. For each target point the ordinary kriged estimate was computed (GOOVAERTS, 1997):

$$I^*_{OK}(x;z_c) = \sum_{\alpha=1}^{n(x)} \lambda_\alpha^{OK}(x;z_c) I(x_\alpha;z_c) \qquad (5)$$

where λ_α^{OK} are the weights of the indicator random variable $I(x;z_c)$. The IK weights were obtained by the following equation (GOOVAERTS 1997):

$$\begin{cases} \sum_{\beta=1}^{n(x)} \lambda_\beta^{OK}(x;z_c) C_I(x_\alpha - x_\beta;z_c) - \mu_{OK}(x;z_c) = C_I(x_\alpha - x;z_c) & ,\alpha = 1,....,n(x) \\ \sum_{\beta=1}^{n(x)} \lambda_\beta^{OK}(x;z_c) = 1 \end{cases} \qquad (6)$$

where λ_β^{OK} are the weights assigned to the covariance function $C_I(x;z_c)$ and μ_{OK} is the Lagrange parameter (JOURNEL and HUIJBREGTS, 1978). At the same grid points the indicator kriging standard errors were calculated to assess the uncertainty of the predicted catch probabilities (see above) (KALUZNY et al., 1998). Finally, for each cut-off the median probability for the years 1996-2001and median IK standard errors were estimated at each grid knot, yielding maps of the median probabilities and median IK standard errors for each cut-off, respectively. All calculations were done using the software S-plus (version 6.1.2., Insightful Corp.) and the module S+SpatialStats (KALUZNY et al., 1998; VENABLES and RIPLEY, 2002).

3 Results

3.1 *Preparatory data analysis*

The post plot of all the sampled stations within the time period of interest (1996-2001) shows the lowest sampling effort in the northernmost parts of the German EEZ and spots of high spatial density of stations in the centre (Fig. 1). This area coincides with a meso-scale survey area called „box A“ of the German Small-scale Bottom Trawl Survey, GSBTS (EHRICH et al., 1998). We can further discern a decrease of „positive“ catches from South to North and likewise from East to West. This directional trend had to be considered in the subsequent structural analysis.

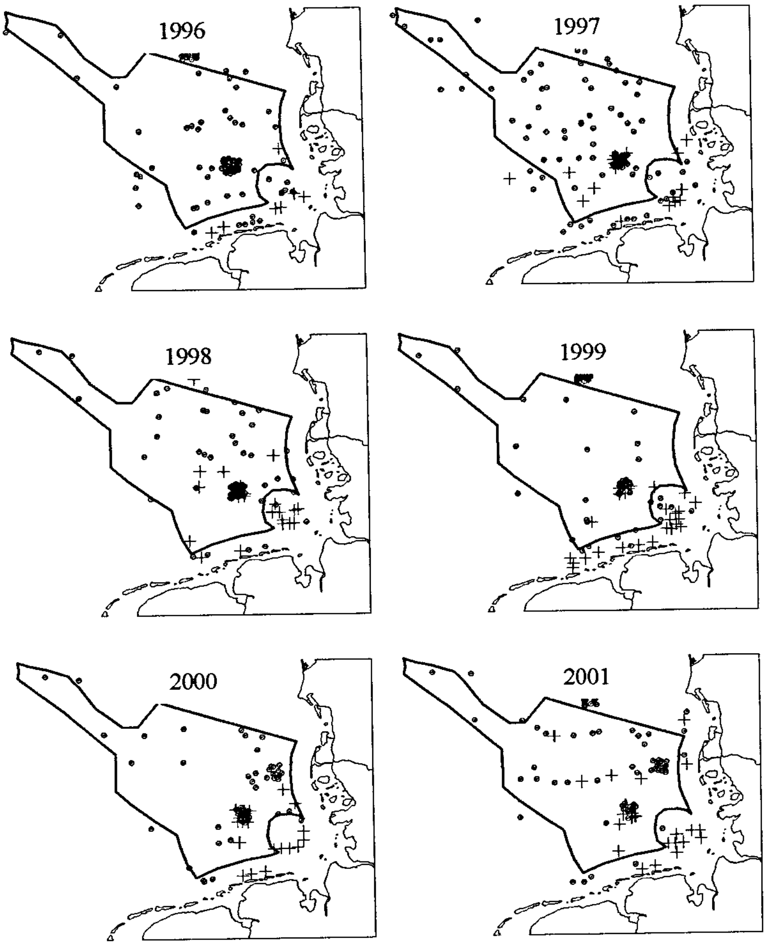

Fig. 2: Annual sampling effort in the EEZ and adjacent coastal areas with spatial distribution of positive catches of twaite shad. (+) sampling stations with a minimum of one caught twaite shad, (O) 0-catches.

The annual post plots from 1996-2001 (Fig. 2) show that the allocation of hauls is similar throughout the years, with the only exception of 1999, when sampling effort in the EEZ has been lowest compared to all other years. Generally, highest numbers of positive catches of twaite shad occur in coastal areas but not within the EEZ. The c.p.u.e. frequency distribution shows that 80 % of all hauls are 0-catches (Fig. 3, top). Taking into account only non-zero catches, highest frequencies occur for the c.p.u.e. classes 0.07 - 0.21 (4.19 %) and > 0.7 (4.86 %) kg x 30 min^{-1} (Fig. 3, bottom). The lowest frequency is calculated for the class 0.63 - 0.7 (0.67 %) kg x 30 min^{-1}. The average weight of twaite shad for 1986 and 2001 is 0.07 kg, giving the smallest non-zero cut-off value for the IK procedure. The average distance to the nearest neighbour is 1.7 km.

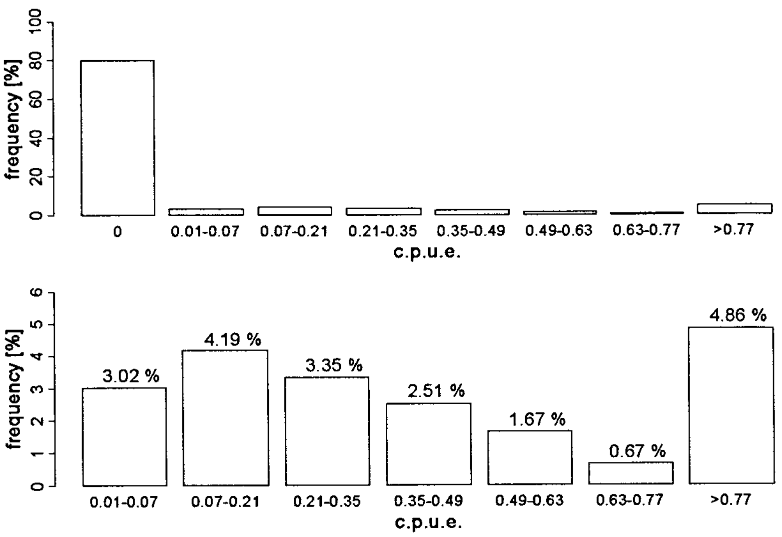

Fig. 3: Frequency distribution of biomass index (c.p.u.e.) classes of twaite shad, taking into account also zero-catches (top) and excluding zero-catches (bottom).

3.2 *Structural Analysis*

All averaged indicator semivariograms were computed to a maximum distance of 100 km, with 10 distance classes and a class width of 15 km (Fig. 4). An increase of the values of the indicator semivariance with increasing distances between stations is detected for each cut-off, though differences in spatial continuity at different cut-offs occur. The calculated indicator semivariograms at the c.p.u.e. cut-offs 0, 0.07, 0.21, 0.35, 0.49 and 0.7 kg x 30 min^{-1} fitted with the Gaussian models are presented in Fig. 4. The indicator semivariogram for $z_c = 0.21$ only indicate a poor spatial continuity, regarding a relative nugget of 61.5 %, while the indicator semivariogram for $z_c = 0.7$ indicates a well developed spatial continuity with a relative nugget of 18.8 % (Table 1). The estimated range varies from 36.9 km to 63.5 km. Thus, the practical range (actual distance of influence around each point) is 64 km for the cut-offs 0; 80 km for cut-off 0.07; 87 km for cut-offs 0.21; 95 km and 96 km for the cut-offs 0.35 and 0.49 and 110 km for cut-off 0.7 kg x 30 min^{-1}. The appropriate model parameters are listed in Table 1. The fitted models give a fair description of the data, indicated by values of the modified Cressie statistic around 0 and by results of the cross-validation procedure which yield means of the standardised errors around zero and standard deviations around 1.

Table 1: Estimated parameters (nugget, sill and range) of Gaussian models fitted to the averaged experminental indicator semivariograms with information on the relative nugget ($C_0/C+C_0$ [%]), on the goodness-of-fit statistic and on the statistics of the standardised error, derived from cross validation (mean *Iscore*, SD *Iscore*). See Materials and Methods section for details.

cut-off (z_c) (c.p.u.e.)	0	0.07	0.21	0.35	0.49	0.7
nugget (C_0)	0.09	0.10	0.09	0.06	0.03	0.02
sill (C)	0.09	0.07	0.06	0.06	0.08	0.07
range (a) (km)	36.86	46.12	50	55	55.92	63.48
practical range (km)	63.84	79.88	86.60	95.26	96.85	109.95
relative nugget	51.36	57.24	61.53	52.45	24.76	18.82
MCS	0.0004	0.0009	0.0027	0.0074	0.0058	0.0095
mean *Iscore*	-0.0042	0.0004	0.0007	0.0015	0.0068	0.0073
sd *Iscore*	1.13	1.08	1.02	1.04	1.38	1.46

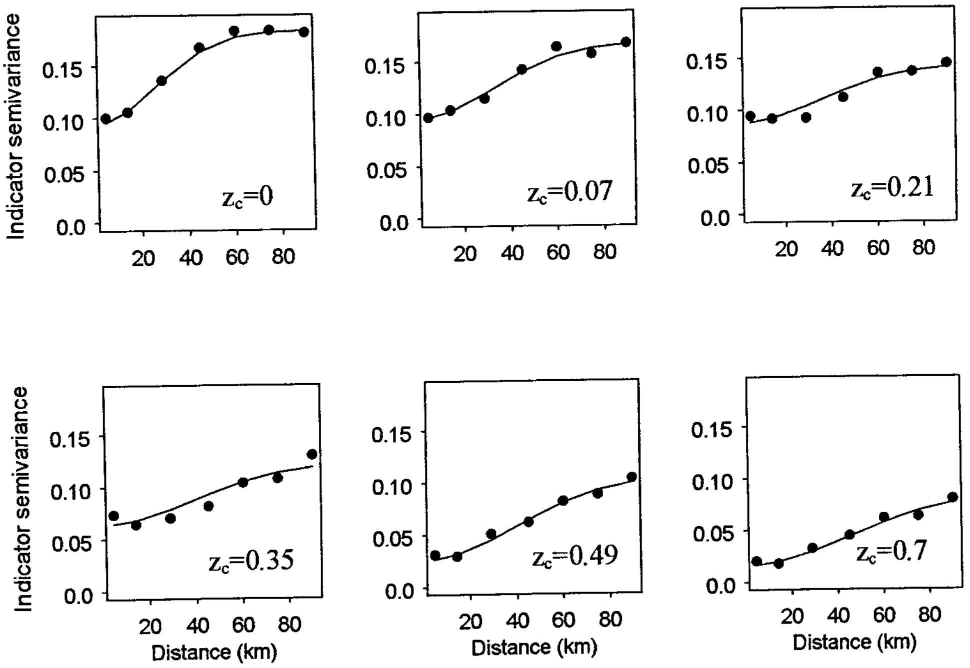

Fig. 4: Averaged (1996-2001) directional experimental indicator semivariograms (direction: East/West, corrected for geometrical anisotropy by the factor of 2.2) for the c.p.u.e. cut-off values, z_c of 0, 0.07, 0.21, 0.35, 0.49 and 0.7 kg x 30 min^{-1}, fitted by Gaussian models (model parameters in Table 1).

3.3 *Estimating spatial patterns*

The annual probabilities for cut-off 0 kg x 30 min^{-1} of the years 1996-2001 are presented in Fig. 5 as an example. Estimations rely on ordinary indicator kriging based on the estimated mean models. Decreasing probabilities from East to West and from South to North are evident for each year and highest probabilities are found in the Elbe- and Weser-estuary; in 1996 and 1999 increased probabilities are also visible in the Ems-estuary; all these cases being outside the EEZ (Fig. 5). Similar annual probabilities (not shown here) have been obtained for the other cut-off values considered. Corresponding annual indicator kriging standard errors are shown in Fig. 6, generally showing increasing annual uncertainty for all cut-offs at the borders of the investigation area.

The calculated median probabilities for all cut-offs and median IK standard errors are presented in Figs. 7 and 8, again showing highest median probabilities in the Elbe- and Weser-estuary. Moreover, decreasing median probabilities are visible from East to West and from South to North. Comparing the different cut-off values, median probabilities are highest (80 % and 70 %) in the Elbe- and Weser-estuary for cut-offs 0 and 0.07 kg x 30 min^{-1}. On the other hand, median IK standard errors (Fig. 8) decrease from cut-off 0 to 0.7 kg x 30 min^{-1}, but are generally higher for all cut-offs at the borders of the grid used for the kriging procedure.

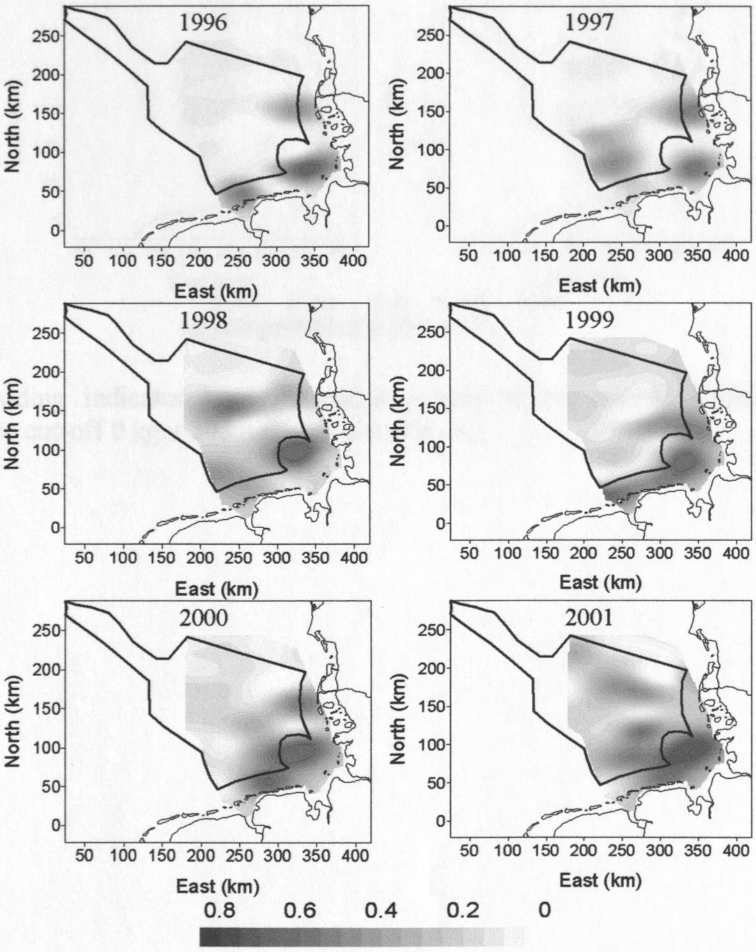

Fig. 5 Annual estimated probabilities (1996-2001) of exceeding the c.p.u.e. cut-off value (z_c) of 0 kg x 30 min^{-1}. Results of indicator kriging based on the mean estimated Gaussian variogram model (Fig. 4, Table 1).

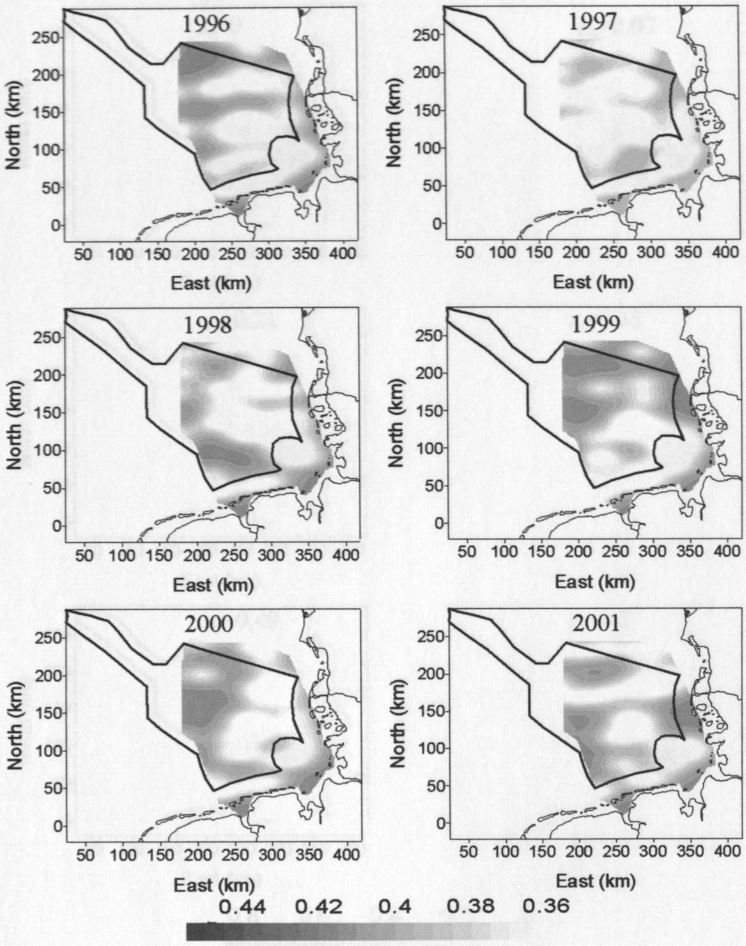

Fig. 6: Corresponding indicator kriging standard errors of the annual (1996-2001) estimated probabilities for the cut-off 0 kg x 30 min^{-1} (see also Fig. 5.)

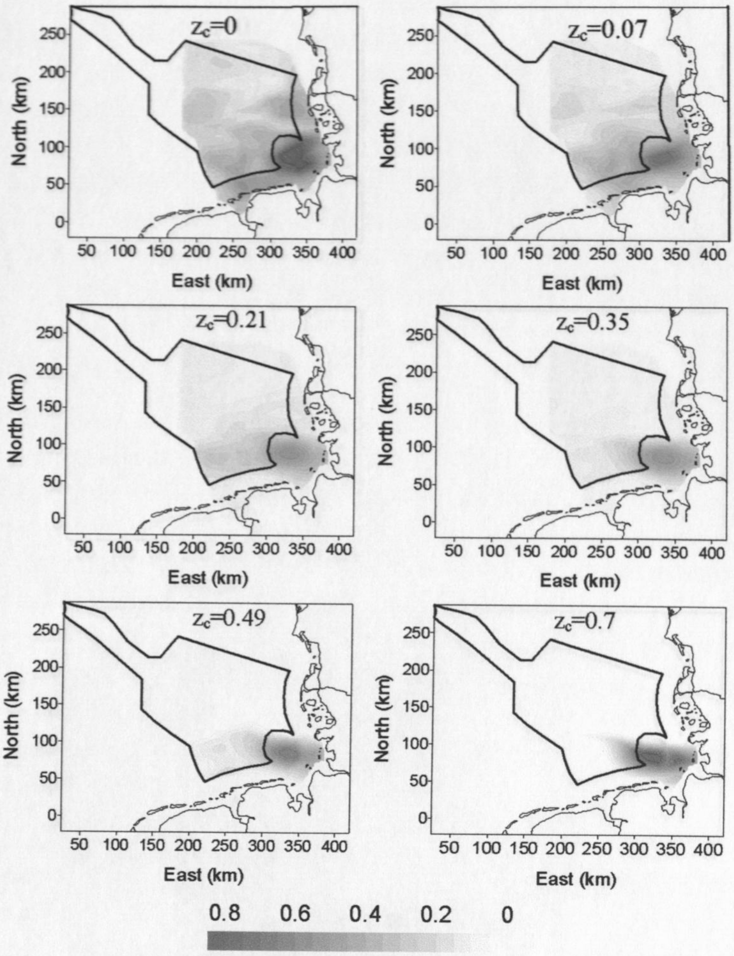

Fig. 7: Median estimated probabilities (1996-2001) of exceeding the c.p.u.e. cut-off values (z_c) of 0, 0.07, 0.21, 0.35, 0.49 and 0.7 kg x 30 min^{-1}.

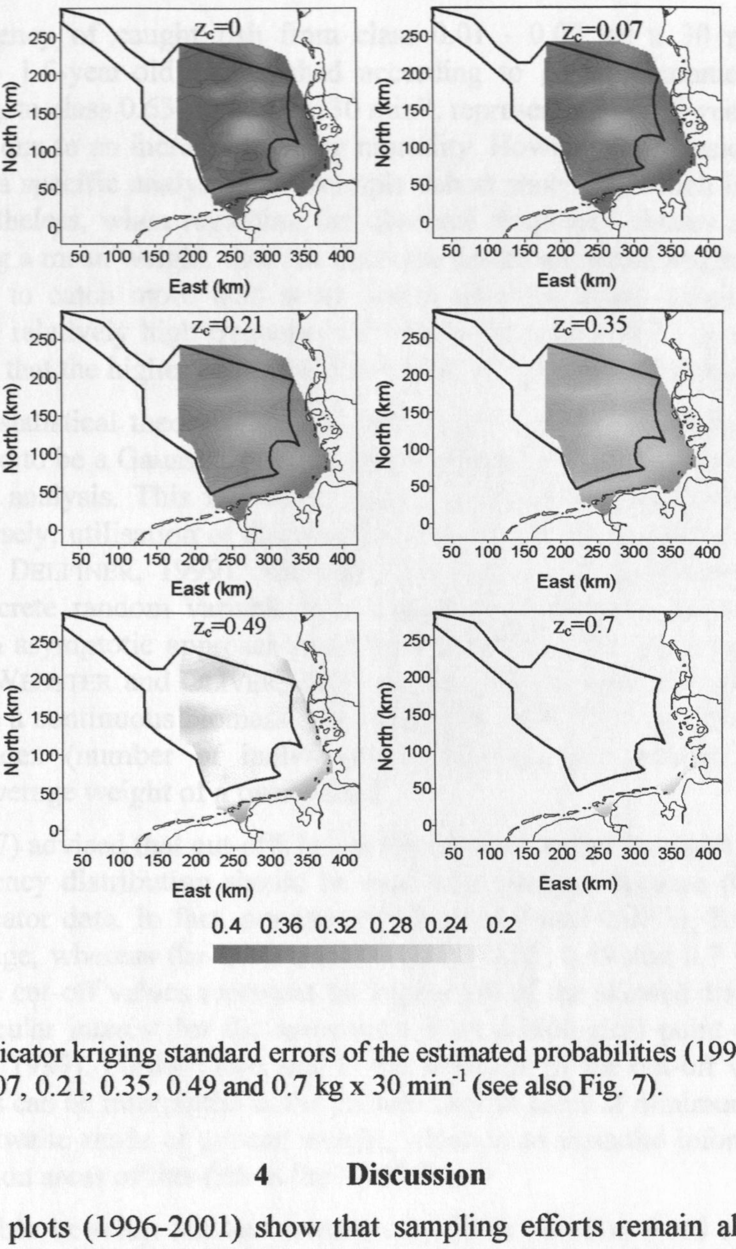

Fig. 8: Median indicator kriging standard errors of the estimated probabilities (1996-2001) for cut-off values (z_c) of 0, 0.07, 0.21, 0.35, 0.49 and 0.7 kg x 30 min^{-1} (see also Fig. 7).

4 Discussion

The annual post plots (1996-2001) show that sampling efforts remain almost stable with years with the only exception of 1999, when sampling effort within the EEZ was lowest. Most importantly, the spatial distributions of stations with positive catches appear to be similar throughout the years (Fig. 2). Hence, the annual post plots support the assumption of a time-invariant process leading to the spatial distribution of twaite shad in this area. This assumption is important for the subsequent spatial analysis of the catch data (RIVOIRARD et al., 2000).

The c.p.u.e. frequency distribution (Fig. 3, top) is highly skewed, perhaps more than can be expected from a lognormal distribution, probably due to the high percentage of 0-catches. As a result, deviations from a Gaussian distribution are obvious. MOYEED and PAPRITZ (2002) have shown that linear kriging performs worse as the data become more skewed. Thus, evaluating our catch data with non-linear geostatistics gives reason to expect more precise results, since non-linear kriging methods have the advantage that their predictions are more precise when a Gaussian random process is inappropriate to model the observation (MOYEED and PAPRITZ, 2002).

Decreasing frequency of caught fish from class 0.01 - 0.07 kg x 30 min^{-1}, eventually representing 1 to 1.5-year-old twaite shad according to growth parameters taken from www.fishbase.org, to class 0.63 - 0.77 kg x 30 min^{-1}, representing 4 to 5-year-old fish (Fig. 3 below), might be due to an increased fishing mortality. However, conclusions about fishing mortality require a specific analysis (for example cohort analysis), which is out of scope in this study. Nevertheless, when regarding the observed frequency classes as multiples of a twaite shad having a mean weight, then the decrease described above might be explained by the small chance to catch more than seven fishes with the mean weight at one station. Consequently, the relatively high frequency of 4.86 % for class > 0.77 kg x 30 min^{-1} might be due to that fact that the higher tail of the distribution is accumulated within this class.

According to geostatistical theory (CRESSIE, 1991, p.31), the overall underlying stochastic process is regarded to be a Gaussian process, thus implying continuos variables to be used in any geostatistical analysis. This fact is not always explicitly stated in standard reference books, but conversely, utilisation of discrete random variables is also not directly suggested (e.g. CHILÈS and DELFINER, 1999). Although it is possible to approximate a probability function of a discrete random variable by a Gaussian distribution, the estimated kriging results of such an asymptotic approach must be treated with care, also regarding indicator transformations (WEBSTER and OLIVER, 2001, p. 12). Thus, to achieve most reliable results we decided to use a continuous biomass index (catch per unit effort) in this study instead of an abundance index (number of individuals). Therefore, our selected cut-offs reflect multiples of the average weight of a twaite shad.

GOOVAERTS (1997) advised that cut-offs below the first or beyond the ninth percentile of the cumulative frequency distribution should be used with caution, because they depend on a few pairs of indicator data. In fact, our cut-off values of 0 and 0.07 kg 30 min^{-1} are in the recommended range, whereas the other cut-offs (0.21, 0.35, 0.49 and 0.7 kg 30 min^{-1}) are beyond. But these cut-off values represent the higher tail of the skewed distribution and are therefore of particular interest for the assessment from a biological point of view (ISAAKS and SRIVASTAVA, 1989). Furthermore, due to the selection of the cut-off values, estimated catch probabilities can be interpreted as the probabilities to catch at minimum 1 or more than 1, 3, 5, 7 and 10 twaite shads of a mean weight, which is an essential information to search for main distribution areas of this fish in the North Sea.

In theory, a number between ten and twenty cut-offs is recommended (JOURNEL, 1983), although it is a good practice to choose only a few well-defined cut-offs, for which estimates are promising regarding the goal of the study (ISAAKS and SRIVASTAVA, 1989). The indicator semivariograms, corrected by the direction of the major axis (east-west), display spatial structures at all cut-offs, but some differences in spatial continuity among the various cut-offs are obvious (Fig. 4). In many cases the spatial continuity of high cut-off values is not the same than of low ones as pointed out by ISAAKS and SRIVASTAVA (1989).

The value of the „relative nugget“ (Tab. 1) is a measure of the strength of spatial continuity of the indicator variables. In this study, spatial continuity is highest for cut-off 0.7 kg x 30 min^{-1} (18.8 %) and lowest for the cut-off 0.21 kg x 30 min^{-1} (61.5 %). This is due to the fact that positive catches for high cut-off values are grouped together, while those for low values form clusters or are almost randomly distributed (like the indicator variables at the cut-off 0.21 kg x 30 min^{-1}; but note that only post plots and not the spatial distributions of indicator variables are shown). We infer that spatial patterns derived from low cut-off values represent structural information of the distribution of the species of interest, while spatial patterns derived from high cut-off values represent the occurrence of high fish biomass, thus indicating „hot spots".

In general, indicator semivariogram curves are less erratic than normal variograms of the random variable. They do not suffer from adverse effects of erratic outliers, since an indicator variable is either 0 or 1. On the other hand, ISAAKS and SRivastava (1989) pointed out that indicator semivariograms are very easily affected by clustering of the sample data set. Some clustered samples remained in the centre of the EEZ, as sampling effort peaked locally, but the number of 0-catches increased as well. Additionally, in order to derive reliable estimates for the small distance classes of the experimental indicator semivariograms, the locally dense sampling points should be considered in the data set for a geostatistical analysis. Therefore, dense sampling stations from the centre of the EEZ, which are identical with a distinct meso-scale survey area called „box A" of the German Small-scale Bottom Trawl Survey, GSBTS (EHRICH et al., 1998), were taken into account.

As a result, these partially very closely aggregated sampling stations might have caused the indicator semivariograms to appear very continuous for small distance classes, leading to the selection of a Gaussian model instead of a model type which has a more linear behaviour at small distances, such as the spherical model. But even if the Gaussian component would be replaced by a less continuos one, for example a straight line, this would have a slope almost equal to zero and thus our data would be described similarly than using a Gaussian model. This would also apply to other model types, since the value of the nugget effect largely determines the degree of smoothness of the IK predictions. However, we selected the Gaussian model because it gives the best description of the data.

Overall, the Gaussian model selected to provide an objective criterion for all indicator semivariograms may differ due to the species-specific spatial pattern within small-scale arrays. Nevertheless, the average patch diameters obtained from semivariograms increased from 0 to 0.7 kg x 30 min^{-1} with 64 km for cut-off 0, 80 km for cut-off 0.07, 86 km for cut-off 0.21, 95 and 96 km for the cut-offs 0.35 and 0.49 kg x 30 min^{-1} and 110 km for cut-off 0.7 kg x 30 min^{-1}. These results are in good agreement with realistic ecological characteristics of a migrating fish species. Moreover, the indicator semivariogram for cut-off 0 kg x 30 min^{-1} also takes into account biomass indices less than 0.07 kg x 30 min^{-1}.

The goodness-of-fit statistics suggests that the estimated probabilities of exceeding certain cut-offs, give a fair description of the reality. In consequence, the areas of increased probabilities of catching twaite shad can be looked upon with some confidence (Figs. 7 and 8). Regardless of the cut-offs selected, probabilities are high in the Elbe- and Weser-estuary and are lowest in the northernmost areas of the EEZ. This corresponds to the ecology of the twaite shad, which migrate into the rivers for spawning and move back afterwards to coastal waters. On the other hand, special areas of conservation for this endangered species farther away than 12 nm from the coast, i.e. within the EEZ, cannot be discerned from this study. Therefore, decision makers should take into account coastal areas and estuaries to protect this anadromous fish species.

In conclusion, spatial analysis involving non-linear geostatistics and indicator kriging has proven to be a promising tool to provide standardised criteria for the evaluation, assessment and implementation of potential Special Areas of Conservation, taking into account the ecology of the species of interest, by incorporating species-specific spatial patterns into the decision process.

5 Acknowledgements

The present study based on data provided by the Institute of Sea Fisheries, Hamburg (thanks to Ingo Wilhelms who kindly compiled the catch data from the database). It is part of the PhD thesis of V. Stelzenmüller at the Carl von Ossietzky Universität, Oldenburg, Germany, supported by the Scholarship Program of the German Federal Environmental Foundation (Deutsche Bundesstifung Umwelt, Osnabrück; No. 20002/290). The German Federal Agency for Nature Conservation (BfN, Bonn, FKZ: 802 85 230, UFOPLAN 2002) funded a project evaluating a first version of this modelling approach. Special thanks to H.-P. Bäumer and two anonymous referees for helpful comments.

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ZUSAMMENFASSUNG

Zunehmende Nutzungskonflikte in der Meeres- und Küstenregion der Nordsee sowie der Rückgang der natürlichen Ressource „Fisch“ erfordern neben akkuraten Bestandsabschätzungen vor allem auch eine präzise räumliche Analysen der artspezifischen Verteilungsmuster der Fischpopulationen innerhalb diskreter Seegebiete.

Das Ziel dieser Arbeit bestand zum einen darin, mit modernen statistischen Methoden der räumlichen Statistik (Geostatistik) die räumliche Verteilung von ausgewählten Fischpopulation auf kleiner und großer Maßstabsebene und deren Veränderung mit der Zeit in Abhängigkeit verschiedener Einflussfaktoren zu analysieren. Informationen über räumliche Muster der Fischpopulationen in Wechselwirkung mit physikalischen und biologischen Variablen können zum Verständnis von ökologischen Prozessen beitragen und ermöglichen eine adäquate Bewertung von Folgen von Eingriffen in die Meeresumwelt. Zum anderen sollte in dieser Arbeit der Einfluss von artspezifischen Verteilungsmustern auf kleiner Maßstabsebene auf die klassischen Bestandsabschätzungen untersucht werden.

Anhand von künstlich erzeugten Fangdaten mit definierten Eigenschaften wurde der Einfluss von Stichprobenumfang, Verteilung der Daten und verschiedene Level an kleinskaliger Variabilität auf die Leistungsfähigkeit gängiger geostatistischer Methoden in den Fischereiwissenschaften getestet (Kapitel 1). Dabei zeigte sich, dass je höher die kleinskalige Variabilität in den Daten ist desto mehr Stichproben notwendig sind, um genaue und präzise Abschätzungen der einzelnen Modellparameter eines gängigen Modelltyps zu erzielen. Weiterhin führte ein geringer Stichprobenumfang (20-40) zu teilweise fraglichen Abschätzungen der Modellparameter. Insgesamt hatte der Stichprobenumfang einen größeren Effekt auf die Leistung der getesteten Schätzverfahren als die Verteilung der Daten. Somit wurden für alle folgenden Analysen, für welche weniger als 50 Stichproben zur Verfügung standen, nur diejenigen Verfahren verwendet, die nach dieser Simulationsstudie als robust einzustufen sind.

Anhand von kleinskaligen Langzeit-Messdaten wurde die zeitliche Konsistenz der räumlichen Musterausbildung der Klieschen im Sommer 1996-200 in der Deutschen Bucht untersucht (Kapitel 2). Die Ergebnisse zeigten, dass eine moderate räumliche Abhängigkeit in den Fangdaten von zwei Größenklassen von Klieschen in jedem Jahr präsent war. Dabei bildeten große Tiere eine fleckenhafte Verteilung mit einer durchschnittlichen Patchgröße von 3.2 km und kleine Tiere mit einer durchschnittlichen Patchgröße von 1.1 km aus. Durch die geostatistische Bestandsabschätzung konnte die Unsicherheit in der Berechnung des mittleren Fangs reduziert werden. Die berechnete jährliche flächige Abschätzung der Biomasse Kliesche in Box A zeigte keine „hot spots“ in der Verteilung der Tiere. Durch diese Ergebnisse wurde eine Methodik entwickelt, mit deren Hilfe mögliche Effekte von Offshore Windkraftanlagen auf das Schutzgut „Fisch“ quantifiziert werden könnten.

Die Ergebnisse der Simulationsstudie zeigten, dass die Höhe der kleinskaligen Variabilität und der Stichprobenumfang die Genauigkeit einer räumlichen Analyse erheblich beeinträchtigen kann. Daher wurde ein Probenahmekonzept entwickelt, dass die kleinskalige Variabilität in den Fangdaten besser erfassen und somit zu einer Reduktion der solchen führen sollte (Kapitel 3). Für die Hälfte der analysierten Fangdaten von verschiedenen Größenklassen von Kliesche und Wittling konnte eine deutliche Reduktion der Unsicherheit in der Abschätzung des mittleren Fangs durch das getestete Probenahmedesign erzielt werden. Somit stellt dieses, für die in der Deutschen Bucht untersuchten Arten, eine kostengünstige und effektive Methode dar, um kleinskalige Variabilität besser erfassen und somit genauere Bestandsabschätzungen erzielen zu können.

Weitere Bestandteile dieser Arbeit waren die Untersuchung des Einflusses der räumlichen Dimension des Untersuchungsgebietes auf eine räumliche Analyse sowie die Zusammenhänge zwischen Musterausbildung von Fischpopulationen und Umweltvariablen (Kapitel 4). Die Ergebnisse zeigten, dass obwohl die Unterschiede in den Untersuchungsmaßstäben eher klein waren, deutliche Abweichungen in der Modellierung der Fangdaten auftraten. Dabei wurden die größten Differenzen für den Schellfisch und den Wittling ermittelt, die ein hohes Maß an Habitatassoziation im Hinblick auf die Wassertiefe zeigten. Weiterhin scheint in der nördlichen Nordsee die kleinere Untersuchungseinheit (Box D) die Grenze darzustellen, für die artspezifische Verteilungsmuster erheblichen Einfluss auf die klassische Berechnung der Variabilität des mittleren Fangs haben können. Mit größer werdendem Untersuchungsmaßstab ist mit einem ansteigenden Einfluss der räumlichen Strukturierung auf die Berechnung von Abundanzindizes zu rechnen. So ist eine adäquate Analyse der Zusammenhänge zwischen der räumlichen Strukturierung der Populationen der Zielart und den Habitatbedingungen notwendig, um genauere Abundanzabschätzungen zu erzielen.

Der Einfluss des Fanggeräts auf die räumliche Analyse von kleinräumigen Fangdaten von drei Größenklassen von Klieschen wurde in Kapitel 5 untersucht. Die Ergebnisse zeigten, dass die Verwendung eines für die Zielart effizienten Fanggerätes zur besseren Erfassung der räumlichen Struktur führt. Jedoch ist dies nicht gleichbedeutend mit einer automatischen Reduzierung der kleinskaligen Variabilität in den Fangdaten. Die im Rahmen dieser Untersuchung entwickelten qualitativen Anforderungen an eine adäquate Strukturanalyse fordern im Falle von geringerer Effizienz des Fanggerätes eine hohe Abundanz der Zielart und umgekehrt. So kann im Rahmen eines Gebietsmonitorings nicht erwartet werden, dass der Einsatz eines Fanggerätes zu genauen geostatistischen Analysen von Fangdaten mehrere Zielarten führt.

Abschließend wurde mit Hilfe von nicht-linearen geostatistischen Methoden Fangwahrscheinlichkeiten für die gefährdete Wanderfischart Finte (*Alosa fallax*) in der AWZ der Nordsee und den angrenzenden Küstengewässern berechnet, um für diese Art ökologisch wertvolle Flächen identifizieren zu können (Kapitel 6). Im Allgemeinen wurden die höchsten Fangwahrscheinlichkeiten für Finten im Sommer zwischen 1996 und 2001 in den Flussmündungsbereichen von Weser und Elbe berechnet. Diese hohen Fangwahrscheinlichkeiten sind vermutlich durch die Laichwanderungen in bzw. aus den Flussmündungsbereichen begründet. Somit müssten Schutzmaßnahmen für diese Gebiete veranlasst werden, da sie die Hauptverbreitungsgebiete darstellen. Innerhalb der AWZ wurden hingegen keine erhöhten Fangwahrscheinlichkeiten gefunden, so dass keine potentiellen Schutzgebiete für die Finte in der AWZ vorgeschlagen werden können.

Als Synthese der durchgeführten Analysen am Beispiel der Plattfischart Kliesche lässt sich feststellen, dass auch auf kleiner Maßstabsebene eine räumliche Abhängigkeit in den Fangdaten herausgearbeitet werden kann. Daher ist für derartige Untersuchungen eine geostatistische Analyse zwingend notwendig, um die durch die räumliche Struktur erzeugte Variabilität in den Fangdaten zu berücksichtigen. In allen Fällen konnte für die Kliesche eine Verringerung der Variabilität bei der Schätzung des mittleren Fangs mit Hilfe geostatistischer gegenüber der klassischen Berechnung der Variabilität erzielt werden. Weiterhin konnte deutlich gezeigt werden, dass unterschiedliche Größenklassen (Altersklassen) von Klieschen unterschiedliche Aggregationsmuster ausbilden, wobei diese im Sommer und Winter variieren. Im Winter konnten keine signifikanten Unterschiede in der durchschnittlichen Patchgröße zwischen den Größenklassen sowie männlichen und weiblichen Klieschen festgestellt werden. Insgesamt zeigte sich jedoch, dass größere

Klieschen dazu tendieren, größere Aggregationen zu bilden. Weiterhin wurden gute Übereinstimmungen in der räumlichen Verteilung von männlichen und weiblichen Klieschen gefunden. Dies weist darauf hin, dass eine mögliche Ursache für die Patchbildung im Winter im Laichverhalten zu suchen ist. Die zeitliche Analyse der räumlichen Musterbildung zeigte, dass diese im Sommer und Winter konsistent ist, jedoch keine dauerhaften „hot spots" vorzufinden waren. Weiterhin konnte gezeigt werden, dass die Unterschiede in der Fangeffizienz unterschiedlicher Geräte (der 7m-Baumkurre und dem Kabeljauhopser) mit zunehmender Größe der Tiere kleiner wurden. Somit sind räumliche Analysen und die daraus abgeleiteten Abschätzungen des mittleren Fanges großer Klieschen auf Basis dieser Fanggeräte vergleichbar.

Zusammengefasst können die vorliegenden intensiven Untersuchungen über die Verteilungsmuster verschiedener biologischer Gruppen der Kliesche und deren natürliche Variabilität auf kleiner Maßstabsebene als wichtige Referenz für die Bewertung von Effekten von Eingriffen in die Meeresumwelt herangezogen werden. Durch die erarbeitete Methodik könnten Fangdaten der Kliesche im Rahmen eines „Windparkmonitorings" in der Deutschen Bucht adäquat evaluiert und die dabei gefundenen räumlichen Populationsmuster mit den vorliegenden Referenzuntersuchungen verglichen werden. Die untersuchten Faktoren, welche erheblichen Einfluss auf die Richtigkeit und Präzision kleinskaliger räumlicher Analysen haben können, sollten bei der Konzeptentwicklung von Langzeituntersuchungsreihen, deren Ziel es ist räumliche Fragestellungen auf Basis von Fischereidaten zu bearbeiten, Beachtung finden.

Im Rahmen des bestehenden Nutzungskonfliktes in der Meeres- und Küstenregion stehen neben der Ressource „Fisch" weitere Untersuchungsobjekte im Fokus räumlicher Fragestellungen. Beispielsweise ließen sich durch weitere geostatistische Analysen von Umweltvariablen, Schlüsselarten des Benthos und/oder der Fischfauna, zusammengefasst in einem Geographischen Informationssystem (GIS), einheitliche ökologisch wertvolle Flächen definieren. So erweisen sich die in dieser Arbeit verwendeten Methoden als ein sehr viel versprechendes Instrumentarium und die erzielten Ergebnisse als wichtige Basisinformation für ein erfolgreiches Gebietsmanagement in der Nordsee.

DANKSAGUNG

Zuallererst möchte ich mich bei Prof. Dr. Ekkehard Vareschi bedanken, der meine Promotion in der Arbeitsgruppe Aquatische Ökologie ermöglichte. Im Besonderen danke ich Dr. Gerd-Peter Zauke für die fachkompetente Unterstützung und seinen großen persönlichen Einsatz, den ich sehr zu schätzen weiß. Desweiteren bedanke ich mich bei allen anderen Mitarbeitern der Aquatischen Ökologie für ihre Hilfsbereitschaft, ganz besonder aber bei Edith Kieselhorst, die mir in vielen orgnisatorischen und technischen Fragen zur Seite stand.

Ein maßgeblicher Anteil meiner Promotion beruht auf der Zusammenarbeit mit Dr. Siegfried Ehrich vom Institut für Seefischerei in Hamburg. Seine fachliche und persönliche Unterstützung war für mich von großer Bedeutung und verlangt daher besondere Anerkennung. Nicht unerwähnt darf in diesem Zusammenhang die Mithilfe von Ingo Willhelms vom Institut für Seefischerei bleiben, durch dessen Einsatz die Datenbasis für diese Arbeit bereit gestellt wurde. Mein Dank geht auch an die Besatzung der Walther Herwig III, die immer bemüht war mir meine Arbeit an Bord zu erleichtern, und durch deren Engagement die hohe Qualität der Daten sicher gestellt wurde.

Ich möchte mich insbesondere bei Dr. Hans-Peter Bäumer bedanken, der mir durch seine Diskussionsbereitschaft und die Beratung in statistischen Fragen über so manche Hürde geholfen hat.

Ein wichtiger Bestandteil meiner Promotion war mein Auslandsaufenthalts am Institut de Ciències del Mar in Barcelona. Es ist mir daher ein besonderes Bedürfnis, Dr. Francesc Maynou und Marta Rufino zu danken, die diese Zeit nicht nur fachlich sondern auch persönlich zu einem wertvollem Erlebnis machten.

Mein Dank gilt der Deutschen Bundesstiftung Umwelt (DBU), für die finanzielle Unterstützung durch ein Promotionsstipendium (Nr.: 20002/290), aber auch für die bereichernden Veranstaltungen. Besonders möchte ich mich bei Frau Dr. Schlegel-Starmann für ihre Betreuung bedanken.

Bedanken möchte ich mich beim DAAD, denn erst durch ein ein Kurzzeitstipendium für Doktoranden wurde der Forschungsaufenthat in Spanien ermöglicht.

Allen meinen Freunden gilt mein Dank dafür, daß sie mich während der gesamten Zeit durch Höhen und Tiefen begleitet haben. Hervorheben möchte ich allerdings meine Eltern, die an mich geglaubt und mir stets Mut zugesprochen haben. Danke Frank, daß du immer da warst und mich nie daran hast zweifeln lassen, daß ich es schaffe.

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PRAKTISCHE TÄTIGKEITEN UND LEHRERFAHRUNG

August 2001	**Bankangestellte im Servicebereich**, Oldenburgische Landesbank
Okt. 2001 – Feb. 2002	**Wissenschaftliche Hilfskraft** im Hochschulrechenzentrum der CvO Universität bei Dr. Hans-Peter Bäumer ▸ Entwicklung eines Verfahrens zur Anwendung räumlicher Statistik in Verbindung mit Habitatmodellen für Tagfalter
Feb. – März 2002	**Beraterin im Bereich Umweltmanagement, Lineas Consulting GmbH, Hamburg** ▸ Analyse der Zusammensetzung von Fischgemeinschaften und ihre Veränderung mit der Zeit in elf Standartuntersuchgebieten in der Nordsee mit multivariater Statistik
Aug. – Okt. 2002	**Mitverantwortliche Durchführung des Forschungsvorhabens: „Prüfung der fachlichen Notwendigkeit zur Benennung von FFH-Gebieten zum Schutz der Fischart Finte“** im Auftrag des Bundesamt für Naturschutz, Vilm ▸ Untersuchung von Verbreitungsgsschwerpunkten der gefährdeten Wanderfischart Finte in der Nordsee und Definition potentieller Schutzgebiete
Mai 2003	**Mitverantwortliche Leitung eines Geostatistik Workshops** ▸ Inhaltliche Planung und Konzeptentwicklung ▸ Entwicklung der Arbeitsmaterialien ▸ Teilweise Durchführung der PC-Übungen
Okt. 2003 – Feb. 2004	**Mitverantwortliche Leitung des Statistikkurs: „Anwendung von Geostatik in den Umweltwissenschaften“** an der CvO Universität, Oldenburg ▸ Vorbereitung der Arbeitsmaterialien ▸ Anleitung der praktischen Übungen

AUSLANDSAUFENTHALTE UND SEEREISEN

Feb. – Aug. 1999	**Studienprojekt am Interuniversity Institute**, Eilat, Israel bei Dr. Anton Post ▸ Untersuchung vom UV-absorbierenden Substanzen in marinen Algen Verbindung mit Taucheinsätzen
Januar 2001	**Seereise mit dem Fischereiforschungsschiff „Walther Herwig** III“ in die Deutsche Bucht; Fahrtleitung Dr. Siegfried Ehrich ▸ Datenerhebung für die Diplomarbeit
Januar 2002	**Seereise mit dem Fischereiforschungsschiff „Walther Herwig** III“ in die Deutsche Bucht; Fahrtleitung Dr. Siegfried Ehrich ▸ Umsetzung eines neuen Probenahmedesigns
Mai – Aug. 2002	**Forschungsaufenthalt am Institut de Ciéncies del Mar, CMIMA, Barcelona, Spanien** bei Dr. Francesc Maynou ▸ Erarbeitung von robusten Methoden der Geostatistik zur Analyse von Fischereidaten ▸ DAAD Auslandsstipendium für Doktoranden
Januar 2003	**Seereise mit dem Fischereiforschungsschiff „Walther Herwig** III“ in die Deutsche Bucht; Fahrtleitung Dr. Siegfried Ehrich ▸ Modifikation eines Probenahmedesigns zur Untersuchung klein-skaliger Variabilität
Mai – Juli 2003	**Forschungsaufenthalt am Institut de Ciéncies del Mar, CMIMA, Barcelona, Spanien** bei Dr. Francesc Maynou ▸ Durchführung einer Simulationsstudie, um Präzision von den in den Fischereiwissenschaften gängigen geo-statistischen Verfahren zu testen ▸ Teilnahme an spanischen nationalen Fischereisurvey MEDITS an Bord der „Cornide de Serverda“, Fahrtleitung: Dr. Luis Gil de Sola
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August 2004	**Seereise mit dem Fischereiforschungsschiff „Walther Herwig** III“ in die nördliche Nordsee (Shetland Islands bis Deutsche Bucht); Fahrtleitung Dr. Siegfried Ehrich ▸ Mitverantwortliche Durchführung der Arbeiten im Fischlabor

PUBLIKATIONEN

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VORTRÄGE UND POSTER

Oktober 2001	**„Geostatistische Auswertung von Fangdaten am Beispiel der Kliesche in der Deutschen Bucht"**, Bundesforschungsanstalt für Fischerei, Institut für Seefischerei, Hamburg
September 2002	**„Verteilungsmuster der anadromen Wanderfischart Finte (*Alosa fallax*) in der Nordsee"**, 2. Statusseminar, BfN Aussenstelle Vilm
März 2003	**„Estimating spatial distribution patterns, fish density and its variance by applying geostatistics"**, Institut für Hydrobiologie und Fischereiwissenschaft, Hamburg
September 2003	**"Spatial distribution of the twaite shad, Alosa fallax (LACEPÈDE, 1803) in the Southern North Sea: an application of non-linear geostatistics and indicator kriging"**, Posterpräsentation, StatGIS03 - Interfacing Geostatistics, GIS and Spatial Databases. International Workshop, Pörtschach, Österreich
November 2003	**„Abschätzungen von Verteilungsmustern und Definition von möglichen Schutzgebieten für die anadrome Wanderfischart Finte (*Alosa fallax*) in der Nordsee mittels nicht - linearer Geostatistik"**, Tag der Umweltmodellierung des Zentrums für Umweltmodellierung, Oldenburg
März 2004	**„Auf der Suche nach potentiellen marinen Schutzgebieten mittels moderner statistischer Methoden"**, Kulturkreis Oldenburg

Poster:

Stelzenmüller, V., Zauke, G.-P. & Ehrich, S.: Meso-scaled investigation on spatial distribution of the flatfish species *Limanda limanda* (dab) within the German Bight: A geostatistical approach. Poster, Second International Symposium on GIS and Spatial Analyses in Fishery and Aquatic Sciences, Brighton, UK, September 2002

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Erklärung

Hiermit versichere ich, dass ich diese Arbeit selbstständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel verwendet habe. Die Dissertation wurde zu Teilen bereits veröffentlicht.

Oldenburg, 26.10.04

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(Vanessa Stelzenmüller)

Erklärung

Hiermit versichere ich, dass die Dissertation weder in ihrer Gesamtheit noch in Teilen einer anderen wissenschaftlichen Hochschule zur Begutachtung in einem Promotionsverfahren vorliegt oder vorgelegen hat.

Oldenburg, 26.10.04

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(Vanessa Stelzenmüller)