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UK inshore Special Protection Areas: a methodological evaluation of site selection and definition of the extent of an interest feature using line transect data

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Contents

List of Tables

List of Boxes

List of Equations

List of Figures

Abbreviations

AIC	Akaike's Information Criterion
BNG	British National Grid
CCW	Countryside Council for Wales
EEC	European Economic Community
EC	European Community
EU	European Union
EN	English Nature
ESRI	Environmental Systems Research Institute Inc.
GAM	Generalised Additive Models
GIS	Geographical Information System
GLM	Generalised Linear Models
GPS	Global Positioning System
JNCC	Joint Nature Conservation Committee
NCC	Nature Conservancy Council
NERI	National Environmental Research Institute in Denmark
ROC	Receiver-Operating Characteristic
SAST	Seabirds At Sea Team (of the JNCC)
SNH	Scottish Natural Heritage
SPA	Special Protection Area
UK	United Kingdom
UTM	Universal Transverse Mercator
WWT	Wildfowl and Wetlands Trust

1 Executive summary

The EU Birds Directive (79/409/EEC) provides for the protection, management and control of naturally occurring wild birds of EU Member States. Article 4 of the Birds Directive requires that Member States identify and classify the “most suitable territories” in size and number for rare or vulnerable species listed in Annex I (Article 4.1), and for regularly occurring migratory species not listed in Annex I (Article 4.2). In the UK, these protected areas are known as Special Protection Areas (SPAs).

Although the UK’s SPA network currently is mostly limited to the terrestrial, freshwater, and the estuarine environments (Stroud *et al.* 2001), Article 4 of the Birds Directive states that protection of these bird species should take place “in the geographical sea and land area” (79/409/EEC). Therefore, the Joint Nature Conservation Committee (JNCC), in collaboration with the four statutory country agencies; English Nature (EN); Scottish Natural Heritage (SNH); Countryside Council for Wales (CCW); and the Environment and Heritage Service (Northern Ireland; EHS), is undertaking to provide advice on protection of birds found in the marine environment. Initial work on the implementation of the Birds Directive in the marine environment has been reported in Johnston *et al.* (2002). Three strands of work have been identified:

i. seaward extensions of existing seabird breeding colony SPA boundaries beyond the low water mark;
ii. inshore feeding areas used by concentrations of birds (e.g. seaducks, divers and grebes) in the non-breeding season; and
iii. offshore areas used by marine birds, probably for feeding but also for other purposes.

Other aggregations not captured in the former three strands may also be identified.

The methodological basis for identifying inshore marine SPAs for seaducks, divers and grebes under strand ii) is discussed in this report.

Many seabird species form important wintering aggregations in UK inshore marine waters (Dean *et al.* 2003). This report presents the current scientific methodological basis for site selection and defining the extent of the interest feature (a natural or semi-natural feature for which a site has been selected) with a view to providing guidelines for setting appropriate marine SPA seaward boundaries for inshore aggregations of divers *Gaviidae*, grebes *Podicipedidae*, and seaducks *Anatidae* outwith the breeding season.

In order to assess whether an area qualifies for SPA status, a basic requirement is to know the local population size and bird distribution within that area. Usually it is impossible to count all individuals in a population or to survey all areas, so representative samples are measured to enable estimation of the local population size and likely distribution. This report describes the analytical techniques used for (a) generating total estimated population sizes to aid in marine SPA site selection, and (b) defining the extent of each interest feature, including some consideration of site boundary location. Aerial and boat-based survey count data from Carmarthen Bay, Wales (Webb *et al.* 2004); the outer Tay area, Scotland (McSorley *et al.* in prep.); and Liverpool Bay, England and Wales (Webb *et al.* in prep.) are used as case studies for illustrative purposes.

1.1 SPA site selection in the marine environment

Site selection depends, in part, on the estimation of an accurate population size. Population size (within a given area) can be estimated from line transect sampling data using a variety of techniques including; (a) extrapolation of density; (b) distance sampling; and (c) summed interpolated (kriged) abundances.

Extrapolation of density (mean sample density or overall density) to the entire study site is a relatively crude method that does not take into account the decline in detection rates (detectability) of birds at increasing distance from the survey platform. Extrapolation techniques also make some major assumptions about the representivity of the samples, such as a normal frequency distribution and no spatial autocorrelation, which are highly likely to be violated in biological count data.

Distance sampling, a commonly used population size estimation method (Buckland *et al.* 2001), is similar to extrapolation of the sample density; however, the sample density is corrected for a decline in detectability with increasing distance from the survey platform. As with density extrapolation, distance sampling does not model the spatial autocorrelation inherent in many ecological data-sets.

Examples of the application of geostatistical interpolation are prevalent in the mining industry (Clark and Harper 2001), but limited within the field of biology. Interpolation, in this case kriging, uses the inherent spatial autocorrelation between pairs of points (a relationship describing the degree of correlation between pairs of points with increasing separation distance) to generate a high resolution, regular grid of estimated values (e.g. pollutant concentration values, or bird density etc.) across an entire study site, using a representative sample of data from that study area. In this report we evaluate past and present kriging techniques employed by JNCC. Two kriging methods are evaluated: ordinary kriging and ordinary indicator kriging (Marinoni 2003; Pebesma *et al.* 2000a). By evaluating these two kriging methods, we recommend the most suitable kriging method for interpolation of zero elevated count data (count data with a high frequency of zero-values) with skewed positive sightings (a non-normal frequency distribution). We also discuss the applicability of indicator kriging, a non-parametric interpolation method that is useful for modelling scarce species' distributions, to line transect data.

The main findings of the geostatistical analyses are as follows; (a) back-transformation of ln (natural log) transformed data must incorporate Lagrangian multiplier and variance components; (b) ordinary kriging alone overly smoothes count data effectively decreasing the estimated densities; and (c) ordinary indicator kriging takes into account count data frequency distribution, and thus, is a more suitable interpolator of zero elevated count data than ordinary kriging alone. Future kriging developments, in particular cokriging, are discussed in the context of identification of SPAs in the marine environment.

Population size estimation using summed interpolated abundances involves summing the output from interpolation, namely a regular grid of bird density (number.km^{-2}) values that are converted into abundances (number of birds), to give an estimated total population size across the entire study area. Although this method of estimating population size models spatial autocorrelation, it does not take into account declines in detectability of birds with increasing distance from the survey platform.

In this report, we provide a critique of population estimation methods and outline a prioritisation protocol for deployment of the most appropriate population estimation method.

We propose that the most appropriate method of estimating population size is determined, in part, by the data source, but that if data conform to the method's assumptions, distance sampling techniques should be prioritised. Summed abundances from ordinary indicator kriged densities also may be used as a secondary source or the primary source if data do not conform to the distance sampling assumptions. Extrapolation methods are relatively crude and as such should not be accorded the same priority as these other two techniques. Extrapolation of density and output from kriged data may be used to generate population size estimates in sub-areas.

Site selection also depends on 'regularity' of occurrence of a qualifying species; in this report we discuss further what is meant by 'regularity' and make recommendations for data requirements for inshore waterbird SPA site selection.

1.2 Defining the extent of an interest feature

We present the rationale for the determination of possible generic thresholds for identifying significant aggregations, and thus, important areas for qualifying species, which aids in defining the extent of the interest feature. We critically assess four different parameters upon which a threshold may be applied. These parameters include:

1. kriged probability of occurrence;
2. kriged density;
3. slope of the gradient of kriged density;
4. ranked percentages of total population size using kriged density (proportional distribution).

We propose that the most appropriate parameter for selection of a threshold is proportional distribution for species with modelled density, and probability of occurrence for species with modelled presence/absence. A threshold of 98% of the total population size is the most appropriate threshold value for modelled density data. A threshold equating to the minimum estimated probability value (excluding zero) where a species is observed to be present, is the most appropriate threshold value for modelled presence/absence data.

In this report, we outline a method for combining data from several surveys and qualifying species to aid in defining the extent of the interest feature. We discuss inclusion or exclusion of 'satellite' aggregations (those small aggregations more than 500m from the core aggregation) according to Webb and Reid's (2003) guidelines, and the minimum data requirements for determining the extent of the interest feature: We recommend that a minimum of three separate surveys, covering at least two different years, should be used for defining the extent of the interest feature, and that data from qualifying species should only be used (Webb and Reid 2003). We recommend that close proximity of an SPA boundary to the edge of the interest feature(s) should be avoided; we discuss how data issues preclude the placement of a boundary no less than 250m of the interest feature(s). Final determination of any SPA site boundary (seaward and landward) and classification of the site rests with the relevant agency(s).

2 Introduction

In 1979, the European Community (EC) adopted the Council Directive on the Conservation of Wild Birds (79/409/EEC), which is referred to as the Birds Directive. The Birds Directive applies to naturally occurring wild birds in the European territory of European Union (EU) Member States, and provides for the protection, management and control of these species. Article 4 of the Birds Directive requires that Member States identify and classify the most suitable territories in size and number for rare or vulnerable species listed in Annex I (Article 4.1), and for regularly occurring migratory species not listed in Annex I (Article 4.2). In the UK, these areas are known as Special Protection Areas (SPAs).

The current Special Protection Area (SPA) network, outlined in Stroud *et al.* (2001), is mostly limited to the terrestrial, freshwater and, to some extent, the estuarine environments; no wholly marine SPAs are presented therein. However, Articles 4.1 and 4.2 of the Birds Directive state that protection should take place "in the geographical sea and land area" (79/409/EEC). Therefore, the Joint Nature Conservation Committee (JNCC) – in collaboration with the four statutory country agencies; English Nature (EN); Scottish Natural Heritage (SNH); Countryside Council for Wales (CCW); and the Environment and Heritage Service (Northern Ireland; EHS) – is undertaking to provide advice on protection of seabirds and waterbirds found in the marine environment. Initial work on the implementation of the Birds Directive in the marine environment has been reported in Johnston *et al.* (2002): Three strands of work have been identified:

i. seaward extensions of existing seabird breeding colony SPA boundaries beyond the low water mark;
ii. inshore feeding areas used by concentrations of waterbirds (e.g. seaducks, divers and grebes) in the non-breeding season; and
iii. offshore areas used by marine birds, probably for feeding but also for other purposes.

Other aggregations not captured in the former three strands may also be identified.

The methodological basis for identifying inshore marine SPAs for waterbirds under strand ii) is discussed in this report.

One of the key aspects to this work is the establishment of marine SPAs for inshore aggregations of waterbirds outwith the breeding season, in particular divers *Gaviidae*, grebes *Podicipedidae*, and seaducks *Anatidae* (hereafter referred to as waterbirds). Many of these species form large aggregations in UK inshore marine waters, outwith their breeding seasons, making the UK an important wintering area for these birds (Dean *et al.* 2003).

In the current report, we do not discuss in detail the Birds Directive (79/409/EEC), the SPA network (found in Stroud *et al.* 2001), or the site-by-site details of the application of the Birds Directive in the marine environment (found in McSorley *et al.* in prep.; Webb *et al.* 2004; Webb *et al.* in prep.). Nor do we present any boundary setting guidelines for marine SPAs; these will be presented in other documents (for example Webb and Reid 2003) and regularly updated on the JNCC website at http://www.jncc.gov.uk/. Where information already has been presented in other reports, the appropriate resource has been cross-referenced.

The inshore marine SPA site selection guidelines are based on the existing guidelines for terrestrial SPAs (Stroud *et al.* 2001). Stage 1 guidelines allow consideration of sites based on the number of birds regularly meeting or exceeding a qualifying national or international threshold for a species, or exceeding 20,000 individuals for an assemblage of species. Stage 2 guidelines allow further consideration of these sites or other sites based on species' population status, ecology or movement patterns, or on the nature of the sites themselves (Stroud *et al.* 2001).

An evaluation of the application of existing site selection guidelines for UK inshore marine SPA site selection is currently in production (Webb and Reid 2003). However, in summary, the guidelines are considered appropriate for selection of marine SPAs for inshore aggregations of waterbirds outwith the breeding season, with caveats on the data requirements, such year of data collection, data quality and number of years of survey data.

This report describes and critically assesses the analytical techniques used for (a) generating total estimated population sizes from line transect data to aid in site selection for inshore SPAs, and (b) investigating distribution patterns with a view to determining generic thresholds for defining the extent of the interest feature (a natural or semi-natural feature for which a site has been selected), with discussion on the minimum data requirements. Recommendations for limitations of the proximity of the interest feature and any SPA boundary are presented.

2.1 Methods for site selection of inshore SPAs

As with the terrestrial SPAs, site selection for SPAs in the marine environment depends, in part, on the estimation of a site population size for each species. However, unlike the terrestrial SPAs, data on the abundance and distribution of birds in the marine environment are scarce. Data from several sources may be utilised to provide estimates of the population size: These include counts from land, boats and aircraft. In the inshore environment, it is sometimes possible to make a total count of all birds in the marine environment from the land, where the limit to the aggregation is clearly visible to the observer; these are relatively rare occasions that may include counting birds in very restricted, confined marine habitats such as a narrow sealoch. However, in the inshore marine environment aggregations of birds usually form beyond the field of view of a land based observer and so, since 1979, there has been a steady increase in aerial and boat-based surveys of the coastal, offshore and inshore areas of the UK by the Nature Conservancy Council (NCC), and subsequently by the Joint Nature Conservation Committee (JNCC). It was not until the early 21st century that extensive systematic line-transect surveys were carried out. It is upon these latter types of data that this report is based.

Ecological data often comprise samples from a much larger population; usually it is impossible to count all individuals in a population or to survey all areas, so representative samples are measured. The total population size can be estimated from sample counts using a variety of techniques, including; (a) extrapolation of density; (b) distance sampling; and (c) summed interpolated (kriged) abundances.

Extrapolation of density (mean sample density or overall density) to the entire study site has been used in estimating breeding colony population size for Atlantic puffins *Fratercula arctica* and Manx shearwaters *Puffinus puffinus* (Harris and Murray 1981; Walsh *et al.* 1995). However, these estimates were based on sample counts of relatively evenly spaced entities (in this case burrows), unlike the at-sea counts of patchy aggregations of birds on the water. Extrapolation is a relatively crude yet quick method of estimating the population size in the study area.

Distance sampling, a commonly used population size method (Buckland *et al.* 2001), models the relationship between the number of individuals counted and their distances from the survey platform to assess any declines in detection rates with increasing distance from the survey platform. This method requires that data are collected in line transects or point counts (Bibby *et al.* 1992), with associated distance data (perpendicular distance from the survey platform to the observation). Line transects are presented in this report; however, strip transects (transects with no perpendicular distance data collected) are also discussed. The density of birds derived from distance sampling is extrapolated to the entire study area. The programme *Distance 4.0* (Thomas *et al.* 2002) is the most commonly and effectively used programme that generates population estimates from line transect data.

It is also possible to estimate the density of organisms (and thus, total population size) in unsampled areas using either the relationship between sampled data and environmental variables, such as conventional multivariate modelling e.g. generalised linear or additive models (GLMs or GAMs; Suarez-Seoane *et al.* 2002), or the relationship between neighbouring sampled data points, such as geostatistical modelling i.e. variography followed by interpolation using kriging. Both methods will generate a spatial distribution map of estimated numbers of a species across the entire study area, using only a sample of the total population size; however, unlike conventional multivariate modelling, geostatistics do not require any other variables apart from the bird density and the spatial locations of the sample points. But, recent developments in analytical procedures have made it possible to include spatial autocorrelation in GLMs and GAMs (Pebesma *et al.* 2000a), and also to include covariables in geostatistics (Zeiler *et al.* 2000). These techniques are currently beyond the scope of JNCC's analytical repertoir, but will be considered when more readily available.

Birds often form aggregations in response to environmental variables such as prey availability, tidal or weather conditions, or through a preference to be with or near conspecifics (flocking) or other species. Such aggregations result in survey data that are spatially autocorrelated; neighbouring data points have highly correlated values. Spatial autocorrelation of data violates assumptions of data independence for many modelling techniques. However, geostatistics use this intrinsic spatial autocorrelation in the sampled data to predict data values in unsampled areas. This spatial relationship may be described using a variety of tools, including the semivariogram (see Clark and Harper 2001; Cressie 1991; Webb *et al.* 2004). It is possible to use this spatial relationship, expressed in the semivariogram, in interpolation (e.g. kriging) to generate a regular grid of values, made up of equal size grid cells, across the entire area.

JNCC have applied geostatistical modelling techniques to both seabird and waterbird, aerial and boat-based survey data, to generate distribution maps of the density of seabirds and waterbirds in the marine environment (Begg and Reid 1997; McSorley *et al.* 2003; McSorley *et al.* in prep.; Robinson *et al.* 2002; Webb *et al.* 2004; Webb *et al.* in prep.). This modelling approach of 'filling in the gaps' in survey data is preferred to more conventional generalised linear or additive modelling because our data are highly spatially autocorrelated, and also high resolution co-variables are not readily available at present. There are several ways to interpolate marine bird distribution survey data using kriging; in this report we critically assess two methods, ordinary kriging and ordinary indicator kriging, to determine the most appropriate method for interpolating marine bird survey densities. We also will discuss the applicability of indicator kriging, a non-parametric interpolation method that is useful for modelling presence/absence data collected from species that are observed as singletons or in very small clusters, to line transect data. Survey data from the outer Tay area, Scotland, Carmarthen Bay, Wales, and Liverpool Bay, England and Wales (McSorley *et al.* in prep.; Webb *et al.* 2004; Webb *et al.* in prep., respectively) are presented as case studies.

Evidence of a qualifying number of birds using a site does not necessarily infer that a site will be classified as a marine SPA: Stages 1.1-1.3 of the SPA guidelines state that qualifying numbers should use a site "regularly"; a term that has been taken from the Ramsar site selection criteria (see JNCC 1999). In the UK SPA selection guidelines (JNCC 1999), the Ramsar site selection criteria are used to define the term regular for SPAs.

"A wetland regularly supports a population of a given size if:

i. the requisite number of birds is known to have occurred in two thirds of the seasons for which adequate data are available, the total number of seasons being not less than three; or

ii. the mean of the maxima of those seasons in which the site is internationally important, taken over at least five years, amounts to the required level (means based on three or four years may be quoted in provisional assessments only).

In some instances, however, for example species occurring in very remote areas or which are particularly rare, areas may be considered suitable on the basis of fewer counts."

To date, there are no inshore sites in the UK where there are five seasons (years) of best quality count data and few where there are three years. Most sites will have count data of variable quality, in which qualifying numbers may be proved to occur in some years, but because of the tendency toward significant under-counting in many land-based surveys, it cannot be assumed that qualifying numbers do not occur in other years. In these cases, strict application of the Ramsar criteria would result in under-representation of sites that meet Stages 1.1-1.3 of the SPA guidelines.

The first definition may be applied more easily to count data for inshore non-breeding waterbirds, because it can still be applied if suitable data are only available for three years, or even if there are two years with good data and one with poor data (Webb and Reid 2003)

2.2 Methods for defining the extent of the interest feature

Once it has been established that a site qualifies for marine SPA status on the basis of the regular occurrence of qualifying numbers of one or more species, the extent of the interest feature must be defined, which should include the most important areas identified for the qualifying species concerned.

Defining the extent of the interest feature based on land based counts is difficult as little information on the spatial location of birds is collected. Counts from a ship or a plane using line transects are spatially explicit; information on the locations of individuals or flocks is collected. The following procedure should be followed when analysing aerial or boat-based transect data to aid in the spatial extent of the interest feature:

1. determine the locations of significant aggregations of qualifying species, and thus important areas; and
2. define the extent of the interest feature with reference to data requirements, and core and 'satellite' aggregations.

The output from geostatistical models based on line transect data in the form of estimated densities may be used to define the most important areas for a species. A threshold value derived from the kriged values may be used to differentiate important areas from marginal areas. Thresholds may be applied to several types of parameters derived from the kriged values including: estimated density; estimated probability of occurrence; slope analysis (the rate of change of density between neighbouring grid cells); and proportional distribution (the ranked percentage of the total population size for each grid cell). These parameters and possible threshold values are assessed critically and quantitatively in this report, to determine the most appropriate method to separate important areas from marginal areas, and thus, aid in defining the extent of the interest feature for each qualifying species.

The interest feature must be defined using data from several surveys to ensure that all of the important areas for each qualifying species are included: It is recommended that a minimum of three separate surveys, covering at least two different years, should be used for defining the extent of the interest feature, and that data from qualifying species should only be used (Webb and Reid 2003). Occasionally 'satellite' aggregations, small aggregations of birds disjunct from the main core aggregation, may be identified during spatial modelling. In this report, we discuss how these are identified and the rationale for inclusion or exclusion of these 'satellite' aggregations within the interest feature is presented. Once the extent of the interest feature has been determined, a seaward marine SPA boundary may be set, according to boundary setting guidelines (Webb and Reid 2003).

3 Case study data sources and processing

In this report we present case studies based on waterbird density and distribution data collected outwith their breeding season. These data were collected using a line-transect technique from boats and/or planes in outer Tay area, Scotland; Carmarthen Bay, Wales; and Liverpool Bay, England and Wales (McSorley *et al.* in prep.; Webb *et al.* 2004; Webb *et al.* in prep; respectively). The following section briefly describes these data collection methods, which are described in full by Dean *et al.* (2003) for aerial surveys, and Cronin and Webb (1998) and Webb and Durinck (1992) for boat-based surveys.

3.1 Carmarthen Bay aerial surveys

These data are presented in full in Webb *et al.* (2004).

The Carmarthen Bay data were collected by the Wildfowl and Wetlands Trust (WWT) under contract to CCW using the aerial survey method developed in Denmark by the National Environmental Research Institute, Denmark (NERI) (Dean *et al.* 2003; Kahlert *et al.* 2000).

Three aerial surveys of Carmarthen Bay were conducted on 28 October 2001, 9 December 2001, and 17 February 2002 during periods of light wind (Beaufort scale force three or less) and good visibility (≥1km).

Surveys were designed following a line transect sampling method in order to obtain abundance estimates for the target species using distance sampling methods (Bibby *et al.* 1992; Borchers *et al.* 2002; Buckland *et al.* 2001). A regular array of parallel line transects, spaced 2km apart and orientated along Ordnance Survey grid lines (north-south), was randomly imposed on the survey area (Figure 3.1). The north-south orientation was chosen so that transects were parallel to the gradient of habitat features likely to affect bird distributions in the bay (e.g. sea depth and sediment). Similar locations of survey transects were flown during each of the three surveys.

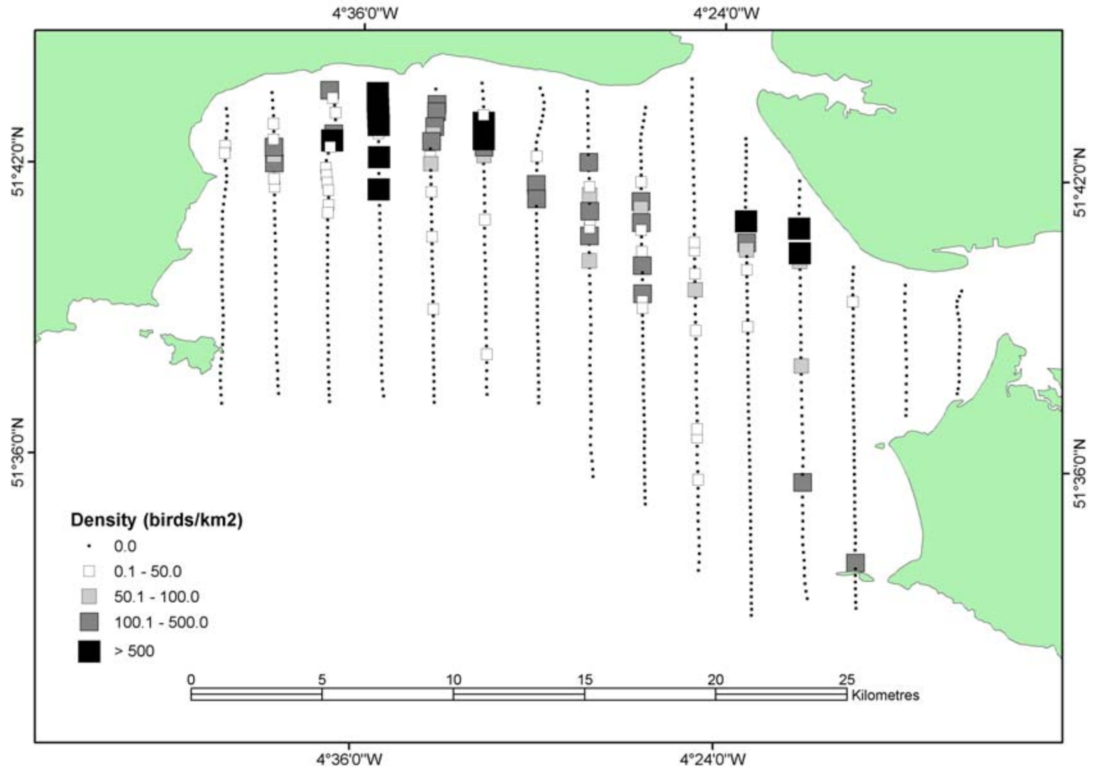


Figure 3.1 Map of Carmarthen Bay showing the distribution of black scoter observations in February 2002.

A Partenavia PN-68 aircraft was flown along the transect lines at constant speed and altitude. Following test flights using this type of aircraft in the Kattegat, Denmark, altitude and speed were standardised at 76m (250feet) and 185km.h^{-1} (100knots) respectively. These standards optimise detection and identification of birds and minimise flushing of birds by the approaching aircraft (Kahlert *et al.* 2000). During each survey flight, the position of the aircraft was calculated by an onboard GPS and automatically downloaded at 5-second intervals to a laptop computer.

Observations were made concurrently by one port observer and one starboard observer. For all target species, observers recorded the species, number, time and perpendicular distance from the transect line directly onto audio-tapes.

Birds were identified to the most specific taxonomic level possible. The number of birds recorded was either the exact number counted or (where large aggregations were encountered) an estimate of flock size. The time recorded was the time (to the nearest second) that the bird/flock passed abeam (at right angles to the length of the aircraft). The distance recorded was the perpendicular distance of the bird/flock from the transect line. Perpendicular distances were recorded in three bands; A, 44-163m; B, 164-427m; and C, 428-1000m. Observers determined these distances using fixed angles of declination from the visual horizon, easily measured using a clinometer. Transect lines were spaced 2km apart, such that the outer limit of band C was halfway between adjacent transect lines. The inner limit of band A was set at 44m because the design of the aircraft prevents observers from viewing a strip of water approximately 44m wide either side of the transect line.

The positional and observational data were entered into separate Corel Paradox database tables. The position data (collected at five-second intervals) were interpolated to define the position of the aircraft at each one-second time interval. The position and observation database tables were then linked by a common time field. We excluded all data from the turns between transects, as observers may fail to see birds while the aircraft is banking.

3.2 The outer Tay area aerial and boat-based surveys

These data are presented in full in McSorley *et al.* (in prep.).

3.2.1 Aerial surveys

Two aerial surveys were conducted from a Partenavia (P-68) aircraft, the first on 13 and 15 December 2001 (counted as one survey as each day had incomplete coverage) and the second on the 26 February 2002. These aerial surveys were conducted using the line-transect method as described in section 3.1 and in Dean *et al.* (2003). Parallel line transects, placed approximately 2km apart and orientated along lines of constant latitude (east-west), were randomly imposed on the survey area.

The resulting data were one-second sample counts of all birds (including flying birds) within an approximately 950m wide transect (split into three distance bands: A, 44 – 163m; B, 164 – 427m; and C, 428 – 950m) on both sides of the aircraft.

3.2.2 Boat-based surveys

A single boat-based survey was made from the MV *Chalice*, on 24 and 25 January 1998. The survey was conducted using regular SAST methods as described in Webb and Durinck (1992), but with some minor modification (see Cronin and Webb 1998); 10 x 42 binoculars were used to detect seaduck and divers, which tend to take evasive action some distance ahead of approaching boats and cannot be adequately surveyed using the naked eye. The perpendicular distance to birds was recorded within a 300m wide transect (split into four distance bands: A, 0 – 50m; B, 51 – 100m; C, 101 – 200m; and D, 201 – 300m). Where birds were flushed from the water within the transect well ahead of the approaching boat, the perpendicular distance could not be accurately determined. These birds were recorded simply as 'in transect'. Flying birds were counted using the snapshot method (Webb and Durinck 1992). The resulting data were one-minute sample counts of all birds (including flying birds) within a 300m wide strip-transect (split into four distance bands) on one side of the boat. Where one transect was surveyed on two days (24 and 25 January), data were excluded from the first day, when conditions were less suitable. A total of 12 transects was surveyed on 24 and 25 January 1998. Transects were orientated along lines of constant latitude (east-west) at approximately 2.8km intervals.

3.3 Liverpool Bay aerial surveys

These data are presented in full in Webb *et al.* (in prep.).

The Liverpool Bay data were collected using a line-transect aerial survey method, as described in section 3.1, by WWT on; 3-4 November 2001; 7, 10 and 17 December 2001; 15-17 January 2002; 13-15 February 2002; 11-12 and 17 March 2002; 10-11 April 2002; 16 and 18-19 August 2002; 15 and 17 November 2002; 6-7 December 2002; 10-11 January 2003; 7-8 February 2003; and 8-9 May 2003.

Parallel line transects, placed approximately 2km apart and orientated along Ordnance Survey grid lines (east-west and north-south), were randomly imposed on the survey area. Generally, transects were placed east-west in the north of the study area, and north-south in the south of the study area.

The resulting data were 1-second sample counts of all birds (including flying birds) within a 1000m wide transect (split into three distance bands: A, 44 – 163m; B, 164 – 427m; and C, 428 – 1000m) on both sides of the aircraft.

3.4 Calculation of sample density

Data for both aerial and boat-based surveys may be processed into sample densities at known locations along the transects, for display purposes, for calculation of mean sample density (section 4.1.1.2) and for geostatistical modelling (section 4.1.3). This involves summing the total number of birds counted within a sampling period (e.g. one-minute, 10-seconds) and dividing by the total transect area surveyed during the relevant sampling period. Each sample may be then assigned a spatial position equivalent to the platform's position at the midpoint of the relevant sampling period. Sample densities may be calculated for each surveyed side of the survey platform, using data from each distance band separately or combined data across some or all distance bands and/or sides of the survey platform (Figure 3.2).

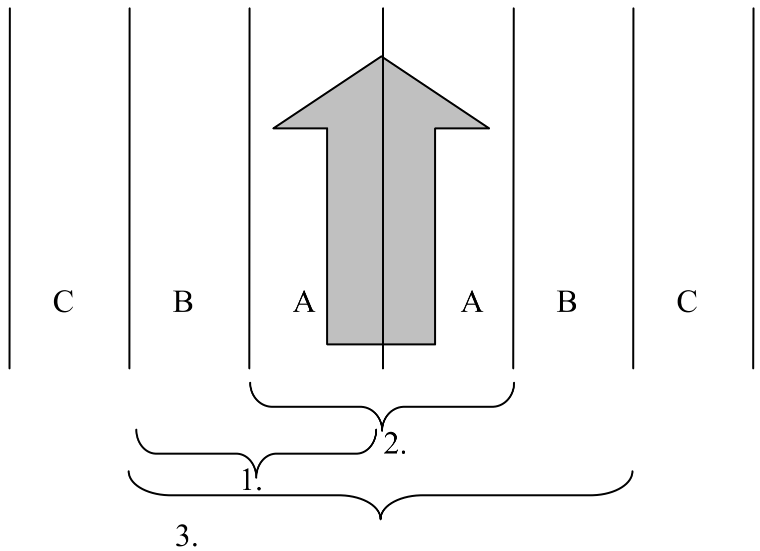


Figure 3.2 Sample densities may be calculated for (1.) each surveyed side of the survey platform, (2.) using data from each distance band separately or (3.) combined data across some or all distance bands and/or sides of the survey platform. Grey arrow is the direction of travel of the survey platform.

4 Site selection

Selection of an appropriate SPA depends, in part, on the calculation of accurate and precise population estimates of potentially qualifying species observed in the area of interest. As mentioned previously, it is usually impossible to count every individual in a study site and so a representative sample must be measured. This sample then may be used to generate an estimate of total population size.

For the assessment of inshore aggregations of birds outwith the breeding season, the data sources were collected using seabirds-at-sea line transect methods (see section 3 for data collection methods). The total population size within an area of interest may be estimated from seabirds at sea transect survey data using a variety of methods, including:

- extrapolation of density;
- distance sampling; and
- summed interpolated (kriged) abundances derived from geostatistical analyses.

The effectiveness of methods for producing accurate total population size estimates may depend on the data distribution. Parametric statistical techniques rely on the assumption that the observed data have an approximately normal frequency distribution (Zar 1999). However, animal count data are rarely normally distributed, usually because of the presence of many zero counts (zero-inflation or zero-elevation; Barry and Welsh 2002; van den Broek 1995; O'Driscoll 1998; Pearce and Ferrier 2001; Ridout *et al.* 2001), and because the positive sightings often show a positively skewed or log-normal distribution (Cox *et al.* 2000; Gregory 1994; Tabachnick and Fidell 1996). This type of distribution consists of many counts with low values and few counts with high values.

It has been noted by many authors that aerial and boat-based seabirds at sea survey data are zero-inflated with a positive skew of non-zero values, there being many counts of low to intermediate density and very few counts of high density (Fauchald *et al.* 2002; McSorley *et al.* in prep.; van der Meer and Leopold 1995; Pebesma *et al.* 2000a; Webb *et al.* 2004; Webb *et al.* in prep.).

Black scoter *Melanitta nigra* data from Carmarthen Bay surveys are used here as a case study to compare these three methods of population size estimation.

4.1 Methods for estimating population size

4.1.1 Extrapolation of density

Simple extrapolations of the overall sample density and the mean sample density were used to estimate the total number of birds in Carmarthen Bay, Wales. For simple extrapolations each line transect was treated as a strip transect (distance band information is removed); it was assumed that detectability did not decrease with increasing distance from the platform, and thus data was pooled over all distance bands.

4.1.1.1 Extrapolation of overall density.

The overall recorded density may be calculated for each species and survey as the total number of birds recorded during the sample survey divided by the total area surveyed of the strip transects. The population size may be estimated by multiplying this overall density by the total area of the study area.

4.1.1.2 Extrapolation of mean sample density.

The mean sample density is the sum of all sample (in this context a sample is the number of birds counted in a specified time period e.g. 10-seconds) densities, divided by the number of samples to give a mean of the densities, which may be then multiplied by the total area of the study site to yield a total population size estimate.

4.1.2 Distance sampling

Distance sampling techniques are similar to density extrapolation; however, the density calculated using the raw data is adjusted to account for the decline in detection probability of birds at increasing distances from the survey platform. Distance sampling assumes that the probability of an observer detecting a bird on, or close to the transect line is one, but that this probability decreases with increasing perpendicular distance from the transect line. Other important assumptions are that objects are detected at their initial location i.e. if the object (individual bird or flock) moves in response to the survey platform, its initial location before movement is recorded; and that estimation of perpendicular distance or assignment of distance band to the object is accurate. These assumptions are detailed in Buckland *et al.* (2001).

The collection of perpendicular distance data (pooled into a number of distance bands) from the transect line to each observation allows the modelling of the relationship between the probability of detection and perpendicular distance. The detection function from this model may be used to estimate both the proportion of birds away from the transect line that were not detected by the observer(s), and the effective width of the transect. These allow an estimate of the true density of birds to be calculated. Distance sampling methods are described in detail in Buckland *et al.* (2001) and specifically in relation to aerial surveys of marine seabirds in Webb *et al.* (2004).

Aerial and boat-based survey data may be formatted for entry into *Distance 4.0* as text files (data entry procedure described in Thomas *et al.* 2002), as follows:

- For aerial surveys, data for all birds recorded 'in transect', including flying birds, and for which distance band data were recorded may be used. Samples comprise line-transects with associated observations (from both sides of the aircraft), each comprising the identified species, the number of birds counted, the perpendicular distance band within which each individual or flock was observed, and a code identifying the observer;

- For boat-based surveys, data for all birds recorded on the water, 'in transect', and for which distance band data were recorded may be used. Those birds that were not assigned to a distance band (flying birds and birds recorded only as 'in transect' because they were flushed from the transect before distance could be estimated) should be excluded from the distance sampling analyses. Samples comprise line-transects, with associated observations (from one or both sides of the boat), each comprising the identified species, the number of birds counted, the perpendicular distance band within which each individual or flock was observed, and a code identifying the observer.

Data from both aerial and boat-based surveys may be analysed using *Distance 4.0* (Thomas *et al.* 2002) as described in Webb *et al.* (2004). We use half-normal models with zero adjustments. Akaike's Information Criterion (AIC) provides a quantitative statistic for selection of the most 'parsimonious model'. The Principle of Parsimony (Buckland *et al.* 2001) involves maximising precision whilst minimising error; addition of more parameters to a model may improve the fit to the data but at the cost of increased variance. We chose the model with the lowest AIC value.

Observer and cluster size (the number of birds observed in each flock or 'cluster') may be included as covariates or as bases for stratification in the *Distance 4.0* models. Where these do not improve the fit of the models, due to small sample sizes or lack of any relationship to the data, they should be excluded as model parameters, again in the interests of parsimony. Bootstrapping (resampling transects as samples with replacements) may be used to generate a robust estimate of standard error, and thus, 95% confidence intervals (Buckland *et al.* 2001). However, if there are no degrees of freedom remaining to produce confidence intervals, for example, when cluster size or observer is added as a covariate, 2.5 and 97.5 bootstrap percentiles may be used (Thomas *et al.* 2002).

In order to maximise the number of observations used to estimate the detection functions, global detection functions may be estimated across several similar surveys (i.e. several aerial surveys); this is a common technique used when sample sizes are small and is justified if observers are the same, and conditions are not greatly different between each survey (Thomas *et al.* 2002). However, if sample sizes are adequate or if there is evidence that detection functions vary among surveys, then ideally, detection functions should pertain to each survey separately. Estimates of cluster size and encounter rate should be made separately for each survey.

4.1.3 Summed interpolated (kriged) abundances derived from geostatistical analyses

The previous two population size estimation methods are not spatially explicit, that is to say the spatial locations and relationships among all data points are not integral to the analyses. However, geostatistics comprise a suite of spatially explicit statistical modelling tools that were applied widely in the 1980s in mining engineering (Cressie 1991). In the late 20th century, the use of geostatistics expanded to other disciplines including the modelling of the distribution and density of marine birds (Begg and Reid 1997; van der Meer and Leopold 1995; McSorley *et al.* 2003; McSorley *et al.* in prep.; Pebesma *et al.* 2000a and b; Robinson *et al.* 2002; Skov *et al.* 1995; Webb *et al.* 2004; Webb *et al.* in prep.).

Geostatistics quantify and interpret the spatial continuity or autocorrelation that is an inherent feature of environmental sample data (Isaaks and Srivastava 1989). The underlying principle of geostatistical analysis is that of spatial autocorrelation; the probability of two data points having similar values generally decreases with increasing geographical distance between the two points.

The use of semivariograms allows spatial autocorrelation to be modelled by investigation of the degree of dissimilarity between pairs of points separated by varying distances. The semivariogram provides the basis for kriging, a geostatistical interpolation method that is particularly applicable to irregularly spaced data (Cressie 1991), and that generates a grid of regularly spaced values across the area of interest. Kriging uses optimal linear prediction equations (Cressie 1991). The linear predictor generates estimates or predictions of values in areas that have not been sampled using a weighted average of neighbouring values (van der Meer and Leopold 1995). The process is optimised to limit the amount of prediction variance.

Geostatistics require the distances between all pairs of points to be known, so the data array should not have a geographical co-ordinate system (e.g. latitudes and longitudes). Rather, a projected co-ordinate system, with constant lengths, angles and areas across two-dimensions, must be used. Thus, we project geographical data (WGS 1984) onto Universal Transverse Mercator (UTM) projection at the appropriate zone for the study area (maintaining the WGS 84 chart datum), or to the British National Grid (BNG). We used both Surfer v. 8.00 (Golden Software, Inc. 2002) and *EcoSSe 2003* (Clark and Harper 2001) software for semivariography and interpolation.

4.1.3.1 Data processing

Sample densities are used for geostatistical analyses; however, distance sampling (section 4.1.2) should be used to assess whether observer efficiency declines significantly with perpendicular distance from the transect line prior to kriging. If there is a significant decline in observer efficiency over the width of the transect, the sample densities and thus, resultant kriged densities will be underestimated. There are two options for dealing with this in the data used for kriging:

i. if, from inspection of the density function produced by *Distance 4.0*, observer efficiency is uniformly at or near 100% across the entire width of band A, but decreases in subsequent bands, then band A may be treated as a simple strip-transect (bearing in mind that in aerial surveys there will be separate band A sample densities for port and starboard of the plane). Observational data from band A and the area covered by this band then may be used only to calculate sample densities (Box 4.1) (McSorley *et al.* in prep.; Webb *et al.* 2004; Webb *et al.* in prep.). If there is evidence that observer efficiency is uniformly at or near 100% across both bands A and B, the sample densities can be calculated for each distance band on each surveyed side of the survey platform. Similarly (but unlikely) for bands A, B and C together.

ii. *Distance 4.0* estimates the probability of detecting a bird within the entire transect (Buckland *et al.* 2001). This probability may be used to compute a correction factor that can be applied to the sample densities, calculated using data from all distance bands. This correction factor accounts for the number of birds missed as a result of observer efficiency declining with distance from the survey platform (Box 4.1). This method is used in Skov *et al.* (1995 and 2002).

Box 4.1 Worked example of distance sampling estimation and application of correction factors.

Line transects of inshore waters were conducted using an aerial survey platform. Observations were divided into three distance bands; band A (44-163m) was closest to the transect line, band B (164-427m) was the middle band and band C (428-1000m) was furthest from the transect line.

In one 10-second sample period the aircraft travelled 0.6km, covering a total area of 1.147km^2 (total area in band A = 0.143km^2). A total of four red-throated divers *Gavia stellata* was recorded, three in band A, one in band B and none in Band C.

Without accounting for decreasing observer efficiency the sample density was 4/1.147 = **3.49 birds.km^{-2}**.

Using band A observations only the sample density was 3/0.143 = **20.98 birds.km^{-2}**.

Using detection functions (a model describing the decline in detection rates with distance from the transect line), *Distance 4.0* calculated that for the aerial survey data presented here, the probability of detecting divers over bands A, B and C was 0.2, giving a correction factor of 1/0.2 = 5.
Applied to the above density, this gave a corrected density of 3.49*5 = **17.45 birds.km^{-2}**.

The robustness of *Distance 4.0* models determines the most appropriate method of data processing for geostatistics and is discussed in section 4.3.

The following sections outline the analytical process for interpolating sample data to produce a map of estimated abundances for the entire study area, which may be summed to generate a total population size estimate.

4.1.3.2 Semivariogram model fitting

The spatial structure of the data is examined by investigating the degree of dissimilarity between pairs of data points in relation to the separation distance. In general, the degree of dissimilarity between pairs of data points increases with increasing separation distance, until a separation distance is reached over which there is no correlation between the points. When the degree of dissimilarity between pairs of points is plotted against separation distance, the resulting graph or semivariogram has a coherent ‘shape’ or relationship.

This relationship may be modelled by fitting a curve to the semivariogram; the spatial pattern of the observations and how values differ with separation distance will determine the most appropriate shape of the fitted semivariogram model. The shape of the fitted model depends on two parameters; a mathematical function and the ‘nugget effect’:

- The mathematical functions that determine the type of model component include linear, generalised linear, spherical, exponential, Gaussian, and ‘hole effect’ (Clark and Harper 2001). As a result of the shape of the semivariograms, we applied spherical, or less often, Gaussian functions in geostatistical analyses of waterbird aerial survey data (McSorley *et al.* in prep.), as with Skov *et al.* (2002). However, generalised linear functions were also used by Webb *et al.* (2004).

- Field observational data have various errors associated with them; random sampling error and small scale discontinuities in the environment render it unlikely that two hypothetical data points with zero distance separating them will be identical. Such error has been termed the 'nugget effect', a term that is a relic from geostatistics' mining beginnings; in gold deposits no matter how small the distance between a pair of samples, there is likely to be a difference in values due to the gold occurring in small aggregations or nuggets (Clark and Harper 2001). The larger the nugget effect, the smoother the resultant grid. Therefore, data-sets with a high degree of sampling error and/or small scale environmental discontinuities will cause the resultant grid values to be underestimated in areas of high observed values and vice-versa.

However, before any model is fitted to the semivariogram two aspects of the spatial autocorrelation must be investigated, stationarity and isotropy:

- Stationarity occurs when values from a spatial model (means or variances) behave in the same way at all locations in the study area i.e. that the expected value should not depend on its spatial location. Non-stationary (data with a trend) datasets may show a consistent gradient across the surface (Figure 4.1).

  Semi-variograms require stationarity only of the difference in value (or covariance between two values) for a fixed distance and direction (between pairs of points). Lognormal kriging requires stationarity of variance for the back-transformed values. If data are non-stationary, this has to be accounted for in the modelling by fitting a polynomial trend surface and then modelling the residuals using the semivariogram and kriging procedures: Clark and Harper (2001) describe this analysis in full. Our data were stationary, and therefore, posed no non-stationarity issues;

Figure 4.1 An example of a non-stationary (data with a trend) dataset.

- Isotropy: a semivariogram that has a correlation structure that does not differ with respect to orientation of the pairs of points can be explained by an isotropic model (Kitanidis 1997). Anisotropy means that the 'predictability' can change with the relative orientation of the two points under consideration: That is, differences in paired values at a particular distance in one direction may be dissimilar to differences in paired values at the same distance in another direction.

If the correlation structure is anisotropic, such as when the dependent variable is affected by topography, then the model parameters need to be rescaled for anisotropy (Kitanidis 1997). As anisotropy is orientated along a gradient, it lies in the same direction as similar values of the dependent variable (in this case bird density). When a model is rescaled for anisotropy, the similar values along the gradient are weighted more heavily using a power ratio, than the more dissimilar values across the gradient.

Cross-validation may be used as an objective method to quantify the 'best' type of semivariogram model upon which to base the kriging procedure. A cross-validation procedure, based on jack-knifing, is used to generate interpolation errors. An observation (T_i) is removed from the data-set at random and the value at that location is estimated using interpolation (T^*_i), and the error incurred during the estimation is then calculated according to Equation 4.1.

Equation 4.1 Semivariogram cross-validation error calculation.

$$\varepsilon_i = T_i^* - T_i$$

Cross-validation statistics may be calculated by *EcoSSe 2003* (Clark and Harper 2001) and give a quantitative measure of the quality of the semivariogram model fitting procedure. As this procedure utilises data points that are not statistically independent, standard hypothesis testing is not valid (Kitanidis 1997). However, it is possible to compare statistics generated by cross-validation of different semivariogram models on the same data.

In cross-validation the aim is to identify a model that best represents the observed data. Therefore, we chose the model that best satisfies the following series of criteria:

- the average estimated value and standard deviation are most similar to those of the observed values;
- the average error statistic is closest to zero;
- the standard deviation error statistic is closest to one; and
- the semivariogram has as good a visual fit as possible.

It is the final criterion that we deemed most important when fitting a semivariogram model. The model that best fulfilled these criteria, and thus best predicted the observed data, may be utilised in the kriging procedure.

4.1.3.3 Kriging

Kriging is a geostatistical tool that uses the spatial autocorrelative relationship between sample data to interpolate values to unsampled locations. It is based on the concept of a 'weighted average', where a value at an unsampled location is estimated using weighting factors (generically known as 'inverse distance' estimators). That is, the value is interpolated from measured values at neighbouring locations using the semivariogram model (Clark and Harper 2001).

Kriging may be carried out on various types of data; indicator kriging models binary, sample data (presence/absence; 1/0), whereas ordinary and universal kriging model continuous sample data.

Indicator kriging is the geostatistical equivalent of logistic regression; it is a non-parametric modelling technique that does not require normally distributed data. Indicator kriging can model binary, presence/absence, sample data (1/0) to produce a grid of probability of occurrence, with probability values ranging from zero to one. Clearly indicator kriging cannot model continuous density data, so densities cannot be estimated using this method alone.

Ordinary kriging is a parametric tool that models continuous sample data to produce a grid of continuous estimates (for example, bird density); universal kriging is similar to ordinary kriging but models data with a spatial trend (see section 4.1.3.2 for a description of stationarity and modelling trends).

Generally, parametric geostatistics, such as ordinary kriging, are most robust when the distribution of the data values is close to normal (Isaaks and Srivastava 1989). Transformation (for example, using a logarithmic function) of density data may normalise the positive sightings to some extent; however, the problem of zero elevation cannot be solved by a simple transformation.

Nevertheless, ordinary kriging has been carried out on zero elevated, skewed (albeit transformed) data (McSorley *et al.* 2003; van der Meer and Leopold 1995; Webb *et al.* 2004). When ordinary kriging is applied to data with zero inflation, the resultant surfaces are excessively smoothed; the kriged grid comprises overestimated modelled density in areas of observed zero density, and underestimated modelled density in areas of high observed density (Marinoni 2003).

Such potential problems associated with applying ordinary kriging to non-normally distributed data may be avoided by the application of ordinary indicator kriging (I. Clark pers. comm.; Marinoni 2003). Ordinary indicator kriging is a two-stage combined modelling approach that combines one model of probability of occurrence with a second model of the density data (all zero counts removed). Similar non-geostatistical combined models have been applied by Barry and Welsh (2002) and Chamberlain *et al.* (1999).

This combined ordinary indicator kriging approach may be applied to observed bird distribution data. Raw data should be transformed to a binary response variable (i.e. 1/0), and indicator kriging applied to produce a grid of estimated probability of occurrence. For the ordinary kriging modelling, the zeros should be removed from the raw data and the positive sightings data distribution investigated to detect skewness. Logarithmic or square root transformations may be applied to positively skewed data; a $\log_{10}$ or $\log_e$ (hereafter termed log or ln, respectively) transformation is applied to extremely skewed data, whereas a square root transformation is applied to moderately skewed data (Tabachnick and Fidell 1996). Count data, such as those presented here are often extremely skewed, so a logarithmic transformation should be applied. Either log or ln may be used (Zar 1999). However, it is important to check that the geostatistical package being utilised includes the correct back-transformation; *EcoSSe 2003* included a back-transformation for ln transformed data. Ordinary kriging may be applied to the transformed, positive observations only, to produce a grid of estimated transformed densities, which should be back-transformed to give untransformed densities. The two resulting grids generated from ordinary kriging and indicator kriging may be combined by multiplying estimated density values and the estimated probabilities of occurrence values, thereby generating an overall grid of estimated density values: Grids produced in this way have more accurate estimates of positive density and zero values than those produced by ordinary kriging alone (Clark 1993; Marinoni 2003).

There are only a few examples of this type of combined geostatistical model, with most being found in the mining industry (Clark 1993; Marinoni 2003); however, combined geostatistical kriging models are now being used for modelling bird densities (Pebesma *et al.* 2000a). This technique appears to be ideal for application to data from surveys of birds at sea.

Clearly, ordinary indicator kriging can offer an uncomplicated and intuitive method for avoiding the problem of zero elevation that ordinary kriging alone cannot. To quantitatively determine the most appropriate method for interpolating zero-elevated marine bird distribution survey data, we compared the two methods, using aerial survey data and the resultant population size estimates of black scoter distribution in Carmarthen Bay.

4.1.3.4 Summed abundances

In addition to providing distribution maps of estimated densities and distributions of seabirds, population size estimates can be also generated from kriged grids. These grids may be based on any spatial resolution, although, in recent studies we have used a grid of 100 x 100m cells (McSorley *et al.* in prep.; Webb *et al.* 2004; Webb *et al.* in prep.). Total estimated population size of birds is simply derived from the kriged density grid, by converting grid cell densities into abundance (number of birds), and summing the abundances of all grid cells.

4.2 Population size estimation: a case study using black scoter data from Carmarthen Bay

In order to compare population size estimation methods we used aerial survey data of black scoter distribution in February 2002 in Carmarthen Bay, Wales (Webb *et al.* 2004) as a case study. Data sources and collection methods are described in section 3. Due to recent developments in geostatistical analysis software, the following section concentrates on two methods for kriging sample densities from survey data; ordinary kriging and ordinary indicator kriging (as outlined in section 4.1.3.3).

4.2.1 Data processing

Data processing for kriging depends on results from distance sampling. If distance sampling models are very robust, *vis-à-vis* producing estimates with narrow confidence intervals and a good fit for the detection function, the use of correction factors to account for the decreases in observer efficiency with distance from the survey platform (section 4.1.3.1) may be applicable. However, if distance sampling models have very wide confidence intervals or badly fitting detection functions[1], one or more bands can be used as a strip transect, rejecting the bands with data affected by declines in detection rate. The detection functions from *Distance 4.0* analyses may be inspected to determine at which point the detection rate declines, and data from band A or bands A and B may be used for geostatistical analysis (McSorley *et al.* in prep.; Webb *et al.* 2004; Webb *et al.* in prep.). If there is no evidence for

[1] Detection functions generally fit data better if the data is collected in many distance bands (> 3 or 4) to increase the sample size; since our data is collected in 3 or 4 distance bands, the detection functions generally have a poorer fit.

detectability decreasing with distance then all distance band data may be used for kriging (McSorley *et al.* in prep.).

The black scoter data from Carmarthen Bay (Webb *et al.* 2004) were zero-elevated with positively skewed positive sightings.

4.2.2 Ordinary kriging

Originally, ordinary kriging was applied to the black scoter data from Carmarthen Bay as the most appropriate method available of interpolating densities, despite violation of the assumption of data normality (Webb *et al.* 2004). Ordinary kriging of log (density+1) (as with Begg and Reid 1997) was performed for the initial analyses using Surfer v8.0 (Golden Software, Inc. 2002). This package did not provide a built in back-transformation of kriged estimates allowing estimation of total abundance, so back-transformation was carried out manually using a simple formula (Equation 4.2).

Equation 4.2 Simple back-transform for log values where, T_{bt}* = back transformed kriging estimator and T* = kriging estimator

$$T_{bt}^* = 10^{(T^*)} - 1$$

Figure 4.2a shows the back-transformed density distribution of this analysis.

Clark and Harper (2001) and Cressie (1991) have indicated that simple back-transformation using Equation 4.2 is biased. More accurate estimates may be obtained if both the variance and a Lagrangian multiplier[2] are included in the back-transformation (Clark and Harper 2001; Cressie 1991).The geostatistical programme *EcoSSe 2003* (Clark and Harper 2001) includes an automatic back-transform for many transformations. In their programme, they have included Cressie's (1991) back-transformation for ln transformed data (Equation 4.3).

Equation 4.3 Adjusted back-transform for ln values where, T_{bt}* = back transformed kriging estimator, T* = kriging estimator, σ_k^2 = estimation variance produced by ordinary kriging system, λ = Lagrangian multiplier produced as part of the solution to the ordinary kriging equations, and $\bar{\gamma}(T,T)$ = within block variance. From Clark and Harper (2001).

$$T_{bt}^* = \exp^{[T^* + \frac{1}{2}\sigma_k^2 - \lambda + \frac{1}{2}\bar{\gamma}(T,T)]}$$

Thus the analysis of the Carmarthen Bay February data was repeated using ordinary kriging of ln (density) with the variance adjusted back-transform using *EcoSSe 2003* (Clark and Harper 2001) (Figure 4.2b). Use of the adjusted back-transform (Equation 4.3) rather than a simple back-transform (Equation 4.2) effectively increases the grid node density values, rendering modelled densities closer in value to observed densities (Clark 1999). Comparing Figure 4.2a and b, it can be seen that density values are generally much higher when the variance-adjusted back-transform is applied than when the simple unadjusted back-transform is used.

[2] Lagrangian multipliers are unknown quantities used in calculus that allow minimisation (or maximisation) of a function subject to a linear constraint (Clark and Harper 2001). That is, Lagrangian multipliers are a mathematical tool to find extreme points (highest or lowest) of a function, when the variables or parameters in that function are constrained to particular values.

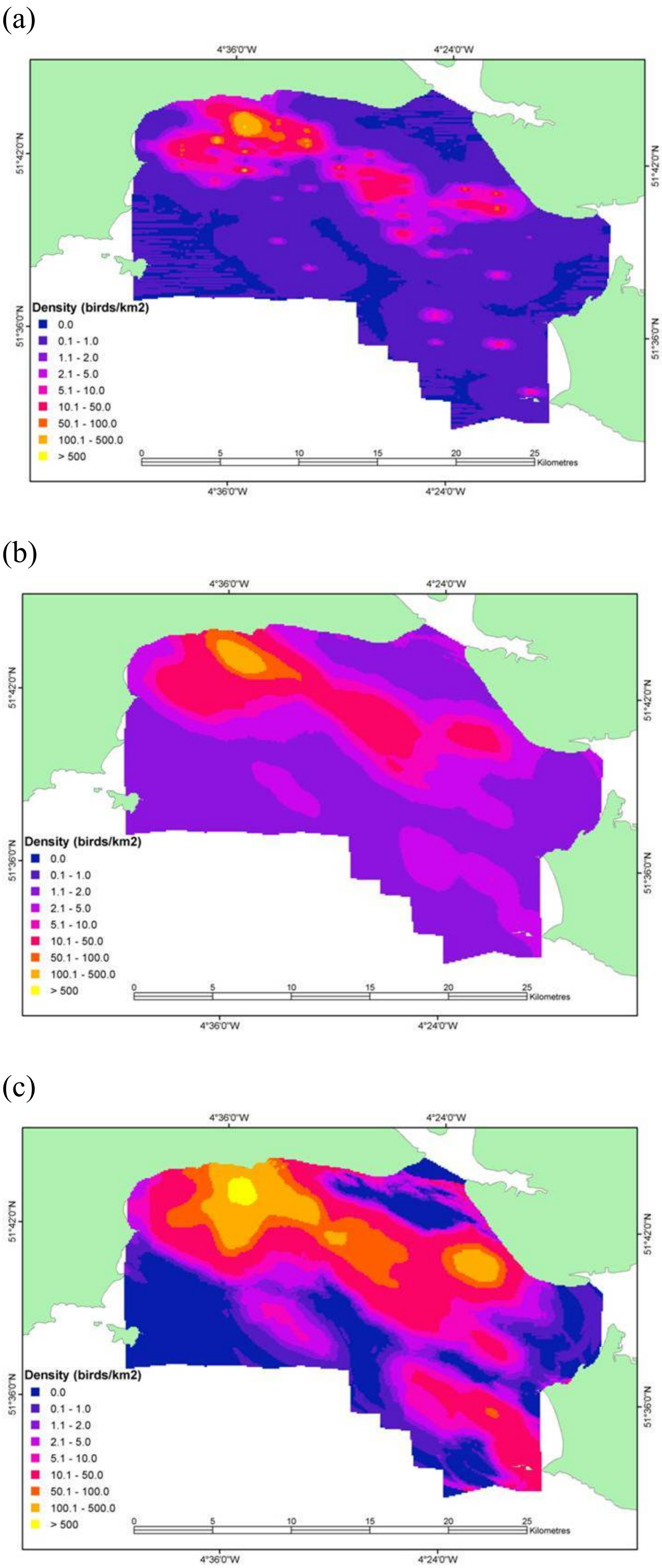


Figure 4.2 Maps of Carmarthen Bay black scoter density (birds.km^{-2}) grids in February 2002, estimated using (a) ordinary kriging with simple back-transform, (b) ordinary kriging with adjusted back-transform, and (c) ordinary indicator kriging (see text).

Figure 4.2a and b also show some evidence of smoothing, with the areas of zero density in the observed data (Figure 3.1) having values higher than expected, and the areas of high observed density having values lower than expected. This pattern is somewhat hidden by the effect of the simple transform used in ordinary kriging seen in Figure 4.2a generating lower densities than expected. However, Figure 4.2b shows that zero density is rarely estimated. In order to alleviate this problem of overly smoothed grid surfaces, as a result of zero-elevation, ordinary indicator kriging was applied to the same data.

4.2.3 Ordinary indicator kriging

We applied ordinary indicator kriging, using *EcoSSe 2003* (Clark and Harper 2001), to the binary and ln transformed black scoter data collected in February 2002 from Carmarthen Bay. This method uses the adjusted back-transform for the ordinary kriging component, and also ensures that the modelling process is not affected by the non-normal distribution of the count data (caused by zero inflation) by inclusion of a non-parametric component, namely indicator kriging.

By using the combined modelling technique of indicator kriging on presence/absence data and ordinary kriging on positive observations only, the resultant model grid was dominated less by the non-normal data distribution (Figure 4.2c). Therefore, this method generated an array of high and low density values (Figure 4.2c) that was more similar to the raw data (Figure 3.1), in contrast to ordinary kriging alone (with the adjusted back-transform; Figure 4.2b), where excessive smoothing occurred.

4.2.4 Comparison of ordinary kriging and ordinary indicator kriging

Comparison of Figure 3.1 (observed density) with Figure 4.2 (kriged densities) shows that the general patterns of kriged density correspond closely to the observed data, with a broad band of relatively high density orientated north-west to south-east in the study area. The scales in Figure 4.2a-c are identical in order to facilitate comparison of the results of the three interpolation methods. The kriged density values show similar distribution patterns in all three maps, particularly in Figure 4.2a and c. Ordinary kriging (Figure 4.2a and b), produces similar density patterns to ordinary indicator kriging (Figure 4.2c), but the absolute density values are affected by the modelling techniques and the back-transformation (I. Clark, pers. comm.).

In summary, as predicted, estimated densities were higher using ordinary kriging with adjusted back-transform (Figure 4.2b), than when using ordinary kriging with simple back-transform (Figure 4.2a). Additionally, estimated densities using ordinary indicator kriging were higher (Figure 4.2c) and less smoothed than for ordinary kriging alone (Figure 4.2b).

The grid cell density (birds.km^{-2}) values may be multiplied by the grid cell area to generate grid cell abundance (total number of birds per grid cell), and then summed over the whole area. The resultant population size estimates (total number of birds in whole area) can be compared with the other two population size estimation methods, namely extrapolation and distance sampling (Table 4.1).

Table 4.1 Black scoter population estimates in Carmarthen Bay using ordinary kriging and ordinary indicator kriging compared with estimates using distance sampling and extrapolation of overall density (from Webb *et al.* 2004). 2.5 and 97.5% percentiles are produced for the *Distance 4.0* estimate as a result of lack of degrees of freedom to produce confidence intervals (section 4.1.2). Data from February 2002.

Method	Calculation	Population size estimate (individuals)
Total number counted	Sum of all observations (total N)	9,116
Extrapolated raw densities	Mean sample density (mean density) x total area	13,281
	Overall density (total N / transect area) x total area	14,346
Distance sampling estimation	*Distance 4.0* (bootstrapped estimate)	14,937
(bootstrap 2.5 and 97.5% percentiles)		(6,205 – 30,449)
Interpolated densities	a) Ordinary kriging (simple back-transform)	1,359
	b) Ordinary kriging (adjusted back-transform)	2,923
	c) Ordinary indicator kriging (adjusted back-transform)	11,683

Table 4.1 shows that the population size obtained from ordinary kriging with adjusted back-transform (Figure 4.2b) was more than twice that using ordinary kriging with simple back-transform (Figure 4.2a). However, both population estimates generated using ordinary kriging (Table 4.1 a and b), were much lower than the total number of black scoter actually observed, indicating that these models underestimate densities. The population estimate for ordinary indicator kriging with the adjusted back-transform (Figure 4.2c), is almost four times greater than that obtained from ordinary kriging with the adjusted back-transform (Figure 4.2b). Table 4.1 also presents population size estimates obtained from distance sampling and from extrapolation of raw density data (mean and overall). The extrapolation methods generated estimates similar to the distance sampling estimate; this is presumably because the birds are fairly evenly distributed within the flocks. In species that behave or flock differently, this is unlikely to be the case; extrapolation methods will be highly affected by the distribution of the birds on the water. Clearly, of the two kriging methods (ordinary and ordinary indicator kriging), ordinary indicator kriging with adjusted back-transform resulted in a population size estimate most similar to the extrapolated and, more importantly, the distance sampling estimates.

As a result of this investigation and assessment of the assumptions of the geostatistical methods, we conclude that ordinary indicator kriging with a variance adjusted back-transform is the most robust method for kriging zero-elevated, ln transformed data.

4.3 Overview of population size estimation methods

Ideally, when assessing potential SPA sites, consideration of population size should be done using estimates of abundance that are both accurate (close to the actual number) and precise (within tight confidence limits). Each method presented here makes certain assumptions about the data used. Therefore, the accuracy and precision of the resulting estimates depends upon the suitability of the data to the analysis, as well as the accuracy and precision of the raw data (for example, the accuracy and precision of the data collection method[3]).

Without knowing the actual number of birds present, one way of assessing the accuracy of the estimates produced by each method is to assess the level of agreement between the results of different methods (Table 4.1). However, it is possible that even if there was close agreement between population size estimates from different methods, these values could be inaccurate or imprecise. The level of precision can currently be estimated only for distance sampling using *Distance 4.0* (expressed as 95% confidence limits around the point estimate).

4.3.1 Extrapolation of density

The extrapolations of mean and overall density are relatively quick and simple methods of estimating total abundance within the sampled area. However, these methods make assumptions about the data used; overall density assumes that birds are uniformly distributed across the study site (i.e. there is no clumping due to social aggregation or habitat selection) and use of mean density is only accurate if sample densities are normally distributed. These assumptions are likely to be violated by zero-elevated, spatially-autocorrelated count data. Extrapolation methods are also relatively crude and the likely accuracy of the estimates is unknown (Marchant and Gregory 1999). Therefore, their main use is likely to be as an additional method with which to compare estimates from distance sampling and kriging, assuming that the extrapolated counts are a realistic reflection of the actual population size.

The use of mean density is questionable; densities were calculated in equal time units e.g. 10-second intervals, and the density calculated for each time unit. However, taking the mean of these sample densities will lead to a biased result because the sampling units were not all exactly the same (the plane moves slightly different distances in each time unit as a result of prevailing wind direction, for example), and the data were non-normal as a result of the zero elevation (Figure 3.1). Therefore, we do not endorse this method for density extrapolation. Although overall density extrapolation relies on data that were not autocorrelated, and it is clear that many of these data were autocorrelated, violation of this assumption does not lead to such biased results.

In common with kriging, the use of data from all distance bands in extrapolation does not account for birds missed by observers at greater distances from the transect line, thus sample densities may be generated using only those data unaffected by declines in detectability (e.g. band A data only). In contrast to the nugget effect in kriging, extrapolation makes no provision for sampling error, so estimates are more likely to be biased.

4.3.2 Distance sampling

Distance sampling is a widely used and accepted statistical method that accounts for major sources of potential underestimation during surveys. The method has been demonstrated to produce accurate population estimates for a variety of organisms (Bergstedt and Anderson

[3] There are several sources of sampling error that affect the accuracy and precision of the raw data, including; observer inability to detect attraction or avoidance of the birds to the survey platform; inaccurate species identification; and poor estimation of flock size, perpendicular distance and time observed abeam.

1990; Buckland *et al.* 1992; Gilbert *et al.* 1996, all in Buckland *et al.* 2001; also Cassey and McArdle 1999), and is widely available and accessible through the use of *Distance 4.0* software (Thomas *et al.* 2002). *Distance 4.0* includes the capability to estimate the precision of estimates in the form of 95% bootstrap confidence intervals.

However, not all survey data are suitable for distance sampling and the estimates generated here are rather imprecise, with very wide confidence intervals, as found by Cassey and McArdle (1999), and in a previous application of distance sampling to this type of survey data by Webb *et al.* (2004). This is unavoidable when analysing this type of clumped, quite sparse data with a limited number of distance bands.

While surveys should be designed and data collected without violating the assumptions of the distance sampling method (see Buckland *et al.* 2001; also Cassey and McArdle 1999), in many cases it is difficult to ensure that the data meet the requirements of the application. This is the case particularly in multi-species surveys where species react differently to the survey platform, or if the survey design represents a compromise between the assumptions of different potential analyses. If distance sampling is to be used as the primary estimate of total population size, it is particularly important that the appropriateness of the data and the assumptions of the analytical method are considered:

- Critically, it is assumed that all birds on or close to the transect line (in this case within band A) are detected. Although no assessment of this assumption has been made for these surveys, it seems likely that a small proportion of birds within band A are missed by observers. If this is the case, population estimates derived using distance sampling will be biased downwards by the same proportion;

- It is assumed that objects are distributed randomly with respect to the survey transects and that they do not show movement in response to the survey platform. Seabird species show varying degrees of avoidance (or attraction) to different types of survey platform. Some species appear to demonstrate significant reaction to boats (Webb and Durinck 1992); this may be also true of aircraft (Banks *et al.* unpublished report), although it is possible that site-specific factors (such as proximity to aircraft run-ways) may greatly affect birds' responses to the survey platform. Avoidance or attraction to the survey platform is likely to result in an underestimate or overestimate (respectively) of abundance;

- Distance sampling may not produce accurate results where the number of samples (transects), or observations is very small (Buckland *et al.* 2001) (as with many analytical techniques). If perpendicular distance band information is not recorded for a large proportion of the data, for example flying birds and birds flushed from the transect before an estimate of the perpendicular distance could be made, many data points will be excluded from analysis. Since only those data for which distance was estimated may be included in the distance sampling analyses, the number of observations may be artificially reduced, resulting in estimates that are lower than those generated by other methods. This can be rectified by the addition of estimated numbers using extrapolation of birds recorded without distance information. For flying birds recorded as 'in transect' using the snapshot method (Webb and Durinck 1992), extrapolation of overall density may be a reasonable estimate of total numbers of flying birds, since flying birds at the time of the snapshot are rather unlikely to be missed. However, for those birds recorded on the water 'in transect' but without distance information, the extrapolation method will not account for those birds missed at greater distances;

- The distance sampling method is designed to estimate the number of objects within the surveyed area. Many marine waterbirds aggregate in tight flocks or clusters; in these cases *Distance 4.0* estimates the number of clusters themselves. Hence, estimates of total numbers of birds are dependent upon estimates of the number of clusters, appropriate estimates of average cluster size, and also on the accurate assessment of the geometric centre of the aggregation by the observers. For species that occur as singletons to clusters of widely varying size (from two to thousands e.g. black scoter), neither the use of average cluster size, nor stratification by cluster size may completely account for the wide variation;

- It is assumed that perpendicular distances are measured without error. The precision of estimates may therefore be limited where observations are assigned a distance band (with only a limited number of distance bands used), rather than perpendicular distance measured, and the mid-point of each distance band used in analysis (McSorley *et al.* in prep; Webb *et al.* 2004; Webb *et al.* in prep.).

Distance sampling does not allow reliable population size estimation using sub-sampling of an area; population size estimation in sub-areas is best carried out using ordinary indicator kriging or extrapolation of density. Sub-sampling may be useful for determining the number of birds in discrete areas or within possible marine SPA boundaries, and as such, is useful for site selection and boundary determination for marine SPAs.

4.3.3 Summed abundances from geostatistics

Kriging is widely used in the earth sciences as a method of spatial interpolation (Kitanidis 1997) and is increasingly being used in the study of bird distributions (van der Meer and Leopold 1995; Skov *et al.* 1995; Villard and Maurer 1996). The extension of its use to derive population estimates is explored in this report, although the precision of such estimates (evaluated by confidence intervals) currently is not known. Although van der Meer and Leopold (1995) estimated the population size of European storm petrels at sea, they used ordinary kriging alone, and recognised the violations of its assumptions such as non-normality caused by highly skewed zero-elevated count data.

In contrast to distance sampling or simple extrapolation methods, kriging accounts for the aggregated, spatially autocorrelated distribution of birds across the survey area and potentially allows for the inclusion of other information such as habitat and environmental factors as covariates (cokriging), which are likely to be determinants of bird distribution.

Not all survey data are suitable for kriging; ideally surveys should be planned and designed with the use of kriging in mind. Although parallel line transects are useful for interpolation, the dataset may be slightly improved by inclusion of one or more transects perpendicular to these parallel transect (with exclusion of overlap data). As with many other analytical techniques, kriging may not produce accurate results in situations where the number of samples (positive observations) is very small (van der Meer and Leopold 1995). Kriging is dependent upon the use of a semivariogram model to describe the autocorrelation present in the data; with small sample sizes there may be no obvious or consistent pattern of spatial autocorrelation in the data, in which case, it will not be possible to generate a semivariogram model. For these reasons, the applicability of kriging to extremely rare species can be inappropriate.

Similarly, the pattern of autocorrelation may be markedly variable over different regions of the study site (see common eider *Somateria mollissima* kriged density grid from data collected in the Tay area in 1998 (McSorley *et al.* in prep.)). In this case, a very strong pattern of autocorrelation based on the data from the mouth of the Firth of Tay dominates the semivariogram, but may not be appropriate to the entire area. This can be addressed by splitting the total survey area into smaller subunits to be analysed separately, but again the problem of small sample sizes may arise (van der Meer and Leopold 1995).

Other potential sources of bias include the choice of sampling scale (the area over which observational data are grouped and density calculated); this may have an effect upon the degree and pattern of autocorrelation that can be identified in the data.

The accuracy of any population estimate derived using kriging is dependent upon the accuracy of the sample data on which the model is based (just like abundance estimates from very large grid cell sizes generate a less precise total population size as a result of lower spatial resolution). In contrast to distance sampling, kriging does not account for potential underestimation of density resulting from decreases in observer efficiency with increasing perpendicular distance from the transect-line. This needs to be accounted for in the sample densities used in the kriging analysis using one of the methods described in section 4.1.3.1 (i.e. using band A or A and B only or correction factors to account for decreases in detectability), both of which are likely to be based on at least a preliminary analysis using distance sampling methods. As mentioned in relation to distance sampling, it is likely that, even in band A, small numbers of birds were missed by observers. However, if these numbers are not great, the sampling error should largely be accounted for in the nugget effect.

While the ordinary indicator kriging method produces population estimates that closely match estimates calculated using other methods (Table 4.1), it is currently limited by being computationally intensive to obtain confidence limits for those population estimates. Hence, no appraisal of its precision can be made easily. The potential exists to estimate confidence intervals in future analyses via iterative simulations within *EcoSSe 2003* (Clark and Harper 2001) but is currently under development, and so is, as yet, unavailable.

The main advantage of kriging over distance sampling for estimating population size, is that kriging may allow the generation of robust population estimates where too few transects were surveyed to obtain a robust estimate using distance sampling (assuming that there are still sufficient positive observations for the spatial autocorrelation to be modelled). Additionally, kriging generates abundance estimates in grid cells that can be summed to produce population estimates across the entire study area, or within discrete sub-areas (i.e. the area within a proposed boundary) based upon the spatial relationships over the entire survey area. This is not possible to do accurately with distance sampling (Webb *et al.* in prep.). Furthermore, if kriging is being utilised to generate a visual representation of the modelled spatial distribution of a species, calculating a population estimate from the grid cell values is a relatively simple method of obtaining an additional population estimate.

One of the disadvantages of kriging over other methods is the amount of computing time and power necessary to interpolate at an appropriately fine resolution and at the scale of hundreds of square kilometres. Additionally *EcoSSe 2003* does not, as yet, generate confidence intervals unlike *Distance v4.0*.

4.3.4 Further developments in kriging

As mentioned above, modelling of seabird distribution and density can be performed using conventional non-spatial modelling that employ covariates, such as GAMs, or using geostatistics that employ semivariograms, such as kriging. A recent development, cokriging, is an integrative, geostatistical modelling technique that employs both the intrinsic spatial relationship of the observed data, expressed in semivariograms, and covariables (such as environmental factors), to estimate density values (Cressie 1991; Isaaks and Srivastava 1989; Kitanidis 1997). To date, there have been very few examples of the application of cokriging in modelling the distribution of animals (ticks, Estrada-Pena 1998; shrimps, Lembo *et al.* 1999), with many studies concentrating on predictive modelling of soil and sediment distributions (Chaplot *et al.* 2000; Leecaster 2003; Zeiler *et al.* 2000).

Cokriging enables the investigator to include covariables into the geostatistical model that may improve the predictive capabilities of that model (Chaplot *et al.* 2000; Zeiler *et al.* 2000). A robust and accurate cokriged model should employ covariables that are measured accurately and at the appropriate spatial scale, which might constrain the predictive power of high resolution spatial models of seabird densities in the inshore environment. When cokriging software and appropriate covariate data become available then we will test cokriging's applicability to population size estimation and to the definition of the extent of the interest feature.

4.4 Prioritisation of population size estimation methods

Although distance sampling and ordinary indicator kriging take into account observer efficiency and spatial autocorrelation (respectively), and both generate population estimates that are less biased than extrapolation of sample density, they require the most data processing and intensive analytical procedures and include many assumptions. As such, their appropriateness to survey data is likely to depend on the survey methodology and distribution of the observations.

Distance sampling is a widely applied method of estimating total numbers and is currently the only method that allows estimation of 95% confidence limits. In contrast, ordinary indicator kriging is primarily designed for modelling distribution data; the generation of accurate population estimates is a *post-hoc* analysis that is largely dependent upon prior distance sampling analysis to determine the need and appropriate method for accounting for missed birds.

Table 4.2 provides a summary of the population size estimation methods.

Table 4.2 Evaluation of different analytical methods for estimating population size from sampling surveys (Webb and Reid 2003).

Analytical method	Quality issues	Confidence intervals for estimated population?	Usefulness for boundary determination
Extrapolation from overall density (total number / total area surveyed x area of site)	Generally safe, but overly simplistic. Affected by degree of population distribution representation by samples.	No	Not possible
Extrapolation from mean sample density (mean sample density x area of site)	Problems when applied to non-normally distributed data and where there is spatial auto-correlation. Population estimates tend to be inaccurate because most survey data are non-normal and samples are not standardised.	Unreliable	Not possible
Distance sampling estimation	Well-documented, statistically robust method for population estimation. Not applicable to small areas with low sample intensity and poor with fewer than 50 observations.	Yes	Not possible and poor sub-sampling capability
Geostatistical analysis (kriging)	Good method if procedures carried out correctly. Increased in use for modelling animal distributions in last decade.	Possible, but as yet, untried	Good
Spatial modelling (e.g. general additive models)	Relatively new procedure; statistically robust, though not to problems of spatial autocorrelation. Requires good quality covariate data, in addition to bird sample data.	Yes	Good

Considering Table 4.2, it is possible to prioritise the various methods in order to obtain the most accurate population estimate/s for site selection for different types of data. Therefore, in assessing the most suitable method for estimating population size from sample data, we recommend the following protocol should be abided by:

1. In cases where the data meet the assumptions of the method, distance sampling, using *Distance* software, should be the primary method of estimating population size for the purpose of Stage 1 judgements under the SPA selection guidelines;

2. If possible, ordinary indicator kriging also should be carried out to model the distribution of birds across the whole survey area. When this has been completed a population size estimate from the models can be readily generated. Therefore, ordinary indicator kriging provides a useful second population size estimate as a precautionary measure, and that may be used to potentially reinforce the distance sampling estimate. When distance sampling is not considered appropriate, ordinary indicator kriging may still provide an accurate population estimate. In addition, ordinary indicator kriging can be used to estimate the likely numbers or proportion of the total population size contained within different sub-areas of the survey area (which may be useful for identifying important areas to be included in a protected

area). Confidence limits of kriged population estimates may be generated via iterative simulations following future development of geostatistical software, such as *EcoSSe 2003* (I. Clark pers. comm.);

3. The extrapolation of overall density can provide a simple method of obtaining further estimates to reinforce the distance sampling and ordinary indicator kriging estimates. However, the assumption of a uniform distribution and the relative crudity of this extrapolation method render extrapolation of overall density potentially erroneous as a sole method for undertaking Stage 1 judgements regarding number of birds for SPA identification.

Webb and Reid (2003) provides guidelines for the selection of marine SPAs for inshore aggregations of non-breeding birds with an evaluation of minimum data requirements to classify sites and an evaluation of Stage 2 judgements of the SPA guidelines.

5 Defining the extent of an interest feature

An SPA should include the most important areas for qualifying species; that is, areas that satisfy Stage 1 and/or Stage 2 of the SPA guidelines (Stroud *et al.* 2001). In the terrestrial environment, habitat and/or ornithological characteristics, that are definable and recognisable, have been used for delineating boundaries; in effect, boundaries are located where they are "clearly identifiable on the ground" (Stroud *et al.* 2001). Clearly, habitats are more difficult to identify in the superficially featureless marine environment, so the limits of possible marine SPAs are more easily defined with respect to the distribution(s) of the qualifying interest features, i.e. the birds themselves. A generic threshold based on modelled bird distribution parameters, and applied to modelled data for each species and from each survey, will determine the extent of the significant aggregations of each species, and therefore, aid in definition of the extent of that species' interest feature. Once the extent of the interest features for all qualifying species have been defined using data from several surveys, seaward boundary determination may be carried out following boundary setting guidelines for SPAs in the marine environment, found in Webb and Reid (2003) and soon to be published on the JNCC website http://www.jncc.gov.uk/.

5.1 Parameters for determination of a generic threshold for definition of the extent of significant aggregations, and thus, important areas

The extent of a significant aggregation may be defined with respect to application of a threshold to one of four different parameters of kriged data:

- probability of occurrence;
- density;
- slope analysis; or
- ranked percentages of estimated total population size (proportional distribution).

5.1.1 Probability of occurrence

As with logistic regression, it is possible to use the probability of occurrence from indicator kriging to categorise a species as present or absent within each unit (in this case, within each 100 x 100m grid cell). In essence, this technique requires a threshold or cut-off probability value that determines whether a probability value in a grid cell (between zero and one) is assigned the category 'presence' or 'absence'. The default logistic regression threshold value for many software programs is 0.5 (Tabachnick and Fidell), such that any probability value greater than 0.5 categorises presence, and any value less than 0.5 categorises absence (Figure 5.1a).

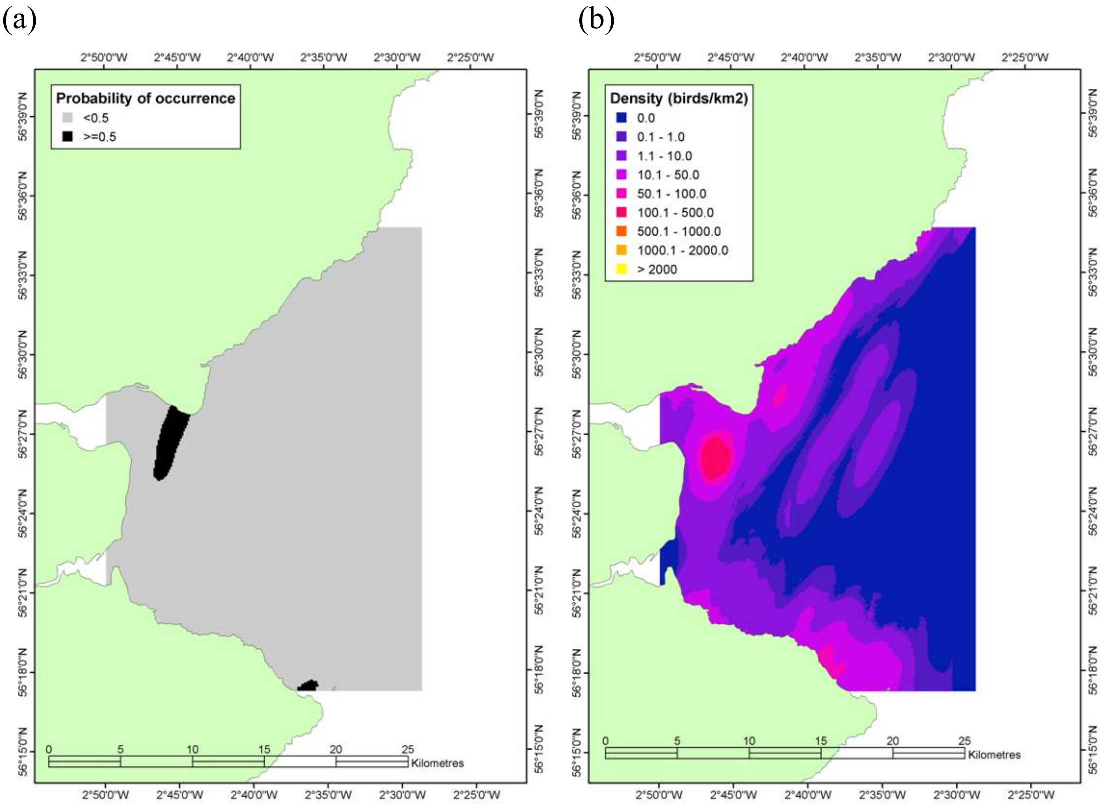


Figure 5.1 Common eider kriged data from 2002 in the outer Tay area showing, (a) probability of eider occurrence, derived from indicator kriging, with arbitrary 0.5 probability threshold, and (b) eider density values, derived from ordinary indicator kriging.

Recently, this arbitrary value of 0.5 has declined in use as it rarely reflects the best value for maximising classification accuracy; the probability output from an indicator kriging model, when converted back to a binary response (zero or one), can be tested using the area under the curve of Receiver-Operating Characteristic plots (ROC; Suarez-Seoane *et al.* 2002) or the Cohen's kappa statistic (denoted $\hat{k}$; Lillesand and Kiefer 2000; Manel *et al.* 2001). It is possible to use an iterative process whereby several threshold values are applied sequentially to the probability output to categorise probabilities into a binary variable, and ROC plots or kappa may be used to determine the optimal threshold that minimises omission (classification of absence, when in reality the species is present) and commission (classification of presence, when in reality the species is absent). ROC plots are computationally intensive, sometimes give an erroneous result with data from scarce species and also are generally correlated with the more simply derived kappa (Manel *et al.* 2001); therefore, kappa is explained in full in this report.

A zero value of kappa shows that the model performs no better than chance; a negative value shows that the model is performing worse than chance; and a positive value shows that the model is performing better than chance. The higher the kappa value, the better the model's performance. Kappa is calculated using Equation 5.1.

Equation 5.1 Formula for calculation of Cohen's kappa coefficient using a classification grid (**Box 5.1**), where x_{ii} = diagonal subtotal for row i, column i; x_{i+} = row subtotal for row i; x_{+i} = column subtotal for column i; and N = Total sample size.

$$\hat{k} = \frac{\theta_1 - \theta_2}{1 - \theta_2}, \text{ where } \theta_1 = \frac{\sum_{i=1}^{r} x_{ii}}{N} \text{ and } \theta_2 = \frac{\sum_{i=1}^{r} x_{i+}x_{+i}}{N^2}$$

To assess the model accuracy using kappa, classification tables are used; observed and predicted values are compared by measuring the frequency of observed values that were correctly and incorrectly (omission and commission) classified according to selected thresholds. Box 5.1 shows examples of this.

Box 5.1 Worked examples of classification grids and calculation of the kappa statistic using theoretical data.

Example 1

Threshold = 0.1

Total sample size = 5,030

	Predicted		Row total (x_{i+})
Observed	0	1	
0	4,800	200	5,000
1	20	10	30
Column totals $(x_{+i})_r$	4,820	210	x_{ii} = 4,810

Kappa = 0.0737 or 7.37%

Example 2

Threshold = 0.01

Total sample size = 5,030

	Predicted		Row total $(x_{i+})_r$
Observed	0	1	
0	4,000	1,000	5,000
1	10	20	30
Column totals $(x_{+i})_r$	4,010	1,020	x_{ii} = 4,020

Kappa = 0.0268 or 2.68%

As a result of the large number of zeros in the data collected using at-sea surveys, these classification accuracy measures generally maximise the number of cells correctly classified as zero (Box 5.1). Indeed, we can incorrectly classify most of the 'presence' cells (Observed = 1), and still generate a model with a high kappa value. The increase in classification accuracy (as measured by Kappa) in the first example (Box 5.1) compared to the second example, despite misclassification of most of the 'presence' cells, clearly demonstrates this. For this reason, kappa may not be the most suitable method for selection of an appropriate threshold value for data that are highly zero-elevated.

Examination of the cross-validation output in *EcoSSe 2003* reveals that the estimated probability values for 'presence' observed values range from zero upwards; indeed, there are usually quite a few grid cells that have a zero probability for which the observed data is coded for 'presence'. The threshold we have decided to use is the minimum probability value for each indicator kriged surface, excluding probability values of zero, where the observed value is equal to one. In this way we maximise the number of classified 'presence' cells where the birds were actually observed, despite accepting a small decline in the Kappa statistic.

A probability level equal to the proportion of samples with birds present in the total sample can be used as a simple threshold value. However, where samples are more zero-elevated than others this proportion will be biased – for example, if a survey's geographical limit is extended into an area where no birds are seen, the proportion of positive sightings to zeros will decrease affecting the resultant threshold value. For this reason, use of this type of threshold may be used but is not the preferred method. In past analyses we have used the proportion of the samples with birds present as a cut-off value (Webb *et al.* in prep.); however use of a threshold value of the minimum estimated probability where the birds are actually present aids in identifying a possible boundary that is very similar in spatial extent to a boundary identified using the proportion of occurrence threshold value.

Identification of boundary thresholds using indicator kriging alone has a significant drawback in that identification of important areas is based only on species occurrence. For those species that form highly aggregated flocks where one observation may consist of a very large number of birds (e.g. black scoter), use of a probability threshold may not be the best way to identify the most important areas since a sampling unit holding either one bird or 100 birds will be categorised as 'presence'. However, for those species that are scarce and dispersed (possibly occurring mostly in very small numbers that preclude modelling of density, e.g. red-throated diver *Gavia stellata*), this type of approach may be suitable.

5.1.2 Density

Ordinary and ordinary indicator kriging allow the generation of estimates of density. The use of a density threshold may have potential advantages over a simple presence/absence approach (compare Figure 5.1a and b). However, the use of a generic threshold value based on the kriged density values of each grid node to identify important areas could potentially lead to bias of the geographical extent of the important areas selected. Two extreme outcomes of this bias are;

i. where the distribution of a species is highly aggregated and the species is present at high densities, application of a threshold value of one bird.km^{-2}, for example, would result in the delineation of large areas containing a low percentage of the site's population size, in addition to the most important high density areas. The resulting interest feature in this case would contain important and marginal areas for that species in that study area; and

ii. conversely, where the species is more dispersed and present at low densities, the use of a threshold value of one bird.km^{-2} would result in the delineation of small areas including only the very highest density areas. The resulting feature in this case might represent an overly small area which may not adequately reflect the extent of bird aggregations present.

Site-specific threshold values would be unlikely to apply to all species present at any given site. The use of a site-specific value for a relatively highly aggregated species, present at high densities such as black scoter, would probably result in the first outcome, whereas the use of the same value for a more dispersed species, present at lower densities such as red-throated diver would probably result in the second outcome.

Similarly, species-specific thresholds would be unlikely to be applicable to all sites where a given species was present, as it is likely that the nature of species aggregations is site-specific. Although previous studies have used species-specific density values as thresholds to identify important areas in marine areas (Durinck *et al.* 1994; Harding and Riley 2000; Skov *et al.* 1995), local environmental factors such as tidal state, freshwater and terrestrial inputs (e.g. sewage, industrial waste), sediments, food availability, and weather conditions probably generate site-specific differences in a species' distribution patterns. Therefore species-specific and site-specific density thresholds may not be suitable for defining the extent of significant aggregations of birds.

5.1.3 Slope analysis

As outlined in Webb *et al.* (2004), slope analysis may be applied to grid cell kriged density values using spatial analysis tools within ESRI's ArcMap(™) v. 8.2. The degree of change in density between neighbouring grid cells (the gradient or slope) may identify the location of those areas where the greatest change (highest slope value) in modelled density occurs. However, the general applicability of this technique to delineate important areas is somewhat limited; the possibility remains that grid cells very low in absolute bird density yet adjacent to cells of even lower density (thus retaining a high slope value) may be identified, erroneously, as important.

5.1.4 Ranked percentages of the total population size (proportional distribution)

The kriged density (birds.km^{-2}) in each grid cell may be converted into abundance (number of birds in each grid cell). Each grid cell then may be expressed as the ranked (in decreasing order) cumulative abundance and presented as a percentage of the estimated total population size (summed grid cell abundances across the entire study area) following Webb *et al.* (2004). We term this 'proportional distribution'.

Application of a threshold value to the proportional distribution to define the extent of the significant aggregations, and thus important areas, has clear advantages over the other methods discussed; it uses modelled density data that can be related directly to the estimated number of birds present, irrespective of the absolute size of that estimate and irrespective of how the birds are dispersed over the study area.

As a result, we recommend proportional distribution as an appropriate ordinary indicator parameter for determination of a suitable threshold to define the extent of the interest feature. Where indicator kriging only is possible, a threshold based on probability of occurrence must be used.

5.2 Identifying a generic proportional distribution threshold for definition of the extent of significant aggregations: a case study

A threshold must be applied to the ordinary indicator parameter, in this case proportional distribution or probability of occurrence to define the extent of significant aggregations of waterbird species. A threshold for probability of occurrence has been determined in section 5.1.1; however, a threshold value for proportional distribution also must be determined. These thresholds are, by their nature, arbitrary values; however, as with the generic probability of occurrence threshold value, the ordinary indicator kriged values themselves may indicate the most appropriate and possibly generic proportional distribution threshold value.

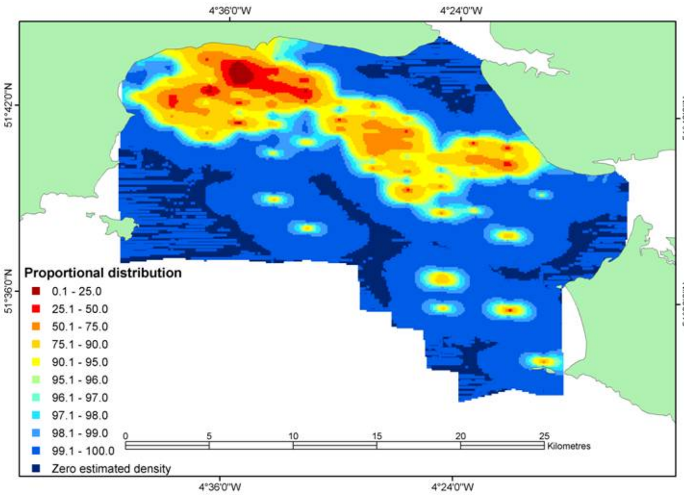
In the following section, data from outer Tay area, Carmarthen Bay, and Liverpool Bay, presented respectively in McSorley *et al.* (in prep.), Webb *et al.* (2004), and Webb *et al.* (in prep.), are used as a case study. Data sources and collection methods are described in section 3. Data processing is presented in section 4.1.3.1, and the full results of all kriging analyses are presented in the previous reports and are not replicated here.

5.2.1 Relationship between proportional distribution and proportional coverage

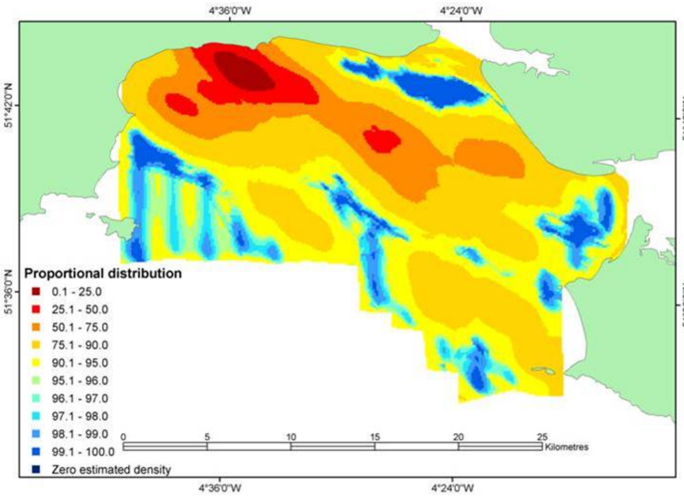
The raw data show that the zero counts covered a very large proportion of the study site's total area (Figure 3.1 presents an example of raw data from Carmarthen Bay); thus, we expected that exclusion of these large areas from within any boundary would leave the total population size largely unaffected. Indeed, we expected that exclusion of large areas of very low density would also leave the final total population size within the boundary, relatively unaffected.

The highest density areas (Figure 4.2) contribute most to the overall estimate of the total number of birds present at the site; a small number of these grid cells (and thus, area covered) contribute to 1% of the total estimated population size (Figure 5.2). Conversely, the lowest ranking abundance grid cells contribute least to the overall estimate of the number of birds present at the site, with a large number of these grid cells contributing to 1% of the total estimated population size.

(a)



(b)



(c)

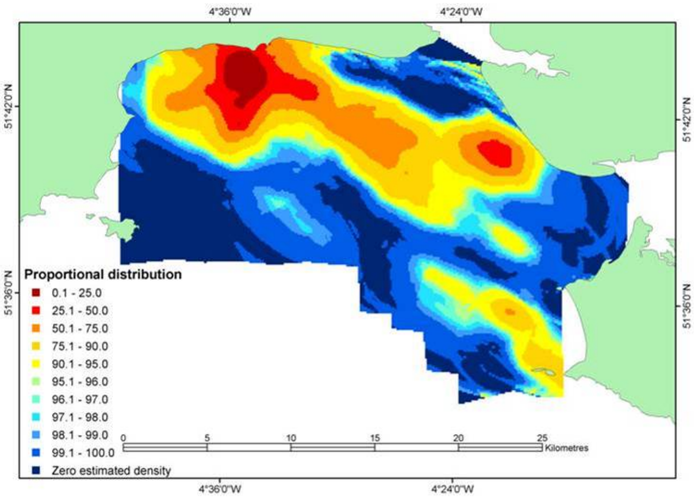


Figure 5.2 Maps of Carmarthen Bay black scoter proportional distribution (ranked percentages) grids in February 2002, derived from estimated densities (**Figure 4.2**) and estimated using (a) ordinary kriging with simple back-transform, (b) ordinary kriging with adjusted back-transform, and (c) ordinary indicator kriging (see text).

We plotted the proportional distribution (section 5.1.4) 1% percentiles against the proportion of the total area covered by that percentile. We used this relationship to generate an optimal proportional distribution threshold value for separating important areas from marginal areas, that maximised the percentage of the total population, whilst minimising the total area required to include that population percentage within the extent of the interest feature.

Figure 4.2 shows that the density is low at the edges of the main aggregations of birds; therefore, a higher number of grid cells, and thus area covered, is required to result in a summed abundance equal to one percent of the total population size. Figure 5.3 and Figure 5.4 show that a high proportion of low density cells, which contribute very little to the total estimated population size, cover a large part of the total area. This is shown in detail in Figure 5.5 and Figure 5.6. In essence, one percent of the total population size at high proportional distribution values (e.g. 98-99%), where grid cell densities are very low, covers a much larger area than one percent of the total population size at low proportional distribution values (e.g. 1-2%) where densities are very high. This is particularly apparent at proportional distribution values greater than 98%; there is little added value in adding these relatively large areas within the extent of the interest feature just to include the final two percent of the total population size.

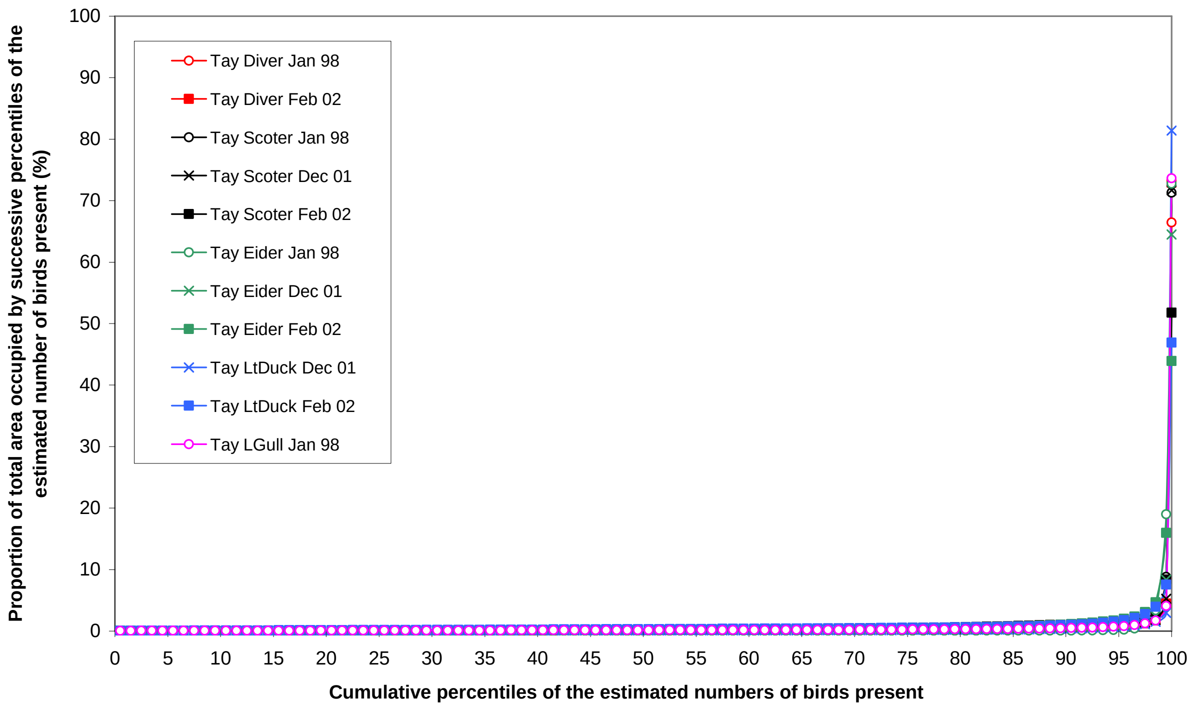


Figure 5.3 Relationship between each cumulative percentile of the estimated number of birds present in the outer Tay area (Tay) in each survey and the proportion of the total survey area occupied by each percentile for all species with modelled densities. Diver = All diver spp.; Scoter = All scoter spp; Eider = common eider; LtDuck = Long tailed duck; LGull = Little gull.

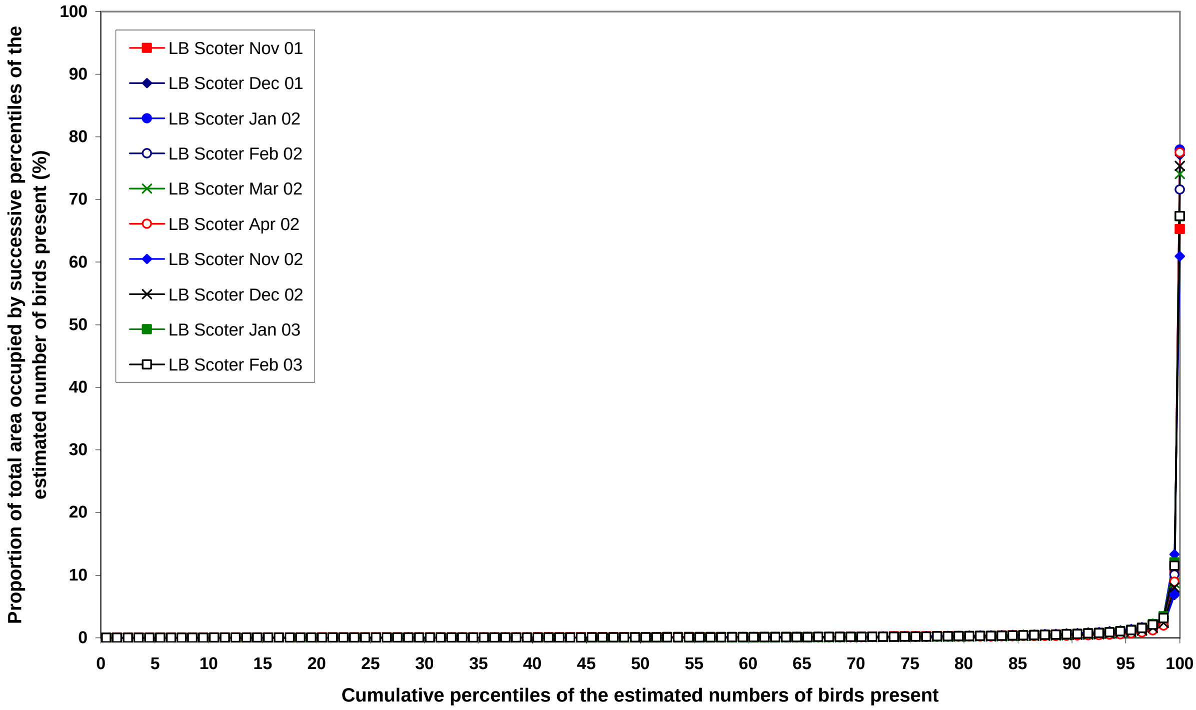


Figure 5.4 Relationship between each cumulative percentile of the estimated number of black scoter present in Liverpool Bay (LB) in each survey and the proportion of the total survey area occupied by each percentile for all species with modelled densities. Abbreviations as **Figure 5.3**.

The relationship, depicted in Figure 5.5 and Figure 5.6, appears to be fairly consistent between species, survey platform, timing of survey, and study area. However, for common eider *Somateria mollissima* in the Firth of Tay in January 1998, there is a more marked increase in the area occupied by grid cells in the 96-97% percentile band. In 1998, common eider were found to be exceptionally aggregated on a small sandbank, which may have had a large effect on the semivariogram used for kriging their distribution. As a result, a very high percentage of the total population size present was counted in a very small area. The analogous increase takes place for all other eider surveys and all other species after the 97-98% percentile.

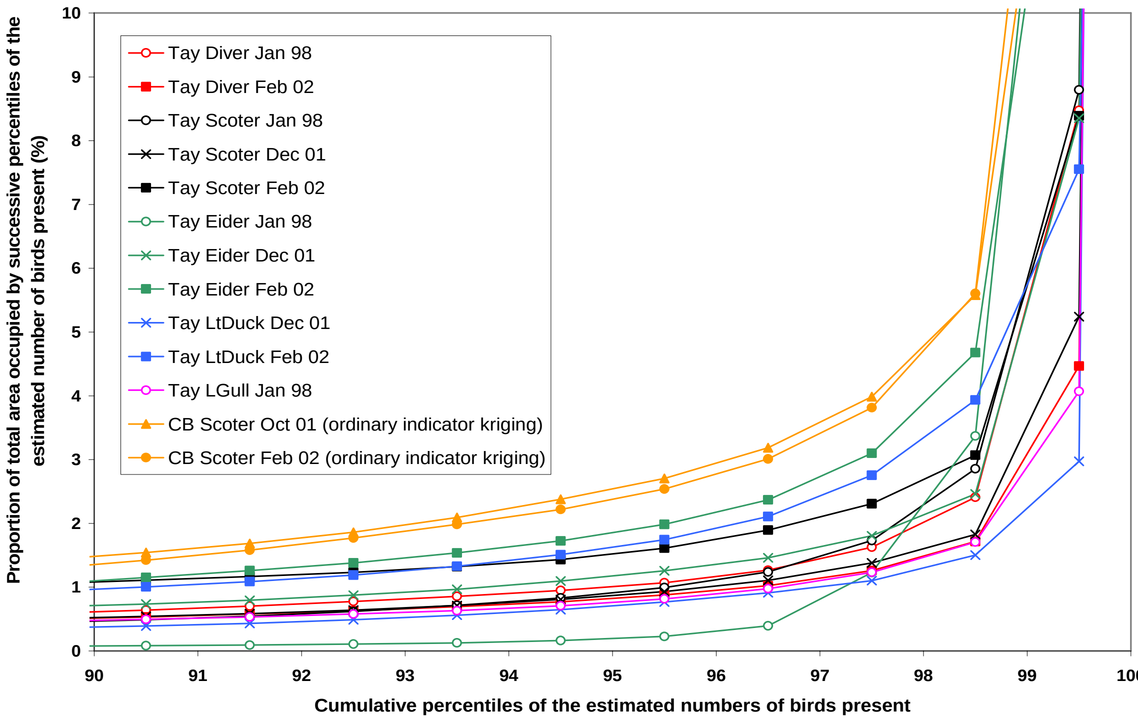


Figure 5.5 Relationship between each cumulative percentile of the estimated number of birds present in the outer Tay area (Tay) and Carmarthen Bay (CB) in each survey and the proportion of the total survey area occupied by each percentile for all species with modelled densities. The highest ten percentiles (90-100%) are presented for clarity. Abbreviations as **Figure 5.3**

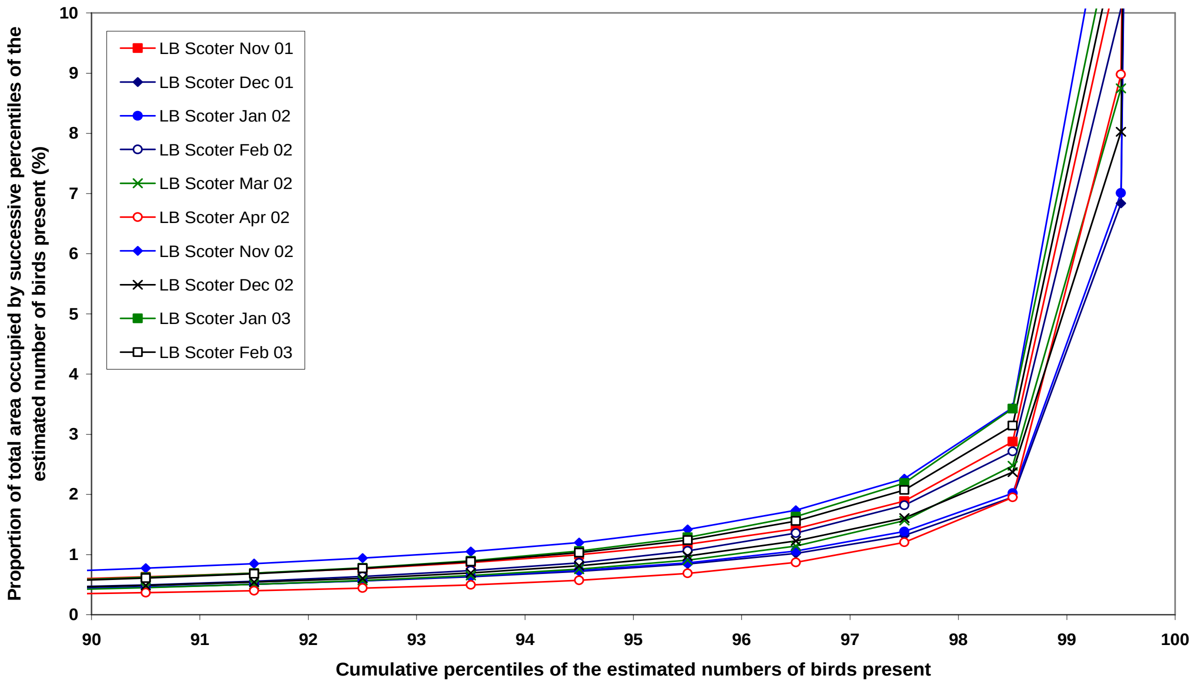


Figure 5.6 Relationship between each cumulative percentile of the estimated number of black scoter present in Liverpool Bay in each survey and the proportion of the total survey area occupied by each percentile for all species with modelled densities. The highest ten percentiles (90-100%) are presented for clarity. Abbreviations as **Figure 5.3**.

A comparison of the relationship between area and population percentile for two surveys of black scoter in Carmarthen Bay shows variation in the relationship between two different geostatistical methods, here investigated. Figure 5.7 shows a comparison of the pattern observed between ordinary indicator kriging with adjusted back-transform and ordinary kriging with simple transform. As with the outer Tay area and Liverpool Bay kriged data (Figure 5.5 and Figure 5.6), similar and consistent patterns were produced where the interpolation method consisted of ordinary indicator kriging with the use of an adjusted back-transformation. However, there were marked differences in patterns when ordinary kriging only was performed to interpolate the data. While the shape and magnitude of the relationship between the percentiles of population and the percent of the total area occupied by that percentile from February 2002 was similar to those found for other species and sites using ordinary indicator kriging, the relationship for the October 2001 black scoter data was not similar. The October 2001 data demonstrated a steady rate of increase between 65% and 98% (Figure 5.7), with a large increase in area after the 97-98% percentile. This is probably due to the excessive smoothing in the kriging process, which is a direct result of using ordinary kriging on zero-elevated data.

However, it is encouraging that the patterns observed for the ordinary indicator data from Carmarthen Bay show remarkably similar patterns to those found in the outer Tay and Liverpool Bay analyses.

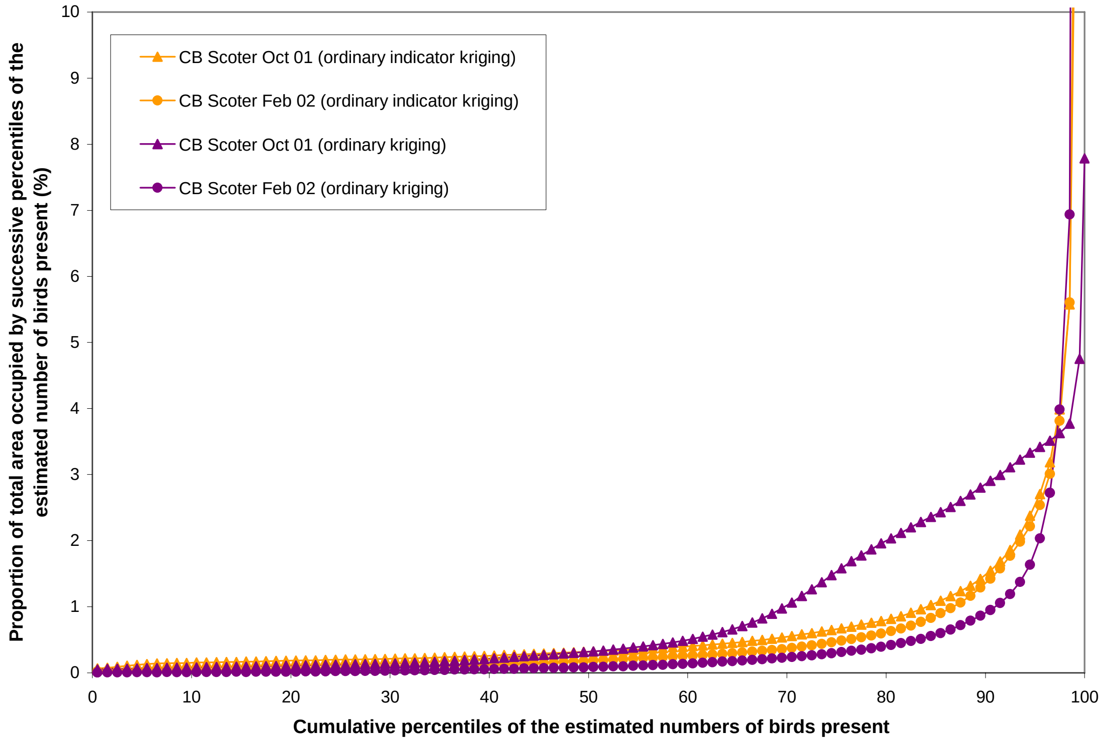


Figure 5.7 Relationship between each cumulative percentile of the estimated number of birds present in each survey and the proportion of the total survey area occupied by each percentile for scoter in Carmarthen Bay**.**

5.2.2 Determination of a generic threshold based on proportional distribution to aid in definition of the extent of the significant aggregations.

As shown above, proportional distribution values derived from ordinary indicator kriging density estimates are a useful tool for highlighting the most important areas used by species within areas where aggregations of birds occur. It is clear from the results presented here that some species of waterbird form coherent significant aggregations, making identification and definition of the extent of the important area possible through selection of a likely generic (but inevitably arbitrary) threshold. The relationships between proportional distribution and area, shown in Figure 5.5 and Figure 5.6, are to be expected given that the grid cell abundances were initially ranked before proportional distribution was calculated. The general relationship demonstrates fairly simply, the balance between the benefit of capturing as much of the local population as possible and the cost of protecting larger sea areas to contain that population. Essentially, the area needed to include the least important percentiles (e.g. 99%-100%) is far larger than the areas required to include the more important percentiles (e.g. 1%-2%). The results in Figure 5.5 and Figure 5.6 suggest that a threshold value somewhere between 97% and 98% of the estimated total numbers of birds would maximise the percentage of the total population included, whilst minimising the total area required.

In Webb *et al.* (2004), we employed ordinary kriging alone for assessing black scoter distribution in Carmarthen Bay. We used proportional distribution maps to determine the most important areas for the species from each survey and an area to be included in the interest feature based on the highest 95% of the total estimated number of birds present. In the absence of any further detailed analysis of the most appropriate threshold, this was based on our best judgement and without prejudice to later defining a generic threshold value for application to other sites. One of the effects of our spatial interpolation method (ordinary kriging with simple logarithmic back transformation) was to smooth out more of the spatial variation in the data than would have been the case if we had used a combination of ordinary and indicator kriging, as presented here.

It would seem likely, given the excessive smoothing of data in the analysis presented by Webb *et al.* (2004), that a 95% threshold was certainly appropriate at the time of ordinary kriging analysis of the Carmarthen Bay data.

Based on ordinary indicator kriging of the Carmarthen Bay, outer Tay and Liverpool Bay data, it would appear that an area that includes 97% of the total estimated numbers of birds of a species would be conservative. A 98% threshold would offer a more precautionary solution.

We recommend:

1. the application of a threshold value of 98% of the total estimated population (by ordinary indicator kriging) for each qualifying species (see site selection guidelines in Webb and Reid (2003)) to define the extent of the significant aggregations; and
2. that this threshold value be applied generically to ordinary indicator kriged data from all qualifying waterbird data in the non-breeding season to aid definition of the extent of the interest features.

5.3 Defining the extent of an interest feature using data from several surveys

Data from several surveys should be used to define the extent of the interest feature for each qualifying species in order to capture the effect of a range of seasons and conditions across the non-breeding season. It is recommended that a minimum of three separate surveys, covering at least two different years, should be used for defining the extent of the interest feature, and that data from qualifying species only should be used (Webb and Reid 2003).

After application of a threshold (either proportional distribution or probability of occurrence depending on the type of analysis performed), a species' kriged grids will have grid cells classified as 'important' (for proportional distribution, an 'important' grid cell will have a value of between 0 and 98%) or 'not important' (Figure 5.8). All of these 'important' grid cells should be considered for inclusion in the interest feature with reference to 'satellite' aggregations (see below), after combined with data from other survey grids for that species. Combination of several grids, generated from data from several surveys, is simplified by ensuring that the 100m^2 grid cells in one grid are in exactly the same spatial locations as grid cells in another grid (Figure 5.8). Effectively, combination of grids with cells classified simply as 'important' or 'not important' ensures that all areas that have been classified once as 'important' may be considered for inclusion in the interest feature.

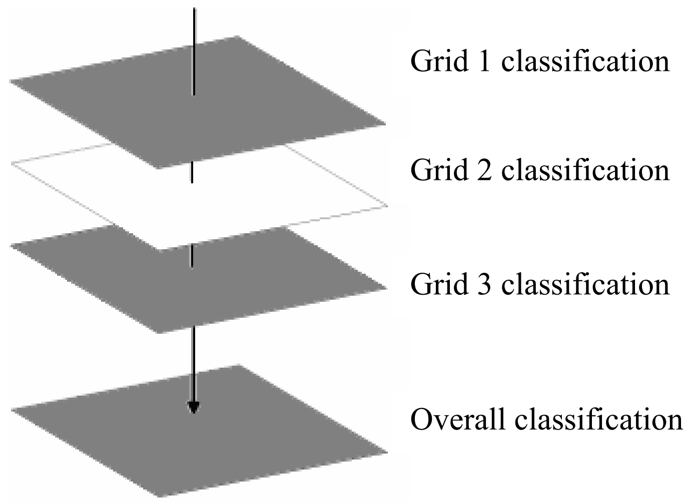


Figure 5.8 Overlay of a grid cell from three different survey grids. Each grid cell is in the same location so that an overall classification of 'important' or 'not important' may be generated for that location. Grey grid cells denote cells that were classed as 'important' (a proportional distribution value of 0-98%, or a probability of occurrence value exceeding the threshold), and the white grid cell was classed as 'not important' (e.g. proportional distribution value of >98%). The overall classification at this location is 'important', and therefore this grid cell may be considered for inclusion in the interest feature.

Classification of 'important' cells occasionally identifies areas that are outwith the main core aggregation. The decision to include these 'satellite' aggregations as part of the interest feature should be based on the regularity of occurrence of that satellite. Therefore, we recommend that satellite aggregations (defined as groups of cells separated from the main aggregation by more than 500m [4]) may be included or excluded in the interest feature on the basis of their regularity of occurrence, and if necessary, referring to any accessory data not used in the spatial modelling (Webb and Reid 2003).

5.4 The SPA boundary

The extent of an inshore marine SPA interest feature can be defined as the area which contains grid cells that have been classified as 'important' at least once for each qualifying species, excluding irregularly occurring satellite aggregations that accessory data have not shown to warrant inclusion. Often, there will be more than one qualifying species, thus each qualifying interest feature must be defined. Once each interest feature has been defined, an SPA boundary may be placed so as to include the spatial extent of all qualifying interest features.

This report is a technical appraisal of methods for defining a waterbird interest feature in the inshore marine environment, and as such is not the forum for outlining boundary setting guidelines. However, important considerations for setting boundaries around these types of features are driven by the data, for example:

- no boundary passes within 250m of an interest feature grid cell[5];
- placement of inward pointing nodes (i.e. corners that point landward) of the boundary falls within 250-500m of an interest feature grid cell.

Boundary setting guidelines can be found in Webb and Reid (2003) and will be regularly updated on the JNCC website (http://www.jncc.gov.uk/). Final determination of an inshore SPA site boundary and classification of the site rests with the relevant agency(s).

[4] The observer error associated with assigning an observation to the correct time is approximately 5 seconds (A. Webb pers. comm.); this equates to the plane moving approx. 250m. Grid cells classified as 'important' and separated by less than 500m (250m from each grid cell) may not reflect a true separation due to observer error in assigning a time to each observation.
[5] As with footnote 4, any boundary that passes within 250m of an interest feature grid cell cannot be said truly to be significantly far enough away as to preclude the risk of excluding important areas.

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