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Editors

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Foreword

Characterising spatial and temporal variation in environmental properties, generating maps from sparse samples, and quantifying uncertainties in the maps, are key concerns across the environmental sciences. The body of tools known as geostatistics offers a powerful means of addressing these and related questions. This volume presents recent research in methodological developments in geostatistics and in a variety of specific environmental application areas including soil science, climatology, pollution, health, wildlife mapping, fisheries and remote sensing, amongst others.

This book contains selected contributions from geoENV VII, the 7th International Conference on Geostatistics for Environmental Applications, held in Southampton, UK, in September 2008. Like previous conferences in the series, the meeting attracted a diversity of researchers from across Europe and further afield. A total of 82 abstracts were submitted to the conference and from these the organisation committee selected 46 papers for oral presentation and 30 for poster presentation.

The chapters contained in the book represent the state-of-the-art in geostatistics for the environmental sciences. The book includes 35 chapters arranged according to their main focus, whether methodological, or in a particular application. All of the chapters included were accepted after review by members of the scientific committee and each chapter was also subject to checks by the editors.

The editors wish to acknowledge the reviewers and the authors of the chapters that make up this book; it would not have existed without their efforts. The editors would also like to thank the sponsors of the conference, who included Cambridge University Press, Wiley, Taylor and Francis, the Ordnance Survey, the GeoData Institute, University of Southampton, School of Geography, University of Southampton and the Remote Sensing and Photogrammetry Society.

Southampton, May 2009 *Peter Atkinson*
Belfast *Christopher Lloyd*

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Geostatistical Modelling of Wildlife Populations: A Non-stationary Hierarchical Model for Count Data

Edwige Bellier, Pascal Monestiez, and Christophe Guinet

Abstract We propose a hierarchical model coupled to geostatistics to deal with a non-gaussian data distribution and take explicitly into account complex spatial structures (i.e. trends, patchiness and random fluctuations). A common characteristic of animal count data is a distribution that is both zero-inflated and heavy tailed. In such cases, empirical variograms are no more robust and most structural analyses result in poor and noisy estimated spatial variogram structures. Thus kriged maps feature a broad variance of prediction. Moreover, due to the heterogeneity of wildlife population habitats, a nonstationary model is often required. To avoid these difficulties, we propose a hierarchical model that assumes that the count data follow a Poisson distribution given a theoretical sighting density which is a latent variable to be estimate. This density is modelled as the product of a positive long range trend by a positive stationary random field, characterized by a unit mean and a variogram function. A first estimate of the drift is used to obtain an estimate of the variogram of residuals including a correction term for variance coming from the Poisson distribution and weights due to the non-constant spatial mean. Then a kriging procedure similar to a modified universal kriging is implemented to directly map the latent density from raw count data. An application on fin whale data illustrates the effectiveness of the method in mapping animal density in a context that is presumably non-stationary.

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1 Introduction

Current wildlife research relies heavily on population monitoring, sometimes performed over large areas (Pollock et al., 2002). Counts provided by field surveys can be used to estimate population sizes (Kingsley and Reeves, 1998; Grigg et al., 1999) or to characterize spatial structures in populations (Isaak and Russel, 2006). The latter has received much recent interest because animals respond to spatial heterogeneity at different spatial scales (Kotliar and Wiens, 1990; Levin, 1992). Therefore, ecological data often include several spatial patterns, which can be regarded as trends at broad scales, patchiness at intermediate and local scale, and random fluctuations or noise at fine scales (Fortin and Dale, 2005). Furthermore, an additional common characteristic of ecological count data is that they are positively skewed and contain much more zeros than would be expected in classical data distribution (Clarke and Green, 1998; Flechter et al., 2005). The form of the distribution is usually due to the patchy nature of the environment and/or the inherent heterogeneity of the species distribution and to sampling coupled to observations processes (Martin et al., 2005). However, standard spatial statistical tools cannot easily deal with count data. When the data are non-Gaussian, hierarchical modelling may be a useful alternative for modelling the spatial distribution of count data (Latimer et al., 2006; Thogmartin et al., 2004). Indeed, ecological approaches and sampling situations should naturally lead to a hierarchical construction (Royle et al., 2005). Although most recent publications solve hierarchical models within a Bayesian framework, hierarchical modelling is not necessarily restricted to Bayesian statistics (Ver Hoef and Frost, 2003; Thogmartin et al., 2004; Cunningham and Lindenmayer, 2005). In a frequentist context, Monestiez et al. (2006) proposed a corrected variogram estimator that takes into account the variability added by the Poisson observation process in order to produce maps of relative abundance.

This paper presents a generalization of Poisson kriging introduced in Monestiez et al. (2006) based on a spatial hierarchical model. The model we propose has two levels: the first level deals with the variability resulting from the heterogeneity of the observation effort and ecological process (i.e. the variability resulting from the sighting process and ecological process themselves), which can naturally be modeled by a Poisson distribution (Monestiez et al., 2006). In the second level we take account of the non-stationarity of the species distribution (i.e. in most situations, populations show a trend in their spatial distribution [Fortin and Agrawal 2005]) by decomposing the spatially non-constant mean, by multiplication of a spatial trend by a stationary field.

Our method can be help to characterize spatial distribution and to address wildlife population spatial distributions through mapping which could be of great interest for management or conservation purposes. Our approach typically applies to animal count data and especially to field transect surveys, a popular method to count animals – including marine mammals (e.g. dugong (Pollock et al., 2006); small cetaceans (Hammond et al., 2002); manatees (Wright et al., 2002)), seabirds (Tasker et al., 1984; Briggs et al., 1985) and terrestrial mammals (e.g. kangaroos

[Caughley and Grigg 1981], impala [Peel and Bothma 1995]) in which individuals or groups of individuals (i.e. "sightings") are recorded at discrete locations.

We provide a case study, with an application based on the spatial distribution of fin whales in a context that is presumably non-stationary.

2 Model

2.1 Hierarchical Model for Animals Sightings

We define a spatial hierarchical model with two levels. The first one models the number of sightings Z into an 1 km-long strip by a Poisson distribution whose parameter Y is a non stationary random field. The second level models Y as the product of a regional drift m and a latent variable X.

For all sites s, we model the number of observed sightings Z knowing Y the latent variable which represents the theoretical sighting density, by independent Poisson random variables:

$$\begin{cases} Z_s | Y_s \sim \mathcal{P}(Y_s) \\ Y_s \quad = m_s X_s \end{cases} \tag{1}$$

where Y_s is the product of a deterministic drift m_s by a positive stationary random field X with unit mean, variance σ_X^2, and covariance function $C_X(s - s') = \mathsf{Cov}[X_s, X_{s'}]$, noted $C_{ss'}$ to simplify notation.

The covariance function $C_X(s - s')$ may be replaced by the variogram function $\gamma_X(s - s') = \frac{1}{2} \mathsf{E}[(X_s - X_{s'})^2]$.

There is no distributional hypothesis on X but the inequality $X \geq 0$.

2.2 Expectation and Variance of Z_s

From Equation (1), it follows directly that:

$$\begin{aligned} \mathsf{E}[Z_s | X_s] &= Y_s = m_s X_s \\ \mathsf{Var}[Z_s | X_s] &= Y_s = m_s X_s \\ \mathsf{E}[(Z_s)^2 | X_s] &= Y_s + Y_s^2 = m_s X_s + m_s^2 X_s^2 \end{aligned} \tag{2}$$

and when deconditioning:

$$\begin{aligned} \mathsf{E}[Z_s] &= m_s \\ \mathsf{Var}[Z_s] &= m_s^2 \sigma_X^2 + m_s \end{aligned} \tag{3}$$

For the covariance expression, the conditional independence of observations at different sites leads to:

$$
\begin{aligned}
\mathsf{E}\big[Z_s\, Z_{s'}\big|X\big] &= \mathsf{Cov}\big[Z_s, Z_{s'}\big|X\big] + \mathsf{E}[Z_s|X_s]\,\mathsf{E}[Z_{s'}|X_{s'}]\\
&= \delta_{ss'}\, m_s X_s + m_s\, m_{s'}\, X_s X_{s'}
\end{aligned}
\tag{4}
$$

where $\delta_{ss'}$ is the Kronecker delta which is 1 if $s = s'$ and 0 otherwise.

2.3 Variogram Expressions

In order to characterize the relationship between the variograms of Z and X, we develop the expressions of the two first moments of $(Z_s - Z_{s'})$.

$$
\begin{aligned}
\mathsf{E}[Z_s - Z_{s'}|X] &= \mathsf{E}[Z_s|X_s] - \mathsf{E}[Z_{s'}|X_{s'}] = m_s\, X_s - m_{s'}\, X_{s'}\\
\mathsf{E}[Z_s - Z_{s'}] &= \mathsf{E}[X]\,(m_s - m_{s'}) = m_s - m_{s'}
\end{aligned}
\tag{5}
$$

The second order moment can be derived from Equations (2) and (4).

$$
\begin{aligned}
\mathsf{E}\big[(Z_s - Z_{s'})^2\,\big|X\big] &= \mathsf{E}\big[(Z_s)^2\big|X_s\big] + \mathsf{E}\big[(Z_{s'})^2\big|X_{s'}\big] - 2\,\mathsf{E}\big[Z_s\, Z_{s'}\big|X\big]\\
&= (Y_s + Y_{s'} - 2\delta_{ss'}\, Y_s) + (Y_s - Y_{s'})^2\\
\mathsf{E}\big[(Z_s - Z_{s'})^2\big] &= \big(m_s + m_{s'} - 2\,\delta_{ss'}\, m_s\big) + \mathsf{E}\Big[\big(m_s X_s - m_{s'} X_{s'}\big)^2\Big]
\end{aligned}
$$

When m_s is assumed to be known and different everywhere (i.e. $m_s = m_{s'}$), we have to develop the two first moments of $\left(\frac{Z_s}{m_s} - \frac{Z_{s'}}{m_{s'}}\right)$:

$$
\begin{aligned}
\mathsf{E}\left[\frac{Z_s}{m_s} - \frac{Z_{s'}}{m_{s'}}\,\middle|\,X\right] &= \frac{1}{m_s}\,\mathsf{E}[Z_s|X_s] - \frac{1}{m_{s'}}\,\mathsf{E}[Z_{s'}|X_{s'}] = X_s - X_{s'}\\
\mathsf{E}\left[\frac{Z_s}{m_s} - \frac{Z_{s'}}{m_{s'}}\right] &= 0
\end{aligned}
\tag{6}
$$

The expression of the non-conditional order-2 moment is derived from Equations (2) and (4).

$$
\begin{aligned}
\mathsf{E}\left[\left(\frac{Z_s}{m_s} - \frac{Z_{s'}}{m_{s'}}\right)^2\,\middle|\,X\right] &= \frac{1}{m_s^2}\,\mathsf{E}\big[(Z_s)^2\big|X_s\big] + \frac{1}{m_{s'}^2}\,\mathsf{E}\big[(Z_{s'})^2\big|X_{s'}\big] - \frac{2\,\mathsf{E}\big[Z_s\, Z_{s'}\big|X\big]}{m_s\, m_{s'}}\\
&= \frac{X_s}{m_s} + \frac{X_{s'}}{m_{s'}} - 2\delta_{ss'}\,\frac{X_s}{m_s} + (X_s - X_{s'})^2
\end{aligned}
$$

$$\frac{1}{2}\,\mathsf{E}\left[\left(\frac{Z_s}{m_s}-\frac{Z_{s'}}{m_{s'}}\right)^2\right] = \frac{1}{2}\left(\frac{m_s+m_{s'}}{m_s\,m_{s'}}\right)-\delta_{ss'}\frac{1}{m_s}+\gamma_X(s-s') \qquad (7)$$

Let $\gamma_{Z/m}(s-s')$ denote the non-stationary theoretical variogram corresponding to the random field (Z_s/m_s), we get for $s \neq s'$ the relationship:

$$\gamma_X(s-s') = \gamma_{Z/m}(s-s') - \frac{1}{2}\left(\frac{m_s+m_{s'}}{m_s\,m_{s'}}\right) \qquad (8)$$

We can check for $s = s'$ that Equation (7) reduces to $\gamma_X(0) = \gamma_Z(0) = 0$
For $s \neq s'$, we also have:

$$\mathsf{Var}\left[\frac{Z_s}{m_s}-\frac{Z_{s'}}{m_{s'}}\bigg|X\right] = \mathsf{E}\left[\left(\frac{Z_s}{m_s}-\frac{Z_{s'}}{m_{s'}}\right)^2\bigg|X\right]-\mathsf{E}^2\left[\frac{Z_s}{m_s}-\frac{Z_{s'}}{m_{s'}}\bigg|X\right]$$

$$= \frac{X_s}{m_s}+\frac{X_{s'}}{m_{s'}}+(X_s-X_{s'})^2-(X_s-X_{s'})^2$$

$$= \frac{X_s}{m_s}+\frac{X_{s'}}{m_{s'}}$$

$$\mathsf{E}\left[\mathsf{Var}\left[\frac{Z_s}{m_s}-\frac{Z_{s'}}{m_{s'}}\bigg|X\right]\right] = \mathsf{E}\left[\frac{X_s}{m_s}+\frac{X_{s'}}{m_{s'}}\right] = \left(\frac{m_s+m_{s'}}{m_s\,m_{s'}}\right) \qquad (9)$$

2.4 Estimation of $\gamma_X(h)$

Let $Z_\alpha, \alpha = 1,\ldots,n$ be the n measurements of $Z(s_\alpha)$. Because of the non-constant mean $m(s)$, it is not meaningful to directly compute experimental variogram on Z_α's, even on the corrected values Z_α/m_α. So we propose a modified experimental variogram for X:

$$\gamma_X^*(h) = \frac{1}{2\,N(h)}\sum_{\alpha,\beta}\left(\frac{m_\alpha\,m_\beta}{m_\alpha+m_\beta}\left(\frac{Z_\alpha}{m_\alpha}-\frac{Z_\beta}{m_\beta}\right)^2-1\right)\mathbb{I}_{d_{\alpha\beta}\sim h} \qquad (10)$$

where $\mathbb{I}_{d_{\alpha\beta}\sim h}$ is the indicator function of pairs (s_α, s_β) whose distance is close to h, where $N(h) = \sum_{\alpha,\beta}\frac{m_\alpha\,m_\beta}{m_\alpha+m_\beta}\,\mathbb{I}_{d_{\alpha\beta}\sim h}$ is a normalizing constant. The weight system directly derives from Equation (9) and the minus-one bias-correction term from Equation (8).

Such estimates can show great sensitivity to rare positive data that neighbour areas with extremely low local mean. It may be necessary to increase the robustness of such estimate by limiting minimum values of m_s (positive and not too close to zero).

A simpler estimates of γ_X can be proposed on subareas where the mean m_s can be assumed constant or when the empirical variogram estimate $\gamma_Z^*(h)$ is restricted to pairs of sampled sites with the same mean m_s:

$$\gamma_X^*(h) = \frac{1}{m^2}\left[\gamma_Z^*(h) - m\right] \tag{11}$$

where m is the locally constant value of m_s.

2.5   Mapping Y by Multiplicative Poisson Kriging

The spatial interpolation of Y is implemented through a Poisson Kriging (PK) at any site $s_o \in \mathcal{D}$. This kriging is a linear predictor of Y_o combining the observed data Z_α weighted by the drift terms $m(s_\alpha)$ and $m(s_o)$ respectively noted m_α and m_o.

$$Y_o^* = \sum_{\alpha=1}^{n} \lambda_\alpha \frac{m_o \, Z_\alpha}{m_\alpha} \tag{12}$$

The unbiasedness of Y_o^* leads to the usual condition on λ_α's.

$$\sum_{\alpha=1}^{n} \lambda_\alpha = 1 \tag{13}$$

The expression of the Mean Square Error of Prediction (MSEP) can also be derived from the kriging estimate expression.

$$\mathsf{E}\left[(Y_o^* - Y_o)^2\right] = m_o^2 \left(\sigma_X^2 + \sum_{\alpha=1}^{n} \frac{\lambda_\alpha^2}{m_\alpha} + \sum_{\alpha=1}^{n}\sum_{\beta=1}^{n} \lambda_\alpha \lambda_\beta \, C_{\alpha\beta} - 2 \sum_{\alpha=1}^{n} \lambda_\alpha C_{\alpha o} \right) \tag{14}$$

By minimizing this expression (14) on λ_i's subject to the unbiasedness constraint, we obtain the following kriging system of $(n + 1)$ equations where μ is the Lagrange multiplier.

$$\begin{cases} \sum_{\beta=1}^{n} \lambda_\beta C_{\alpha\beta} + \dfrac{\lambda_\alpha}{m_\alpha} + \mu = C_{\alpha o} \quad \text{for} \quad \alpha = 1, \dots, n \\[2mm] \sum_{\alpha=1}^{n} \lambda_\alpha = 1 \end{cases} \tag{15}$$

The kriging system expressed with covariance is preferably used for computation when both variogram and covariance exist. The kriging system may be expressed from the variogram using the usual relation $C_{ss'} = \sigma_X^2 - \gamma_X(s - s')$.

The expression of the prediction variance resulting from this kriging system reduces after calculation to:

$$\mathsf{Var}(Y_o^* - Y_o) = m_o^2 \Big(\sigma_X^2 - \sum_{\alpha=1}^{n} \lambda_\alpha C_{\alpha o} - \mu \Big) \qquad (16)$$

It can be easily shown that the kriging of X_o defined as $X_o^* = \sum_{\alpha=1}^{n} \lambda_\alpha \frac{Z_\alpha}{m_\alpha}$ gives the same solutions in λ's and μ, so krigings of Y_o^* or X_o^* becomes equivalent using the relationship $Y_o^* = m_o X_o^*$.

3 Fin Whale Abundance in Pelagos Sanctuary

In the Mediterranean Sea, the fin whale (*Balenoptera physalus*) is the largest marine predator commonly observed. Several hundred to several thousand individuals were estimated to be present in the western Mediterranean Sea during summer (Forcada et al., 1996).

The sighting database used in this study as an illustrative example merges data from different sources, and is fully described in Monestiez et al. (2006). The fin whale surveys mainly focused on the northwestern Mediterranean Sea. Count data were aggregated on cells of 0.1° of longitude by 0.1° of latitude (approximately 90 km^2) in a regular grid. For each year from 1993 to 2001, July and August data were assembled and we computed in each cell the total number of fin whale sightings and the corresponding total searching effort defined as the time (in hours) spent searching inside the cell. So the number of sightings per unit effort or, with some assumptions, the relative abundance can be computed.

In this study, we focused particulary on the Pelagos sanctuary (International Cetacean Sanctuary of the Mediterranean), which was established on November 25th, 1999 by the governments of Italy, France and Monaco. The sanctuary limits are shown in Fig. 1, with the map of searching efforts.

The objective is to map the spatial distribution of fin whales inside the Pelagos sanctuary during the summer of 2001. Due to limitation of the available data subset, we have to assume values for some parameters: mean boat speed is fixed to six nautical knots (11.1 km/h), effective distance of detection to 750 m and mean school size to 1.6 in order to transform hours of searching in surveyed areas and to compute relative abundance estimates from raw sightings of whale schools. For sampled cells, the searching effort was not always exactly the same, so we had to introduce this effort as a factor to the multiplicative drift m_α in order to normalise sighting counts for unit effort. Except this change on m terms, previous estimate expressions and the kriging system remains globally the same.
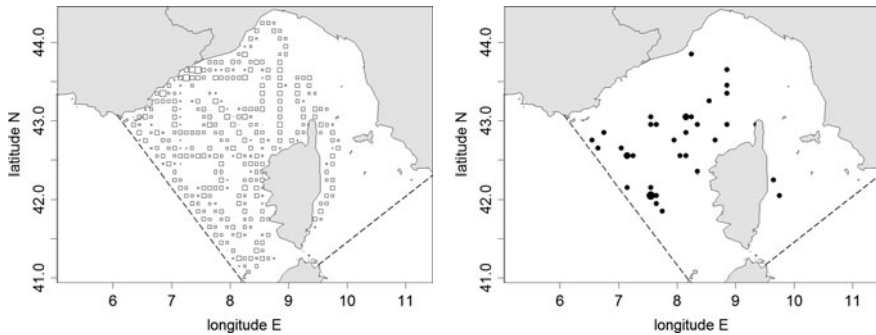
Fig. 1 Map of searching efforts for year 2001 (*left*, the *largest square symbols* are for 3 h of efforts in a pixel of 0.1° by 0.1°) and map of fin whale sightings in 2001 (*right*, number of schools ranging for 1 to 3) that will be used in the multiplicative kriging of the relative abundance. *Dashed lines* give Pelagos sanctuary limits

4 Results

We mapped the spatial distribution of whales by using multiplicative kriging in order to take into account the spatial trend of the fin whales distribution in the northwestern Mediterranean sea.

We first estimate the spatial drift by extracting a smooth long-range spatial component by filter kriging (Wackernagel, 2003) from the 1993–2000 pooled data (excluding the 2001 ones). The resulting map is displayed on Fig. 2 and seems representative of the permanence of the fin whale spatial distribution over years. This long-range component reveals the non-stationarity in fin-whale spatial distribution and could be considered as the potential habitat of fin whales in the northwestern Mediterranean Sea. It is modelled as a deterministic drift. Then the experimental variogram is fitted by a spherical model (Fig. 2) and multiplicative Poisson kriging is applied to fin whale count data.

The two maps of kriged expectations of whale sightings obtained from multiplicative kriging (i.e. taking account for non-stationarity) and from Poisson kriging show some difference (Fig. 3), especially in the western area outside of the Pelagos sanctuary and on the eastern part of the sanctuary which was not surveyed. This observed difference seems be due to the considerations of the deterministic drift in the multiplicative model, since this pattern shows some similarities with the map of the potential habitat. In other respect, the two methods differ in extrapolating context due to the deterministic drift but gives quite close result where the sighting effort is dense enough.

Maps of standard error differ a lot more. It is clear for multiplicative kriging that the drift had a real influence, leading to smaller errors in region of lower whale density and potentially very large errors when extrapolating on high density areas (western region outside Pelagos). The standard error map of Poisson ordinary kriging reflects more conventionally the spatial distribution of sighting efforts with poor
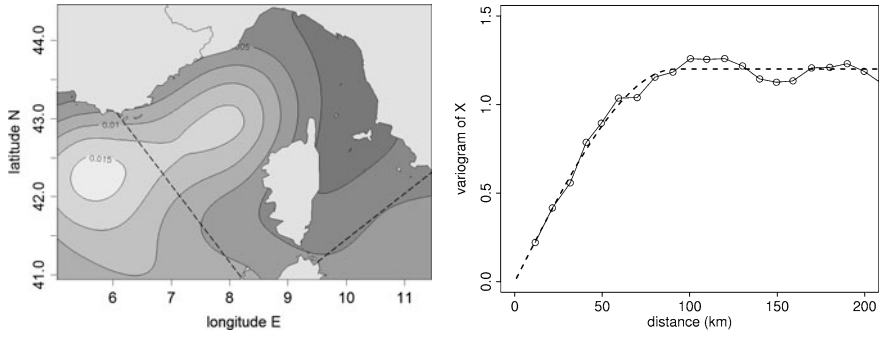
Fig. 2 Map of the drift term (*left*, number of whale schools per square kilometer) and the modified experimental variogram calculated from Equation (10)
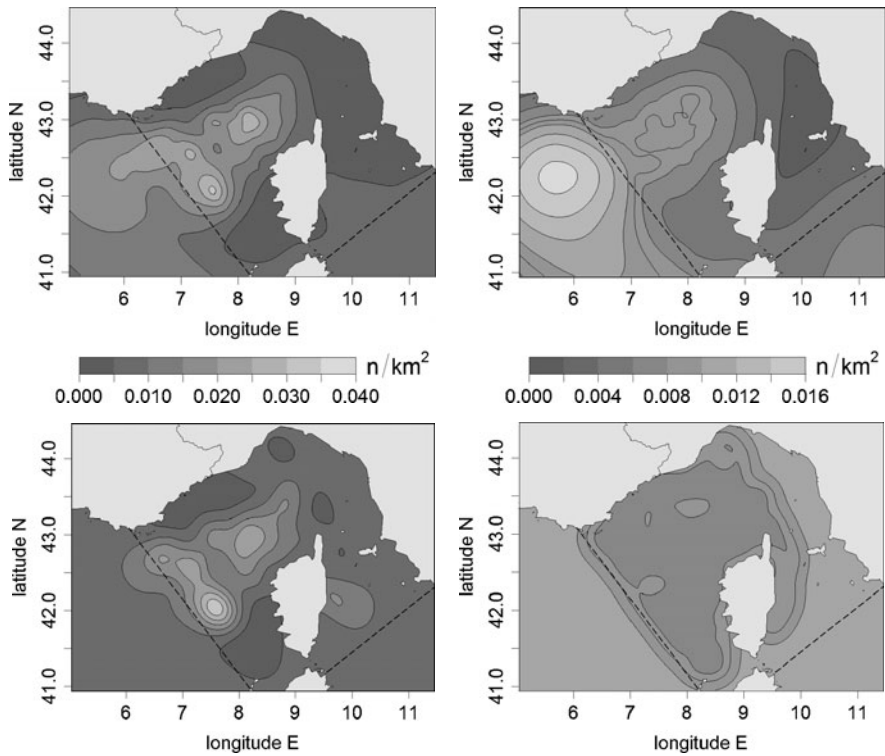

Fig. 3 Maps of kriged expectation of whale school sighting (*left column*, mean number of school per square km) and associated maps of standard error (*right column*, same unit) obtained from multiplicative kriging (*top row*) and from Poisson ordinary kriging (*bottom row*). Map legends are specific to the variables (expectation or standard error) but are identical for both methods

performance on the eastern part of the Golf of Genova. If we focus specifically on the Pelagos sanctuary, the multiplicative approach seems a lot more efficient due to drift information.

5 Discussion

In this study we showed that it is possible to use geostatistics in a non-stationary context of count data and zero inflated distributions since it is specified in a hierarchical spatial model.

It seems also essential to take into account the non-stationarity in the proposed multiplicative kriging because it is a reality for many animal spatial distribution. This non-stationarity can be generally modeled from previous surveys or from habitat proxies when available. When nothing is known, stationarity can be first supposed and a potential drift modeled as the long range variations.

When a good knowledge of potential habitats results from previous sequential surveys, the sampling scheme can be improved using the drift modelling. In this study, we show that taking account of the non-stationarity had a real impact on the map of animal spatial distribution since it reduces substantially the error on low density areas and larger standard error values in high density area; on the contrary the standard error map of Poisson kriging reflects more the spatial distribution of sightings efforts.

Moreover, the advantage of developing a hierarchical model for modelling species distribution in a frequentist context rather than in a Bayesian one is that it avoids specifying the Y distribution unlike Diggle et al. (1998) who had to hypothesize a log-normal distribution for Y; indeed, a frequentist approach does not require any prior distribution. In addition, a diagnostic of the spatial structure of animals can be inferred from the shape of the experimental variogram (Fig. 2), thus allowing the choice of a suitable variogram model which is not the case with model-based geostatistics.

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Incorporating Survey Data to Improve Space–Time Geostatistical Analysis of King Prawn Catch Rate

Ainslie Denham and Ute Mueller

Abstract Commercial fishing logbook data from the Shark Bay managed prawn fishery in Western Australia provide king prawn catch rate data densely informed and irregularly spaced in both the spatial and temporal domains. Space–time geostatistical analysis for the data from the 2001 to 2004 fishing seasons has shown that short term catch rate prediction is possible with the use of the product-sum covariance model and the subsequent kriging estimation process. However the operation of closure lines within the fishery makes it difficult to capture the high catch rate behaviour in areas as they first open to trawling. One of these regions is the Extended Nursery Area which usually opens in the first week of May. Analysis of the survey trawls from seasons 2001 to 2003 in this region in March and April shows there is a moderate positive correlation between the actual catch rate and the survey catch rate. By using the survey catch rate data as additional data in space–time geostatistical estimation of the catch rates for May 2004, the space–time behaviour of the king prawn catch rate data is more successfully captured.

1 Introduction

We consider king prawn logbook catch rate data from the Shark Bay Prawn Managed Fishery in Western Australia and incorporate catch rate data from survey trawls in the preceding months to more accurately reproduce the space–time behaviour of the prawn catch rate in the fishing region. The king prawn catch rate data are densely informed in both the spatial and temporal domains and involve varying locations at successive time instants. Space–time geostatistical analysis for king prawn catch rate data from the 2001 to 2004 fishing seasons, incorporating traditional time series modelling of annual king prawn catch rate trends, has shown that short term catch rate prediction is possible with the use of the product-sum covariance model and subsequent kriging. However, time-limited closure lines operate

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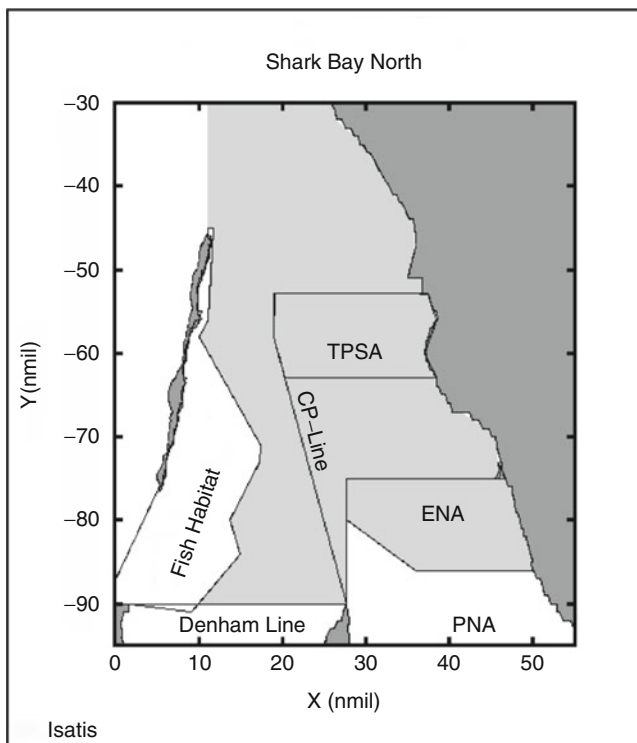e-mail: a.denham@ecu.edu.au; u.mueller@ecu.edu.au

Fig. 1 Shark Bay North fishing region (*light grey*) and permanent and temporary closure lines for the fishery

in the fishery and the timing of the closures is dependent on the lunar phase and survey results. It is therefore difficult to capture successfully the high king prawn catch rate behaviour in areas as they first open to trawling.

Of particular importance is the opening of the extended nursery area (ENA) (Fig. 1) at the start of the last quarter in May producing high catch rates in the newly opened region. Using the catch rate logbook and survey data from the 2001 to 2003 seasons along with the logbook and survey catch rate data from the lunar months of March and April 2004, we investigate to what extent their use improves the reproduction of the catch rate data for the (lunar) month of May of season 2004. The ENA is surveyed in March and April of each season and analysis of data from seasons 2001 to 2004 shows that there is a moderate positive correlation between the actual catch rate and the survey catch rate from preceding months.

Space–time geostatistical estimation of king prawn catch rate for May 2004 is performed using the survey catch rate data as additional information. Multiplicative trend models are employed involving a polynomial trend model and (lunar) weekly seasonal indices obtained from classical decomposition. Spatio-temporal semivariograms of the combined detrended and deseasonalised data for 2001 to 2003 are computed and modelled using product-sum covariance models (De Iaco et al., 2001;