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Evaluation of geostatistical estimators and their applicability to characterise the spatial patterns of recreational fishing catch rates

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ABSTRACT

Western Australians are heavily engaged in recreational fishing activities with a participation rate of approximately 30%. An accurate estimation of the spatial distribution of recreational catch per unit effort (catch rates) is an integral component for monitoring fish population changes and to develop strategies for ecosystem-based marine management. Geostatistical techniques such as kriging can provide useful tools for characterising the spatial distributions of recreational catch rates. However, most recreational fishery data are highly skewed, zero-inflated and when expressed as ratios are impacted by the small number problem which can influence the estimates obtained from the traditional kriging. The applicability of ordinary, indicator and Poisson kriging to recreational catch rate data was evaluated for three aquatic species with different behaviours and distribution patterns. The prediction performance of each estimator was assessed based on cross-validation. For all three species, the accuracy plot of the indicator kriging (IK) showed a better agreement between expected and empirical proportions of catch rate data falling within probability intervals of increasing size, as measured by the goodness statistic. Also, indicator kriging was found to be better in predicting the latent catch rate for the three species compared to ordinary and Poisson kriging. For each species, the spatial maps from the three estimators displayed similar patterns but Poisson kriging produced smoother spatial distributions. We show that the IK estimator may be preferable for the spatial modelling of catch rate data exhibiting these characteristics, and has the best prediction performance regardless of the life history and distribution patterns of those three species.

1. Introduction

The application of geostatistical techniques has become a useful tool to describe the spatial distribution of fisheries catches and catch per unit effort (Mueller et al., 2008; Petitgas, 2009; Rivoirard et al., 2000). This tool can improve managers' understanding of trends in populations over space and time (Walters, 2003), which can facilitate specific management decisions, policy implementation and efficient distribution of resources with respect to geographical fishing areas. However, their application to recreational fisheries data is limited. With recreational fishing considered to be one of the major coastal zone leisure activities worldwide (Cowx, 2002), and an increasing rate of recreational fishing across the globe (Cooke and Cowx, 2004), there is a need for continuous spatial distributions of recreational catch rates (catch per unit of fishing effort).

The focus of fisheries management has traditionally been on commercial fisheries (Henry and Lyle, 2003), but the proportion of fish harvested from recreational fishing can be similar or even higher than that from commercial fishing in some areas (Coll et al., 2004). Indeed, in Western Australia, the participation in recreational fishing has changed from 19% in 1989/90 to 30% in 2011/12, indicating a relative growth of about 50% over that period (Department of Fisheries, 2012b; Lindner and McLeod, 1991). Such increases have highlighted the need to develop and implement resource allocations to both commercial and recreational sectors (Crowe et al., 2013). Furthermore, understanding the spatial distribution of recreational fishing catch rates can help identify high priority areas and guide the establishment of marine protected areas for targeted fish species. Thus, accurate estimation of recreational catch rate distributions in space is an integral component for fishery management and conservation (Wise et al., 2012).

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The traditional way for obtaining continuous surfaces of estimates in a geostatistical framework is to use an interpolation technique known as ordinary kriging (Goovaerts, 1997). Catch rate at any unsampled location is simply computed as a weighted average of data falling within a search window; kriging weights account for spatial patterns in the data and their respective locations (e.g. closer data typically receive more weight in the estimation) (Goovaerts, 1997). However, most data sets collected in recreational fisheries include many zero values mixed with a few extreme values, leading to zero inflated, positively skewed distributions (O'Neill and Faddy, 2003; Taylor et al., 2011). In addition, when expressed as ratios, such data (i.e. catch rate) are impacted by the “small number problem” (Monestiez et al., 2006), that is, rates computed from low fishing effort are less reliable. These properties of the data influence the estimation and modelling of the spatial autocorrelation in the measurements (Kerry et al., 2010; Monestiez et al., 2006), and may lead to incomplete and misleading spatial patterns when the local mean and variance change (Rossi et al., 1992). Furthermore, extreme values in such data sets can strongly affect the characterisation of the spatial pattern and the prediction (Goovaerts, 2009). Hence, the use of the traditional kriging estimator may not be appropriate for such data.

Techniques are available to deal with outliers and skewness. One option is to transform each catch rate into an indicator that takes a value of zero or one depending on whether it exceeds or not a threshold specified by the user. These indicators are then analysed and interpolated using the so-called indicator kriging (Rossi et al., 1992). By treating the data as outcomes of a Poisson process, Monestiez et al. (2006) recently developed a modified kriging estimator known as Poisson kriging where catch rate data based on high observation effort receive greater weight in the estimation and modelling of the spatial autocorrelation, as well as during the interpolation (Monestiez et al., 2006).

To employ geostatistical techniques in spatial catch rate estimation for recreational fisheries, suitable estimators need to be identified for such data. Also, there is a need to understand whether a single estimator can be applied to catch rate data for all species of interest, or whether a different estimator is required for each species with different behaviours (e.g. sedentary versus mobile) and distributional characteristics. In this study, ordinary, indicator and Poisson kriging are evaluated to determine their applicability to characterise the spatial distribution of recreational catch rates of three fishery species (snapper *Pagrus auratus*, baldchin groper *Choerodon rubescens* and blue swimmer crab *Portunus armartus*) with different behaviours and distribution patterns.

2. Material and methods

2.1. Study area and data

The study was limited to the West Coast bioregion of Australia, where about 85% of the recreational fishing in Western Australia takes place (Baharthah, 2008). The data used in this study were obtained from a 12-month survey on recreational fishing by the Western Australian Department of Fisheries (Ryan et al., 2013). The data were collected from March 1st, 2011 to February 29th, 2012 using an off-site phone-diary survey approach involving 2,977 boat-based recreational fishers in the state. Using the recreational fishing boat licence (RFBL) database, a sampling frame was obtained. The survey covered recreational fishers who were at least 5 years old, and held an RFBL for the 12-month period prior to the survey and intended to fish within the period of the survey (Ryan et al., 2013). The data collected from the fishers included for each fishing event: the fishing block visited, the fishing trip duration and the number of fish caught per species. The spatial resolution of the data collected was at the size of the fishing block, which is 10 by 10 nautical miles (NM). The blocks are identified via their centroids. Detailed information about the survey is documented in (Ryan et al., 2013).

The species considered for the analyses are caught by both recreational and commercial fishers and are used as indicator species to represent the status of all the exploited demersal finfish and invertebrate species in the West Coast bioregion of Australia (Department of Fisheries, 2012a; Fletcher and Santoro, 2012). Snapper has a wide distribution across the western Indo-Pacific region (Smallwood et al., 2013). In the study region, it can exhibit spawning aggregations and the juveniles occupy sheltered coastal waters prior to migrating to deeper, more offshore waters (Smallwood et al., 2013). Baldchin groper is endemic to the southern west coast of Australia. Unlike snapper, no spawning aggregations have been reported for this species, and juvenile and adult habitats overlap (Smallwood et al., 2013). The blue swimmer crab is distributed widely throughout the Indo-Pacific region, with adults and juveniles occurring in inshore marine and estuarine waters (Kailola et al., 1993).

For each species and fishing block with centroid u_α the total catch (in number of fish caught) and the fishing trip duration in hours (effort) within the survey year were converted to catch per hour $Z(u_\alpha)$ (catch rate) using the ratio of mean estimator (Jones et al., 1995) to control for heterogeneity in numbers of catches posed by differences in fishing trip duration.

$$z(u_\alpha) = \frac{\sum_{j=1}^{\nu(u_a)} c_j(u_a)/\nu(u_a)}{\sum_{j=1}^{\nu(u_a)} d_j(u_a)/\nu(u_a)} = \frac{\sum_{j=1}^{\nu(u_a)} c_j(u_a)}{\sum_{j=1}^{\nu(u_a)} d_j(u_a)} \quad (1)$$

where $c_j(u_\alpha)$ and $d_j(u_\alpha)$ are the number of fish caught and the boat fishing trip duration (hours) respectively by the jth fisher, and $\nu(u_\alpha)$ is the total number of boats that visited the fishing block u_α.

2.2. Geostatistical estimation

2.2.1. Semivariogram estimators

A prerequisite for geostatistical interpolation is the definition of a model describing the spatial autocorrelation between the observations. A common tool is the semivariogram which measures the average dissimilarity among the observations at pairs of locations as a function of the separation distance vector h (lag). The semivariogram calculated from the sampled data is called experimental semivariogram. The traditional experimental semivariogram denoted by $\widehat{\gamma}_o(h)$ is estimated according to Matheron's method of moments defined as (Matheron, 1965):

$$\widehat{\gamma}_o(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [Z(u_\alpha) - Z(u_\alpha + h)]^2 \quad (2)$$

where $Z(u_\alpha)$ represents the catch rate of a particular species at location u_α, $Z(u_\alpha + h)$ is the catch rate at a location separated from u_α by a distance vector h and $N(h)$ is the total number of pairs of catch rate samples separated by h (Goovaerts, 1997).

In the indicator approach, for each species a series of K thresholds $z_1, z_2, \ldots, z_K$ is chosen to discretise the range of variation for the associated catch rate distribution. For each location u_α the catch rate is transformed into a binary vector of K indicators such that the k^{th} indicator represents the probability that the observed measurement does not exceed a specific threshold z_k (Goovaerts, 1997). If $z(u_\alpha)$ is the catch rate of a particular species at location u_α the indicator variables are defined as (Goovaerts, 1997):

$$i(u_\alpha; z_k) = \begin{cases} 1 & \text{if } z(u_\alpha) \le z_k \\ 0 & \text{otherwise} \end{cases} \qquad k = 1, \ldots, K. \quad (3)$$