Indian Journal of Geo Marine Sciences
Vol. 47 (12), December 2018, pp. 2524-2531

Spatial characterization of commercial fishing catch rate of *Tenualosa Ilisha* in Hooghly-Matlah estuary of India: a geostatistical appraisal

Sanjeev Kumar Sahu[1*], Jatisankar Bandyopadhyay[2]& Malay Naskar[1]
[1]ICAR-Central Inland Fisheries Research Institute, Barrackpore, Kolkata 700120, India
[2]Department of Remote Sensing & GIS, Vidyasagar University, Midnapore, Paschim Medinipur, Pin.-721102, West Bengal, India
*[E.Mail: sksahu_2k@yahoo.com]

Received 14 July 2017; revised 10 August 2017

Geostatistical method, which involved variogram and kriging, was applied to the geo-referenced catch and effort data collated from the logbook of five randomly selected vessels. Variogram analysis unraveled systematic spatial structure of catch rates of the species. No spatial dependence of catch rate was observed beyond the distance of 17.43 km. Kriging method predicted three regions of high, medium and low catch rates. Even though vessels' logbook data was criticized for preferential sampling bias, we established here that application of geo-statistical tools to the same became useful in the present study.

[**Keywords**: Variogram; Kriging; Geostatistics; Commercial vessel; Hooghly-Matlah estuary; India]

Introduction

Tenualosa ilisha (Hamilton, 1822), popularly known as Hilsa (hereinafter referred to as Hilsa), is one of the most important tropical fishes endemic to the Indian Ocean. The Hilsa fishery provides livelihood to millions of people inhabiting the coastal region of India, Bangladesh and Myanmar[1]. The species has gained enormous international importance due to its huge market demands. Bangladesh contributes maximum to the global catch, which is approximately 50% to 60%, followed by Myanmar (20% to 25%), India (10% to 20%) and other countries (5% to 10%)[2]. Unfortunately, this wild stock is declining, as evidenced by dwindled catch in India and Myanmar, and declined Catch Per Unit Effort (CPUE) in Bangladesh[3] . Results of stock assessment of the species have established over-exploitation as one of the reasons for such decline[4,5,6,7], but the techniques applied in those studies did not handle spatial uncertainty. As a result, those studies failed to provide any management recommendation in finer spatial scale, particularly with respect to estuarine system.

Geostatistics coupled with GIS, which is recognized as a powerful tool for handling data with spatial uncertainty, has become an integral part of fisheries resource management. Consequently, several geostatistical approaches have been applied to a wide range of fisheries resources assessment, which include estimating fish abundances from survey data[8,9], reducing the risks of over fishing[10], describing spatial distribution of fish catches and catch rates[11,12]. As a consequence, effective policy implementation, resource allocation and management decision become easier with respect to geographical fishing areas. However geostatistical appraisal made from aforementioned studies demand data to be obtained from scientific research survey based on a regular grid. Alternatively the concept of using commercial fishing vessels to collect scientific resource and environmental data was introduced. To this direction, geostatistical tools have been applied successfully to acoustic data obtained from commercial fishing vessels for monitoring fisheries resource and ecosystem management[13,14]. However, literature on the use of geo-referenced commercial catch and effort data to characterize spatial fish abundance distribution is not so rich[15,16], especially in the developing countries. Very recently, geostatistical tool has been applied to characterize spatial pattern of catch rates of recreational fishing[17].

Though Hilsa has always had international importance, but associated fisheries of the species have poor record of sustainability and ineffective management due to lack of appropriate stock assessment on different spatial scale. One of the reasons was non-availability of appropriate data on spatial and temporal scale, which was usually acquired by following scientific research survey design. In developing countries, collection of such kind of survey data was not carried out due to involvement of huge cost and manpower. Hilsa fishery is no exception. In the face of such data deficient scenario, a first ever attempt has been made in this study to characterize quantitatively the spatial structure of the Hilsa catch rates. The specific aim of the study is to see weather geostatistics has the potential to exploit the strength of commercial vessels' logbook data for achieving the above goal or not.

Materials and Methods

The study area belongs to the Bay of Bengal (BOB) region (Fig 1). Several estuarine systems have been evolved from thecomplicated hydrological network system of two countries India and Bangladesh in the region. Hooghly-Matlah estuary, which belongs to the aforesaid region, is bound between latitude 20^0 35'N and 23^0 20' N, and longitude 87^0 45'E and 89^0 00'E. It is a meso-macrotidal estuarine system formed by the two main rivers Hooghly and Matlahand recognized highly for its commercial fisheries, especially Hilsa fishery. In the present study, the area was specifically selected, as it belongs to one of the prime distribution regions of Hilsa. Longitudinal and latitudinal span of this study area are 170 km and 110 km respectively (Fig. 1).

The data used in this study was collated from the logbooks of five randomly selected fishing vessels, which were engaged specifically to capture Hilsa in the study area. Logbook depicted that geo-referenced catch data was recorded by using Garmin/Novman navigation tools during the year June 2010 to January 2012. GPS locations and times of the start and the end positions of each haul of gear operation were recorded there. Since Hilsa is generally caught by monofilament gillnet gear, there has been no towing for operating the gear. Traversed distance of the gear was due to the normal tidal effect. So the midpoint of the line transect corresponding to each haul was taken

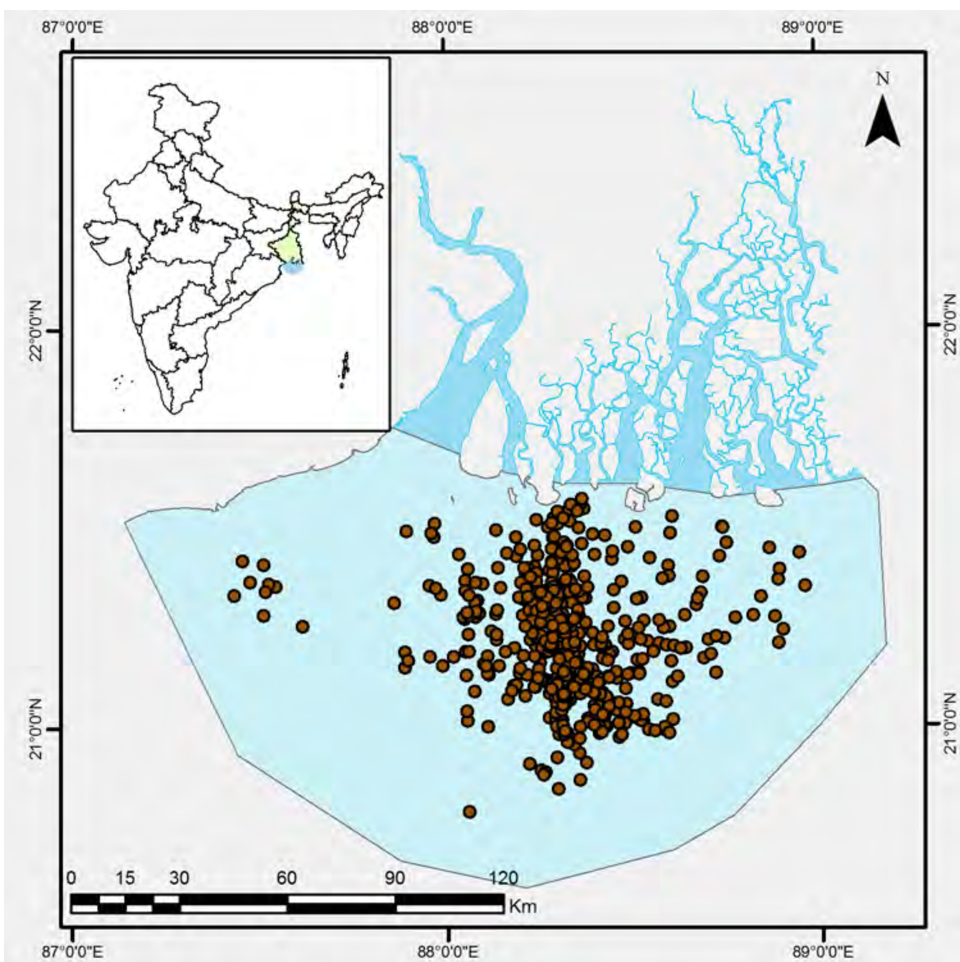

Fig. 1 — The Study area and the locations of recorded Hilsa catch.

as the observed geo-referenced point of the recorded data. In this way the geo-referenced Hilsa catch data were derived corresponding to 513 locations, which were subsequently projected in UTM (WGS 84 UTM zone 45N) projection system for geo-statistical analysis. We used widely accepted Catch Per Unit Effort (CPUE) as the catch rates. It is computed by using the formula written as

$$CPUE = \frac{Catch}{Effort}.$$

We have standardized the effort as the duration of haul of gillnet operation. Technically, the unit of CPUE here becomes Kg/gillnet-hour, hereinafter referred to as Kg/hour.

Basic descriptive statistics and graphical tools were used to explore the data that were subsequently employed for geo-statistics tools. In essence, geo-statistical methods applied in this study involved two steps. First, spatial structure of Hilsa CPUE was quantified by using variogram analysis. Then, kriging method was applied to predict CPUE values for the unsampled locations. Finally, isopleth maps derived from the adopted geo-statistical method were presented for interpretation.

The variogram, which essentially provides a spatial partitioning of the sample variance, has been widely applied to quantify the spatial variability of data. In order to represent mathematically, let the CPUE of Hilsa be the variable $Z(x)$, where x is the geographical location. For constructing variogram, it is assumed that mean and the variance of the increment $Z(x) - Z(x + h)$are constant over the field. This assumption is relatively more realistic in the context of fish abundance data, as in the present case. This means that the variance does not depend on the location of samples and only depends on the distance between samples. Under this assumption, the spatial pattern is characterized by non-directional experimental semivariogram. It is estimated by the formula

$$\hat{\gamma}(h) = \frac{1}{2m(h)} \sum_{j=1}^{m(h)} [Z(x_i) - Z(x_i + h)]^2,$$

where x_i and x_i+h are two locations in the space at a certain distance, which belongs to bin width class of lag h over all directions or specific to a given direction inside the studied area and $m(h)$ is the number of data pairs used to compute semivariogram at distance h. Spatial structure of the $Z(x)$ is represented by a plot of $\hat{\gamma}(h)$against h . Three basic parameters that summarize the structure of spatial dependence are *range*, *sill* and *nugget*. Most semivariogram shows a regular increase of $\hat{\gamma}(h)$with the h up to a certain distance. This distance is called as the *range* of the semivariogram. The *range* of the semivariogram can be interpreted as the distance beyond which no effect of spatial correlation among the sample exists. After the *range* distance, the semivariogram stops increasing and fluctuates around a value called *sill* of the semivariogram. Such a semivariogram is said to be bounded. The *sill*value of such bounded variogram is interpreted as the total variance of the data. Although by definition, semivariogram tend to zero when h tend to zero, the semivariogram cannot be estimated at a distance below those of the sampling scale. Such a discontinuity at the origin of the semivariogram relates to measurement error. So the variogram always start a positive value along the y-axis, which is defined as *nugget* effect.

Empirical variogram models were fitted to estimate the aforementioned parameters. Among several empirical variogram models, we fitted exponential, spherical, Gaussian and stable. Weighted Least Square (WLS) method was applied to fit those empirical models. Best model was selected on the basis of Weighted Residual Sum of Square (WRSS) criterion.

Kriging is a geo-statistical interpolation technique that considers both the distance and the degree of variation between known data points while estimating values in unknown areas. Consequently, the method becomes superior to the non-geostatistical interpolation technique in terms prediction of attribute variables subjected to spatial uncertainty, as in the present case. The general estimation formula for spatial interpolation is given by

$$\hat{Z} = \sum_{i=1}^{n} \lambda_i Z(x_i),$$

where $\hat{Z}$is the estimated value of an attribute at the point of interest x_0, Z is the observed value at the sampled point x_i, $\lambda_i$is the weight assigned to the sampled point, and n represents the number of sample points used for the estimation.

Essentially, kriging involves selection of weights λ_i, which employ the parameters of semivariogram governing the nature and degree of spatial uncertainty[18]. Several variants of kriging are available depending upon the nature of the data fulfilling the assumption made in kriging. We applied ordinary kriging[19], which relies on the stationary mean in search window. This assumption is quite reasonable for the abundance pattern of migratory fish like Hilsa. In order to generate geo-statistical isopleth map a prediction grid with suitable resolution was created on the study area and thereafter prediction of CPUE was made on the grid using above method.

Cross-validation technique by using leave-one-out strategy was applied for evaluating the results of kriging. For this strategy, data values are removed one by one and predicted by kriging using the remaining data. The simple correlation between observed and predicted values was examined for model adequacy. So the deviation of correlation coefficient from unity was considered as a measure of model inadequacy. This correlation must be equal to unity for perfect prediction.

Results

The distribution of CPUE was highly skewed (skewness = 5.014) varying between 0 to 120 kg/hour with mean value of 6.5 kg/hour (Fig. 2). For computational simplicity, a multiplicative factor of 10 was multiplied to CPUE for further analysis. Kriging being sensitive to highly skewed distribution, typical logarithmic transformation was used to overcome this issue (Fig. 2). The skewness (=-0.51) of the transformed CPUE (hereinafter referred to only CPUE instead of "log transformed CPUE" for convenience) was pretty low (Fig. 2). But distributional pattern of the CPUE reflected bi-modality due to inflated zero values (Fig. 2). These were further discarded from the data to attain approximate normality of CPUE for efficient and effective implementation of kriging.

Simple linear regression of CPUE on the longitude and latitude depicted no trend along any of the coordinates (Fig. 3). Statistical test could not reject the hypothesis, $\beta = 0$ for both longitude (p-value = 0.225) and latitude (p-value = 0.771), which also ensured non-existence of linear trend against either of the longitude or the latitude. Hence the stationarity assumption of constant mean over the spatial domain under study holds true, which is crucial for quantifying the nature and magnitude of spatial pattern by variogram analysis and subsequent application of kriging for prediction.

The vital part of experimental variogram computation is to choose the vector of lag distance classes, including a tolerance range of unequally spaced samples, as in our case. (Choosing of lag distance depends on the maximum distance between the data points.) The variogram is usually computed for the half of the maximum distance[20], which is 85 km in the present study. Instead we restricted it to 60 km by discarding the scantily available data locations that could influence the reliability of the variogram. Subsequently, sixty equally spaced distance classes were selected which was sufficient to compute

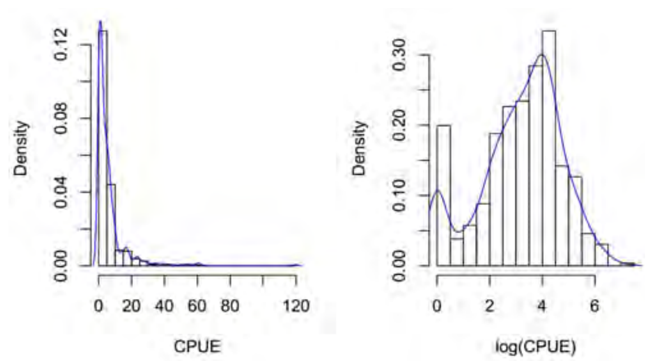

Fig. 2 — Distributional pattern of CPUE and transformed CPUE.

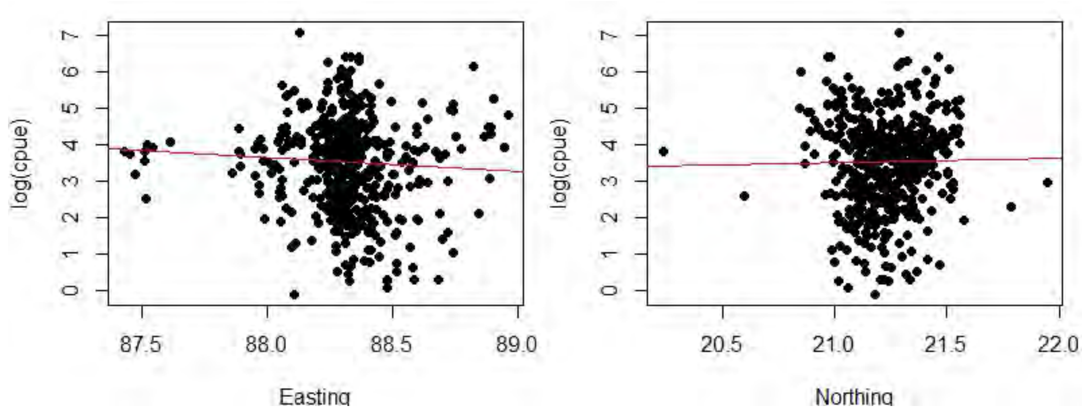

Fig. 3 — Trend of CPUE towards Easting and Northing.

reliable variogram and ensured at least 180 pairs in each bin. This was found to be sufficient to compute reliable variogram. Tolerance angle was fixed at $\pm 20^0$. The plot of experimental semivariance exhibited that it gradually increases and tends to attain a plateau with slight fluctuation. Excepting the spherical model, all others produced very close estimates of the parameters involved. The nugget effects varied between 49% and 79% (Fig. 4, Table 1) of sill, which deviated from zero. In terms of Weighted Residual Sum of Square (WRSS), the goddness-of-fit criteria, stable model was found to be the best-fit followed by exponential model (Table 1). But the asymptotic range (188 km) was beyond the maximum distance (170 km). For exponential model, the increasing semivariance attenuated at the distance of 17.73 km and reache a plateau with the semivariance value of 0.876 at the asymptotic distance of 52.80 km (Fig. 4).

The cross-validation analysis resulted highest correlation of 0.57 for exponential model. The same for stable, spherical and Gaussian models were 0.55, -0.27 and 0.55 respectively. Considering the high degree of uncertainty in the data encountered by the preferential sampling, all the models excepting spherical supported moderate adequacy. We selected exponential model to plug-in into the ordinary kriging method for predicting CPUE over the study domain.

To generate geo-statistical map of CPUE, a grid of 1 km x 1 km resolution was created over the study region. At first, prediction was made on the created grid by using ordinary kriging in which parameters of selected exponential variogram model was plugged-in. Then, standard smoothing was carried out to produce isopleth map (Fig. 5). Contour lines corresponding to quartiles of CPUE (in log scale) were also overlaid to display high, medium and low levels of catch rates (Fig. 5). Predictive map showed that the distribution pattern of the catch rates was rather patchy. It also provided evidence of directional pattern of catch rates.

Discussion

The distribution of CPUE was highly skewed and inflated by zero values. For recreational fishing, Aidoo et al. (2015) have argued that this skewness arises due to fishing ability of fishers. But similar high skewness had also been observed even in case of

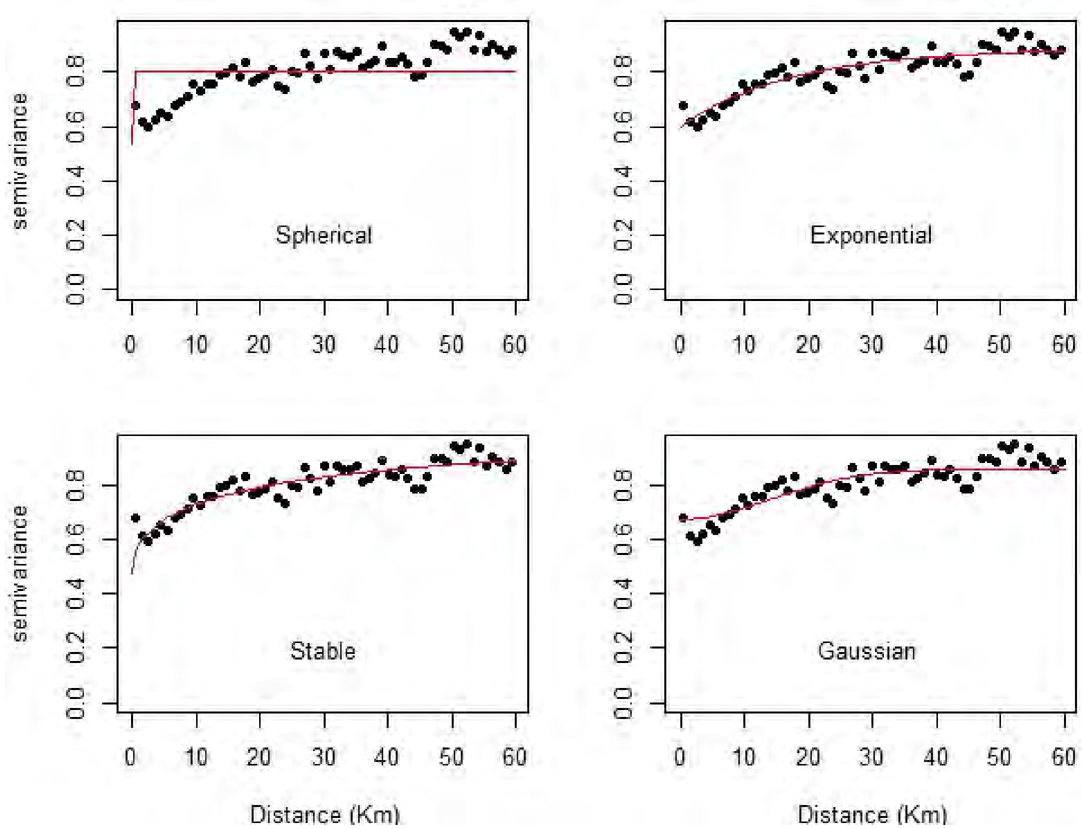

Fig. 4 — Experimental and fitted empirical variogram models.

survey data[21]. In the present case, this was the aggregated effect of fish movement, as Hilsa moves in shoals[22], and preferential fishing induced by fishermen for choosing fishing spot. It partially reflecteddistribution of the abundance of the fish species. Handling such skewness is data specific. We applied standard logarithmic transformation to the 10×CPUE to achieve normality, which was essential for robust application of kriging. Alternative approaches like indicator kriging or disjunctive kriging could have been applied to handle skewness, if logarithmic transformation has failed to attain normality. Moreover, categorization of data for using above method would lead to information loss.

We found that experimental semivariance gradually increases and tends to attain a plateau with slight fluctuation. The fitted empirical variogram model registered finite range with asymptotic value (Fig. 4, Table 1). This indicated that semivariance depended only on the distance between the pairs and is independent of location. Thus stationary assumption for computing semivariogram holds true even for this commercial vessels' logbook data. Slight fluctuation of experimental semivariance registered beyond 22 km provided an indication towards patchy distribution of CPUE. The high nugget values (49% and 60% of sill for stable and exponential model respectively) indicated that there was discontinuity in the spatial grid resolution. Such high nugget values were also observed even for fish abundance study based on scientifically designed survey[23,15,24]. In the present study, two explanations could be derived for this feature. First, it was postulated that irregular grid resolution emanated from the preferential sampling induced by the fishermen. Then, most importantly, it might be due to the very dynamic directional movement of Hilsa fish, which was usually caught in due course of their spawning migration. Fishermen applied their knowledge and took advantage of the situation to choose the place of deployment of the gear. Consequently, it was highly probable to get high differential catch rates within a very short distance, which was affecting the nugget value.

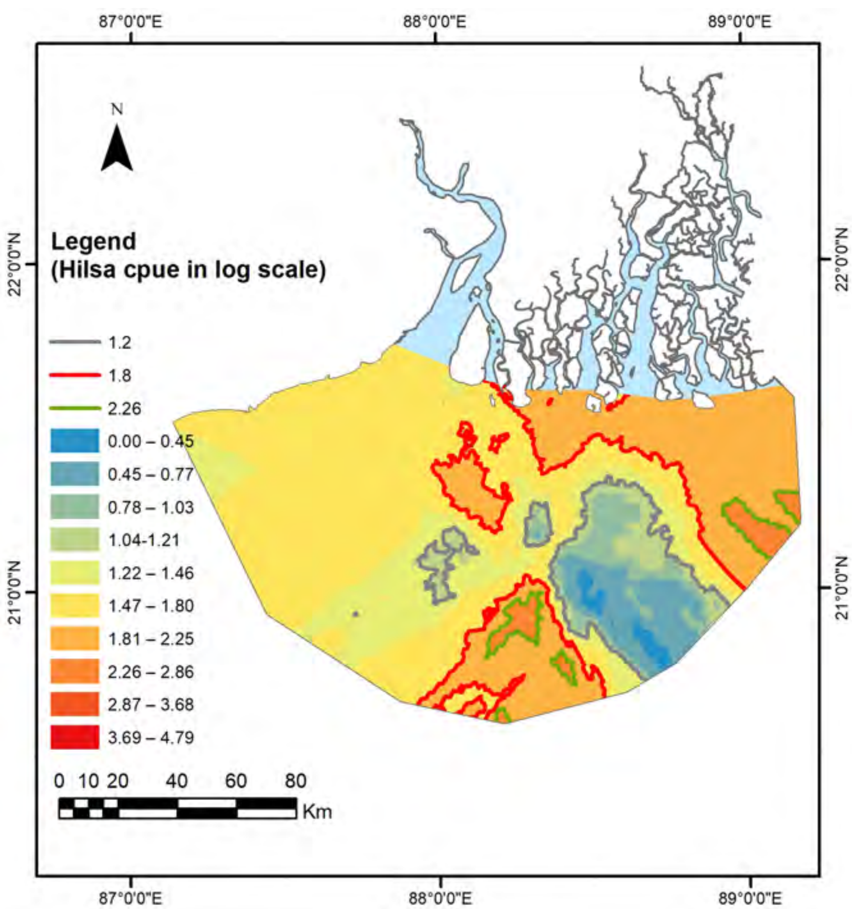

Fig. 5 — Predictive map of Hilsa CPUE (in log scale) in the study region. Contour lines corresponding to three quantiles are demarcated for high, medium and low CPUE.

Table 1 — Comparison of different empirical variogram models

Model	Nugget	Sill	Range (km)	Asymptotic Range (km)	WRSS
Spherical	0.54	0.80	0.37	0.37	472.70
Exponential	0.60	0.88	17.43	52.80	119.74
Stable	0.48	0.98	20.96	188.06	115.11
Gaussian	0.68	0.86	19.91	34.46	148.64

As suspected from variogram pattern, geostatistical map indeed reflected patchiness of the catch rates (Fig. 5). This is due to the fact that the species under study moves in shoal[22]and the fishermen, for obtaining high catch, use their indigenous knowledge to deploy the gear. Similar patchiness in fish abundance was also established in other studies in which data had been obtained from scientifically designed survey data[24,25,26,27]. But, in the present case, we established the same on the basis of vessels' logbook data. Predictive map depicting different levels (high, medium and low) of abundance region will be useful for rationalized fishing, which is one of the requirements to achieve sustainable Hilsa fisheries. For example, fishing restriction in the high abundant region (Fig. 5) may be imposed to control over-fishing. Directional abundance pattern (Fig. 5) reflected in the predictive map provided an indication of spatial movement pattern of Hilsa. For example, relatively higher catch rate was predicted towards the shorelines. Plausible explanation is that Hilsa moves in shoals towards freshwater for spawning migration and becomes vulnerable to catch by commercial fishing. Geo-statistical map also revealed that predictive catch rate of Hilsa was relatively higher towards the North-Eastern direction. This indicated that abundance of Hilsa was relatively more towards Bangladesh than India. As a consequence, Bangladesh contributes more to the global Hilsa catch than India.

The present study demonstrated how commercial fishing vessels' data become useful for spatial characterization of catch rates by prudent application of geo-statistical tools. Use of vessels log-book data was criticized for preferential sampling bias. We could not estimate this bias. Still we found the said data to be useful for this case study on Hilsa. Even the results of the present study are comparable with the results of the studies based on scientific research survey design. Predictive geo-statistical map of catch rates emanated from this study can be useful for exploitation of Hilsa in a sensible manner. Depending upon the stock status normally reflected by the CPUE, deployment of vessel could be controlled for location specific rationalized fishing of Hilsa. This will be a sensible move towards achieving sustainable Hilsa fishery.

Conclusions

The article shows the avenues to investigate spatial structure of Hilsa catch rates without incurring huge cost and manpower which are normally involved in a scientific survey. Approach adopted here can easily be replicated to other distribution regions of Hilsa. By recruiting vessel for keeping geo-referenced record of catch, this approach can be calibrated for implementation on other species in the region where scientific survey-based data is difficult to obtain. of course, it is always desirable to obtain data from statistically sound survey design for better understanding of the spatial structure of the abundance of fish species.

Acknowledgements

The authors sincerely acknowledge the Director, ICAR-Central Inland Fisheries Research Institute for pursuing this work.

References

1 Miah MS. Climatic and anthropogenic factors changing spawning pattern and production zone of Hilsa fishery in the Bay of Bengal. *Weather Clim Extrem*., 7(2015), 109-115. doi:http://dx.doi.org/10.1016/j.wace.2015.01.001.

2 Milton DA. Status of Hilsa (Tenualosa Ilisha) Management in the Bay of Bengal:an Assessment of Population Risk and Data Gaps for More Effective Regional Management. Phuket, Thailand; 2010.

3 BOBLME. *Report of the Hilsa Fisheries Assessment Working Group II*.; 2012.

4 Dutta S, Maity S, Chanda A, Hazra S. Population structure, mortality rate and exploitation rate of hilsa shad (*Tenualosa ilisha*) in West Bengal coast of northern Bay of Bengal, India. *World J Fish Mar Sci*. 4(2012), 54-59.

5 Amin SMN, Rahman MA, C. HG, Mazid MA, Milton DA. Catch per unit effort, exploitation level and production of hilsa shad in Bangladesh waters. *Asian Fish Sci*., 21(2008),175-187.

6 Panhwar SK, Liu Q. Population statistics of the migratory hilsa shad, (*Tenualosa ilish)* in {Sindh}, {Pakistan}. *J Appl Ichthyol*,29(2013), 1091-1096. doi:10.1111/jai.12134.

7 Mohamed MA-R, Qasim M-HA. Stock assessment and management of hilsa shad (*Tenualosa ilisha*) in Iraqi marine waters, northwest Arabian Gulf. *Int J Fish Aquat Stud*., 1(5) (2014), 1-7.

8 Simard Y, Legendre P, Lavoie G, Marcotte D. Mapping, estimating biomass, and optimizing sampling programs for spatially autocorrelated data: case study of the northern shrimp (*Pandalus borealis*). *Can J Fish Aquat Sci*., 49(1992), 32-45.

9 Barange M, Hampton I. Spatial structure of co-occurring anchovy and sardine populations from acoustic data: implications for survey design. *Fish Oceanogr*., 6(2) (1997),94-108. doi:10.1046/j.1365-2419.1997.00032.x.

10 Armstrong J, Armstrong D, Hilborn R. Crustacean resources are vulnerable to serial depletion - the multifaceted decline of crab and shrimp fisheries in the Greater Gulf of Alaska. *Rev Fish Biol Fish*., 8(2) 1998, 117-176. doi:10.1023/A:1008891412756.

11 Mueller U, Dickson J, Kangas M, Caputi N. Geostatistical modeling of the scallop density distribution in Shark Bay. In: *GEOSTATS 2008*(2008),971-980.

12 Rivoirard J, Simmonds J, Foote KG, Fernandes P, Bez N. *Geostatistics for Estimating Fish Abundance*. (Blackwell Science:United Kingdom) 2000, pp 205

13 Melvin GD, Kloser R, Honkalehto T. The adaptation of acoustic data from commercial fishing vessels in resource assessment and ecosystem monitoring. *Fish Res*., 178(2016), 13-25. doi:10.1016/j.fishres.2015.09.010.

14 Niklitschek EJ, Skaret G. Distribution, density and relative abundance of Antarctic krill estimated by maximum likelihood geostatistics on acoustic data collected during commercial fishing operations. *Fish Res*.,178 (2016),114-121. doi:http://dx.doi.org/10.1016/j.fishres.2015.09.017.

15 Petitgas P, Poulard JC, Alain B. Comparing commercial and research survey catch per unit of effort: megrim in the Celtic Sea. *ICES J Mar Sci*., 60(1)(2003), 66-76. doi:10.1006/jmsc.2002.1321.

16 Fox DS, Starr RM. Comparison of commercial fishery and research catch data. *Can J Fish Aquat Sci*., 53(12) (1996),2681-2694. doi:10.1139/f96-230.

17 Aidoo EN, Mueller U, Goovaerts P, Hyndes GA. Evaluation of geostatistical estimators and their applicability to characterise the spatial patterns of recreational fishing catch rates. *Fish Res*., 168(2015), 20-32. doi:10.1016/j.fishres.2015.03.013.

18 Clark I, Harper W V. *Practical Geostatistics 2000*. (Geostokos (Ecosse) Limited, Scotland) 2001, pp 430

19 Goovaerts P. *Geostatistics for Natural Resources Evaluation*. (Oxford University Press) 1997.

20 Journel AG, Huijbregts CJ. *Mining Geostatistics*. (Blackburn Press) 1978, pp.600.

21 Petitgas P. Use of a disjunctive kriging to model areas of high pelagic fish density in acoustic fisheries surveys. *Aquat Living Resour*.,6 (1993);201-209.

22 Ahsan DA, Naser MN, Bhaumik U, Hazra S, Bhattacharya BS. *Migration, Spawning Patterns and Conservation of Hilsa Shad (Tenualosa Ilisha) in Bangladesh and India*. (Academic Foundation, New Delhi, India); 2014.

23 Adams CF, Harris BP, Marino II MC, Stokesbury KDE. Quantifying sea scallop bed diameter on Georges Bank with geostatistics. *Fish Res*., 106(2010), 460-467.

24 Addis P, Secci M, Manunza A, Corrias S, Niffoi A, Cau A. A geostatistical approach for the stock assessment of the edible sea urchin, Paracentrotus lividus, in four coastal zones of Southern and West Sardinia (SW Italy, Mediterranean Sea). *Fish Res*.,100(2009),215-221.

25 Maynou FX, Sardá F, Ĉonan \`GGerard Y. Assessment of the spatial structure and biomass evaluation of *Nephrops norvegicus*(L.)populations in the northwestern Mediterranean by geostatistics. *ICES J Mar Sci*., 55(1998),102-120.

26 Rueda M. Spatial distribution of fish species in a tropicalestuarine lagoon: a geostatistical appraisal. *Mar Ecol Prog Ser*, 222(2001), 217-226.

27 Georgakarakos S, Kitsiou D. Mapping abundance distribution of small pelagic species applying hydroacoustics and Co-Kriging techniques. *Hydrobiologia*,. 612(2008); 155-169.