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Original Article

Using kriging and co-kriging to predict distributional areas of Kilka species (*Clupeonella* spp.) in the southern Caspian Sea

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Abstract: Understanding ecological and anthropogenic drivers of fish population dynamics and achieving a sustainable yield requires detailed studies on habitat selection and spatial distribution. The objective of this study was to predict spatial density and distribution of kilka species in the southern Caspian sea in relation to satellite-derived sea surface temperature, chlorophyll-a concentration, turbidity and water depths using ordinary kriging and co-kriging geostatistical methods and introduction an appropriate potential fishing area according to the present fishing points. Three hundred and fifty fishing surveys were done in two main kilka fishing ports in the southern Caspian Sea (Anzali and Babolsar ports) from 2015 to 2016. The Geostatistical analysis showed that the co-kriging spatial interpolation method provided the best prediction of fish abundance when chlorophyll-a content was included in model.

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Introduction

The Caspian Sea is the largest inland water body in the world, occupying a deep depression on the boundary of Europe and Asia with a level of approximately 27 m below the world's sea level (CEP, 2002). Three small valuable clupeid fishes known as "Kilka" including common kilka, *Clupeonella cultriventris* Bordin, 1904, anchovy, C. *engrauliformis* Svetovidov, 1941, and bigeye, C. *grimmi* Kessler, 1877 are among the most abundant fishes of the Caspian Sea (Svetovidov, 1963). Kilka fishing was an important source of income and protein for people of the southern Caspian Sea. In addition, kilka species are important food reserve for sturgeons and the Caspian seal (Prikhod'ko, 1979) showing their ecological importance. Annual catches of kilka fishes in the Caspian Sea reached to the highest level *i.e.* 423, 0000 t in 1970 (Ivanov, 2000), constituting about 70% of the total fish catch in the Caspian Sea (Sedov et al., 1997). During the past 30 years, the environmental status of the Caspian Sea has significantly changed due to fluctuations of the sea level, water pollution (Ivanov, 2000), invasive species and overfishing (Fazli et al., 2009).

The relationship between fish abundance and biotic and abiotic features define their habitat suitability (Laevastu and Hayes, 1981). These factors also influence feeding, reproduction, predator avoidance and migration of fish species and, therefore, are considered as spatial characteristics governing the biomass distribution (Horne et al., 1999; Freon et al., 2005). The relationship between fish distribution and environmental factors is supposed to be a non-linear or chaotic *i.e.* spatial fish biomass structure is stochastic in most observation (Webster and Oliver, 2001).

Geostatistical analysis of pelagic fish catch data has been recognized as the best method for modeling of spatial distribution of biomass to understand the relationship between spatial pattern of biomass and environmental features (Simard et al., 2002). The physical and biological characteristics of marine

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ecosystems can be represented by sea surface temperature (SST), chlorophyll-*a* (chl-*a*), turbidity and water depth (Solanki et al., 2005a). Chl-*a* is known as an important oceanographic parameter of productivity (Solanki et al., 2001) that could be related to fish production (Bertrand et al., 2002). SST is assumed to be an index of the physical environment, which controls the physiology of the living organisms (Solanki et al., 2005b; Tang et al., 2003). Turbidity is a fundamental index used to assess coastal and estuarine water quality conditions affecting light attenuation and the plankton productivity (Pennock and Sharp, 1994). According to positive phototropism of kilka species, these factors can affect their fishing yield.

Physical and biological features can be measured using sensors of satellites. This technology is able to provide reliable global ocean coverage of SST and chl-a and Turbidity at a relatively high spatial and temporal resolution, which can be measured from space. The satellite remote sensing is an effective and efficient way compared with field sampling that requires time, cost and limited coverage areas. Meanwhile, geographic information systems (GIS) techniques are widely used in processing satellite images (Castillo et al., 1996). It integrates theoretical aspects of oceanography and ecology with spatial database and statistical functions.

Some studies investigated potential fishing ground of fishes using stepwise regression models in relation to satellite derived environmental factors e.g. SST and chl-a (Nurdin et al., 2015), whereas others used geostatistical methods *e.g.* kriging and co-kriging (Rueda and Defeo, 2001; Georgakarakos and Kitsiou, 2008; Aidoo et al., 2015; Pierre et al., 2016; Woillez et al., 2016). Kriging is an interpolation technique that minimizes the estimated variance measured from a prior model for a covariance. It calculates weights that result in optimal and unbiased estimates. Within a probabilistic framework, kriging attempts to minimize the error variance and systematically sets the mean of the prediction errors to zero. However, a data set will often contain not only the primary variable of interest but also one or more secondary variables. These secondary variables where spatially cross correlated with the primary variable can contain useful information about the primary variable. This information can be included within the estimation process via co-kriging. It seems reasonable to add the cross correlated information contained in the secondary variable to help further decrease in the variance of the estimation error (David, 1977). Co-kriging uses a secondary variable (covariate) that is cross correlated with the primary or sample variable of interest. This can aid to minimize the error variance of the estimation (Isaaks, 1992).

Many aspects of kilka stocks in the southern Caspian Sea such as biology, population dynamic (Karimzadeh et al., 2010) and reproductive cycle (Amiri et al., 2012) have been studied. However, there is no data on spatial distribution of kilka species or their potential fishing grounds. Hence, this study aimed to determine their potential fishing grounds in the southern Caspian Sea using geostatistical methods to produce choropleth maps. A decline has been occurred in the fishing of kilka fishes in the Caspian Sea due to invitation of the warty comb jelly, *Mnemiopsis leidyi*, during last decade and therefore the results of this study can help to management of its fishing by introducing proper fishing grounds.

Materials and Methods

Data collection: The catch points of 350 fishing surveys in Anzali (37°28' N, 49°25'E) and Babolsar) (36°42′N, 52°39′ E) ports as two main fishing regions of kilka in Iranian waters of the Caspian Sea were recorded using a GPS (Fig. 1). Spring (98 points), summer (89 points), autumn (106 points) and winter (57 points) fishing done from 2015 to 2016. A density index (catch per unit of effort, CPUE) was calculated as the catch of 72 vessels (28 vessels in Anzali and 43 vessels in Babolsar ports) per night. The tracked fishing points were standardize using Arc map 10.3 (GIS) and recorded on georeferenced map of the Caspian Sea as a shape file.

Remotely sensed environmental data: The primary satellite data set used in this study were SST, chl-a and turbidity data derived from MODIS measurement. The

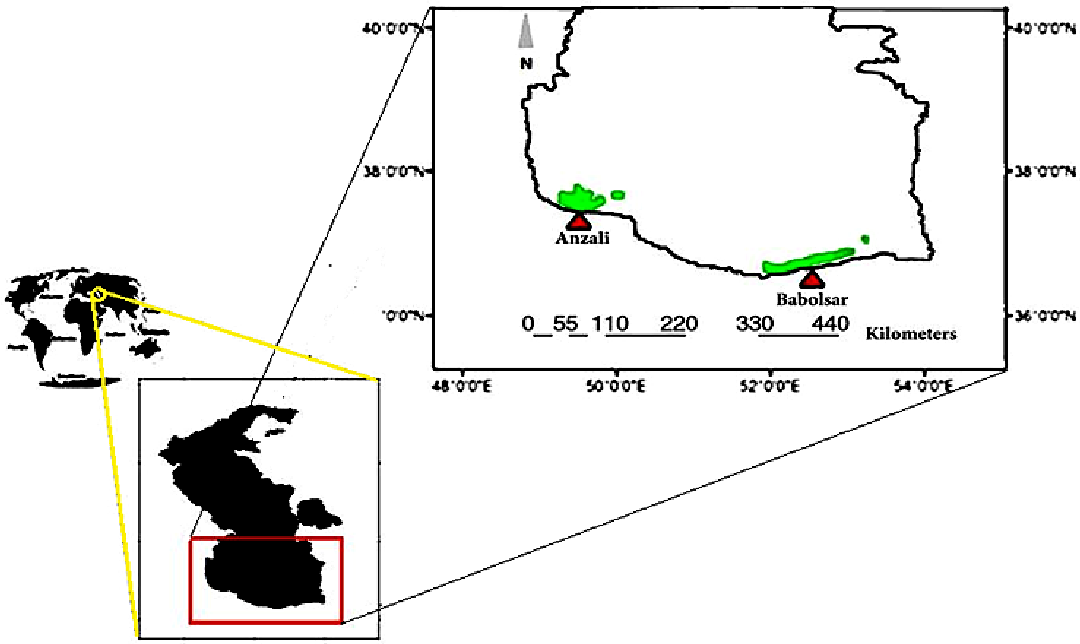

Figure 1. Kilka fishing points (in green) in southern part of the Caspian Sea from 2015 to 2016 (red triangles indicate fishing ports).

SST (°C) and chl-*a* (mg/m^3) level 3 (4 km) monthly standard mapped image data from 2015 to 2016 were downloaded from the ocean color website (http://oceancolor.gsfc.nasa.gov/). The bottom topography data of the Caspian Sea is constructed using the ETOPO1 dataset (Amante and Eakins, 2009). The wavelength 645 nm was used to measure turbidity (NTU) (Chen et al., 2007).

According to schooling of kilka fishes, the geographical latitudes (Lat) and longitudes (Lon) considered as environmental parameters (Petitgas et al., 2001). SeaWiFS Data Analysis System (SeaDAS) version 7.3 was used to extract and process the data (O'Reilly et al. 1998). The data were subset to the study area with geographical Arc map (GIS) 10.3 version software.

Data analysis: Multivariate linear regression analysis was used to identify a main environmental factor or factors influencing spatial changes of CPUE. Kriging and co-kriging methods were applied to estimate the parameters including the CPUE abundance of kilka species. For this reason, ArcGIS 10.3 and GS$^+$ 7.2 software were used. After applying kriging and co-kriging methods, to make an assessment: firstly, an empirical variogram was drawn from data and a theory variogram was fitted. Each time a measured value is omitted in a point and another amount is estimated for it from the neighboring points. Then, the real value is returned to the previous position and this was repeated for all measurement points. The assessment was carried out using determination coefficient (R^2) and the root mean square error (RMSE) and average standard error (ASE) (Goovaerts, 1997).

Data variogram was analyzed to examine the spatial correlation and the spatial structure of variables. To make analysis on the data variogram of the CPUE and other co-factors after normalization, initially, the variogram and cross variogram of variables was drawn by using GS$^+$ and, then, an appropriate model selected.

Results

Statistical parameters such as mean and standard deviation of variation are presented in Table 1 for the environmental factors. For data analysis, a histogram was drawn for each study variable after normalization.

Geostatistical analysis: Since some parameters are affected by environmental factors, they can be involved in the estimation of the main variable by using the co-kriging estimator, if a correlation exists. By the examination of the stepwise correlation among the studied variables, it was observed that there was a

Table 1. Statistical parameters of studied variables.

Parameters	No of data	Mean	Std.
Lat	350	37.30	0.39
Lon	350	50.65	1.4
Chl-a (mg/m^3)	350	0.4	0.2
Depth (m)	350	63	12.43
SST (°C)	350	20.4	6.8
Turbidity (NTU)	350	0.4	0.2
CPUE (kg)	350	2682	1711.2

Table 2. Stepwise regression result.

Survey Years	Dependent variable	No of data	Independent variable	Model R^2	F	Sig.
2015 and 2016	CPUE (kg)	350	Chl-a & SST_4 & Tur& Lon & Lat & Depth	0.26	3.534	0.03
2015 and 2016	CPUE (kg)	350	Chl-a	0.30	4.334	0.01

Table 3. Compare indicator of kriging and co-kriging prediction accuracy.

Model		Variogram Type	Range (km)	RMSE	ASE	R^2
CPUE	Kriging	Exponential	1.03	1187.797	1381.042	0.11
CPUE and chl-a	Co-kriging	Pentaspherical	6.3	1175.457	1355.567	0.15

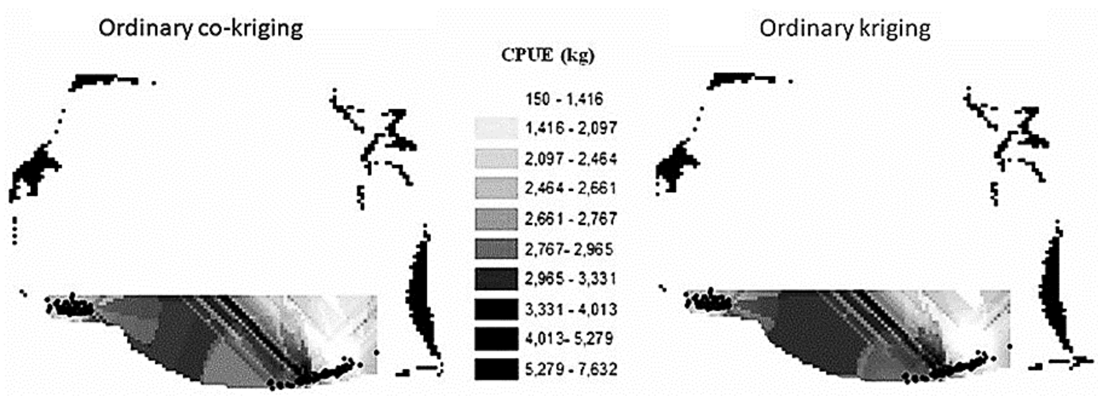

Figure 2. Predicted densities (kg) for kilka fishes, 2015 and 2016, ordinary kriging and co-kriging (black circles = fishing points).

correlation between the CPUE and chl-a concentration (Table 2). Therefore, the estimation of the CPUE spatial changes and the through chl-a by using the co-kriging estimator will be entirely reasonable. After evaluating different models, it was demonstrated that the exponential and pentaspherical models were best suited for the variables using kriging and co-kriging, respectively and therefore, it was selected as a best fitted model on the data (Table 3).

Evaluation of geostatistical methods: using RMSE, as presented depicted in Table 3, the estimation of CPUE ratio by co-kriging with a RMSE=1175.4 was obviously more precise than kriging method, though the two methods were reasonably accurate. To estimate the CPUE rate, the accuracy of co-kriging was higher than that of kriging (RMSE=1187.7) (Table 3).

Discussion

The results showed that kriging and co-kriging methods can be applied as a tool to estimate the abundance of kilka fishes in areas with data restriction. Chl-a has impacts on created map using co-kriging and have positive linear correlation with CPUE. The positive impact of chl-a on some fishes density distribution has been proven (Gower, 1972; Sachoemar et al., 2012). Visual comparison of MODIS images showed that the chl-a concentration has spatial changes more than SST and Turbidity in south part of the Caspian Sea region. These changes can increase predictive power of co-kriging method and influence fishing distribution of kilka fishes as planktovorous fishes.

According to the choropleth maps (Fig. 2), the CPUE of kilka is more likely in eastern and western region of the Anzali and Babolsar ports than those of the other parts, respectively. Satellite imagery analysis shows that the western region of the Babolsar port has relatively more phytoplankton concentration throughout the year than the other pars. Sefid River, as the largest river in the north of Iran entering the Caspian Sea at the eastern part of the Anzali port, and its runoff may have an influence on enhancement of kilka CPUE. In addition, it is determined than shore line area between the Rudsar (37°07' 43N; 50°18'51E) and Chalus (36°41'28N; 51°18'15E) in the southern Caspian Sea may has great potential for kilka fishing as a new area (Fig. 2).

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چکیده فارسی

استفاده از مدل‌های کریجینگ و کوکریجینگ در پیش‌بینی پراکنش تراکم کیلکا ماهیان (*Clupeonella* spp.) در ناحیه جنوبی دریای خزر

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چکیده:
آگاهی از عوامل انسانی و بوم‌شناختی موثر بر پویایی جمعیت ماهیان و دستیابی به استحصال پایدار منابع آن‌ها نیازمند انجام تحقیقات مرتبط با زیستگاه گزینی و چگونگی پراکنش مکانی آن ها است. تحقیق حاضر با هدف بررسی و پیش‌بینی تراکم فضایی کیلکا ماهیان جنوب دریای خزر، پیشنهاد نواحی مناسب صید بر اساس نقاط کنونی صید و بررسی ارتباط آن با متغیر های محیطی حاصل از تصاویر ماهواره‌ای با استفاده از مدل‌های کریجینگ و کو-کریجینگ به انجام رسید. عوامل محیطی مورد بررسی شامل دمای آب، تراکم کلروفیل-آ و کدورت سطح آب و همچنین عمق آب در مکان صید بود. تعداد ۳۵۰ سفر صید در آب های ساحلی بنادر انزلی و بابلسر به‌عنوان دو منطقه اصلی صید کیلکا ماهیان در ناحیه جنوبی دریای خزر، در سال های ۱۳۹۴ و ۱۳۹۵ به انجام رسید. بر اساس نتایج با استفاده از روش کو-کریجینگ و با در نظر گرفتن تراکم کلروفیل-آ به‌عنوان فاکتور کمکی نتایج دقیق‌تری حاصل خواهد شد.

کلمات کلیدی: مدلسازی ،پیش‌بینی کمی صید کیلکا ماهیان، دریای خزر.