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Implementing geostatistical analysis to study spatio-temporal distribution patterns of swimming crabs (*Portunus trituberculatus*)

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Abstract

This study attempted to compare the performance of local polynomial interpolation, inverse distance weighted interpolation, and ordinary kriging in studying distribution patterns of swimming crabs. Cross-validation was used to select the optimum method to get distribution results, and kriging was used for making spatial variability analysis. Data were collected from 87 sampling stations in November of 2015 (autumn) and February (winter), May (spring) and August (summer) of 2016. Results indicate that swimming crabs widely distributed in autumn and summer: in the summer, they were more spatially independent, and resources in each sampling station varied a lot; in the winter and spring, the abundance of crabs was much lower, but the individual crab size was bigger, and they showed the patchy and more concentrative distribution pattern, which means they were more spatially dependent. Distribution patterns were in accordance with ecological migration features of swimming crabs, which were affected by the changing marine environment. This study could infer that it is applicable to study crab fishery or even other crustacean species using geostatistical analysis. It not only helps practitioners have a better understanding of how swimming crabs migrate from season to season, but also assists researchers in carrying out a more comprehensive assessment of the fishery. Therefore, it may facilitate advancing the implementation in the pilot quota management program of swimming crabs in northern Zhejiang fishing grounds.

Key words: swimming crabs (*Portunus trituberculatus*), geostatistical analysis, ordinary kriging, spatio-temporal distributions, Zhejiang coastal waters of China

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1 Introduction

Resources of major commercial fisheries in China have declined since the 1980s, and the species structure of catches has changed a lot; crustacean fisheries now have become increasingly important (Zhang et al., 2007). Since 2011, the annual yield of crustacean fisheries in China accounts for nearly 20% national total fisheries' catches, among which swimming crabs make up to over 20% national annual crustacean yield (Fisheries Bureau of Ministry of Agriculture P.R. China, 2012–2019). Swimming crabs are one of the most sought-after species with high demands and economic values. Zhejiang waters are abundant with swimming crab resources, and its yearly production accounts for 35% on average of national catches of swimming crabs from 2011. Therefore, the pilot quota management program targeting on swimming crabs in northern Zhejiang has been launched since 2017.

The pilot program aims at enforcing output controls to limit total allowable catches. Hence, it is important to understand where crabs inhabit and to know current resource status. Usually, researchers use production data over certain years or collect biomass data from sampling stations to monitor resource status, and this study adopts geostatistical techniques to learn how swimming crabs distribute and migrate in waters at a macro-level. Geostatistical analysis, such as kriging interpolation, has been proved to give prediction results at acceptable degrees of accuracy (Srinivasan et al., 2010), and has been wildly applied in scientific research of many disciplines such as atmosphere science, environmental monitoring, soil management (Simard et al., 2002), and it also performs well in fishery studies.

In previous studies, many researchers had used geostatistical analysis to reveal how species population varied with seasons and locations. For instance, in the 1990s, Maravelias and Haralabous (1995) used kriging to analyze spatial patterns of North Sea herring so that the herring spatial organization was clearer and more understandable, and it assisted researchers under-

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standing the behavior of the species and studying the relationship with the environment. Zhang and Cheng (2005) took kriging to study the distributions of small yellow croakers (*Larimichthys polyactis*) in the East China Sea, from which it concluded that the spatial patterns were greatly affected by its ecological behaviors and fishing efforts; Amiri et al. (2017) applied kriging and co-kriging to predict spatial density and distribution of kilka species in order to achieve a sustainable utilization of this species in the southern Caspian Sea, and the research team found that spatial interpolation method gave the best prediction when the environment factor was included in the model, in this case it was chlorophyll *a*. All these researches have confirmed that geostatictal analysis is applicable in fishery studies, but few of them apply the method to study crabs or other crustacean species.

Hence, the broad aim of the paper is to take geostatistical methods to study swimming crab fishery. By this way, researchers can understand swimming crabs' spatio-temporal distribution features, which offers an additional perspective to study crab species or even crustacean species. Furthermore, fishery practitioners and the management can jointly promote more sustainable development and management of crustacean resources.

2 Materials and methods

Investigations were carried out in November of 2015 (autumn), and again in February (winter), May (spring) and August (summer) of 2016. Systematic sampling and simple random sampling procedures were used for collecting samples, and 87 sampling stations in total were set to cover the effective study area of Zhejiang coastal waters (Fig. 1).

Investigations were conducted strictly in accordance to the survey specifications (General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China and China National Standardization Management Committee, 2007). Samples were collected by the same otter trawl fishing vessel with the engine power of 220 kW. The mesh of the fishing gear was 25 mm, and the length of its head line and the foot line were 30 m and 38 m, respectively. When investigating at each station, the work duration was standardized to 1 h with the speed of 3 kn, and a random sample (20 kg) from catches was reserved for further analysis. Catch rate (caught weight per hour)

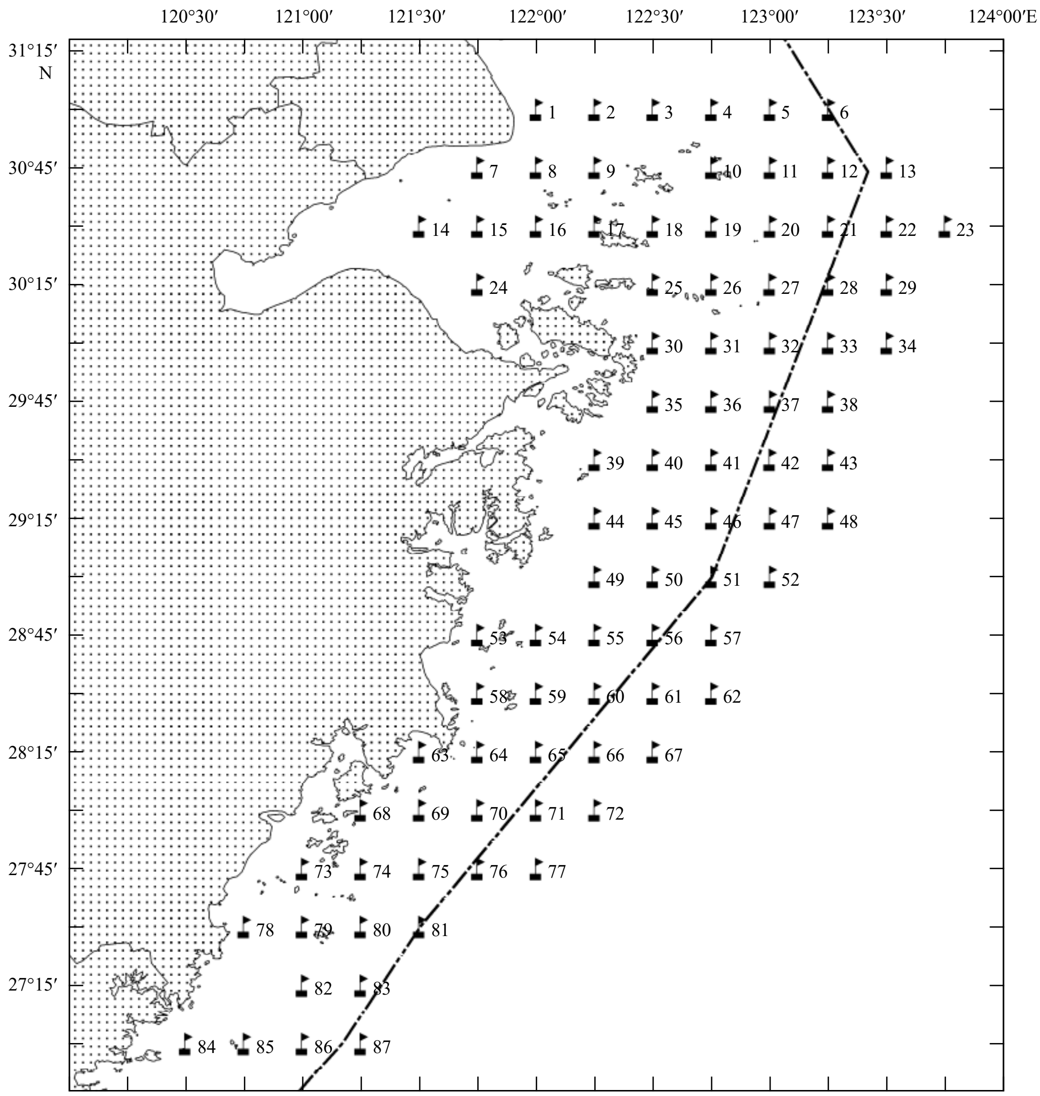

Fig. 1. Zhejiang coastal waters ranges from 27°–31°N, 120°15′–123°45′E. In order to cover effective study near shore waters, sampling stations were set every 0.5° of longitudes and latitudes in the designated area. The dashed line regulates that fishing vessels with total length over 12 m are not allowed to fish westward of the line.

was used to describe swimming crab resources at each sampling station.

2.1 *Data analysis*

The general assumption in geostatistics is that all things in a region are related to each other, but closer things are more strongly related than distant ones (Tobler, 1970). In this study, catch rate is applied to the logarithmic transformation form so that it fits normal distribution. In order to get more accurate results, local polynomial interpolation (LPI), inverse distance weighted (IDW) interpolation from deterministic methods, and kriging from geostatistical methods are taken into comparison. The research group of this study chose these methods for comparisons as they are generally used in geostatistical related studies (Curtarelli et al., 2015).

The LPI regards the study area as a group of smaller planes, and the center value of each plane represents the predication, so unknown values are estimated by several sample planes with a proper polynomial equation, which is described in mathematic form as

$$z\left(x_0\right) = \lambda_0 + \lambda_1 z\left(x_1\right) + \lambda_2 z\left(x_2\right)^2 + \cdots + \lambda_m z\left(x_m\right)^m, \quad (1)$$

where $z(x_0)$ is the estimated value at an unknown point, $z(x_i)$ is the point used for estimation, and λ_i is the weight given for estimation.

IDW interpolation predicts the unknown value of a point from surrounding sampling points, and nearby ones are given more weight than those farther away. The general mathematic form (Burrough et al., 1986) is given below:

$$z\left(x_0\right) = \frac{\sum_{i=1}^{S} z(x_i) d_i^{-k}}{\sum_{i=1}^{S} d_i^{-k}}, \quad (2)$$

where S is the number of points used in estimation, and power k controls the influence (normally $k = 2$). Parameter d_i is the distance between any given pair of points.

Like IDW interpolation, kriging uses surrounding measured values to perform the predication, but weights are not based only on distances between pairs of points but also on the spatial structure of sampling data (Johnston et al., 2001). Since the expected value of the catch rate is unknown, ordinary kriging is selected for comparisons. Ordinary kriging works under two intrinsic hypotheses: (1) the mean of sample data remains constant regardless of location; (2) the variance between pairs of points depends on and only on the distance (Maravelias and Haralabous, 1995). Then unknown values at a random point could be kriged through

$$z\left(x_0\right) = \sum_{i=1}^{S} \lambda_i z\left(x_i\right), \sum_{i=1}^{S} \lambda_i = 1. \quad (3)$$

In kriging, semivariogram is the central, which is key to describing variation quantitatively (McBratney and Webster, 1986), and its empirical form is denoted as

$$\gamma_h = \frac{1}{2N_h} \sum_{i=1}^{N_h} \left[\left(z(x_i) - z(x_i + h)\right]^2, \quad (4)$$

where γ_h is the average semivariance between all pairs of points, $z(x_i)$ and $z(x_i+h)$ are two measured points with distance h, and N_h is the number of pairs of points whose distance is called lag h. Based on the semivariogram, a model could be applied to summarize its feature, and in this study the common used one exponential model was selected to fit the semivariogram, from which three main parameters are obtained, i.e., the range, the sill and the nugget, for further analysis.

The range is the distance at which the model first levels out, and the sill is the semivariance that the model attains at the range, while the nugget indicates measurement errors or smaller sampling intervals (Johnston et al., 2001). The partial sill is equal to the sill minus the nugget, and the variability ratio (partial sill/sill) tells the spatial heterogeneous condition (Li and Reynolds, 1995).

2.2 *Criteria of evaluation*

It is a commonly used method to apply cross-validation to diagnose the accuracy of an interpolator. Cross validation recursively removes one data each time, and then uses the rest to perform the prediction, then the predicted value will be compared with that data to test the accuracy of the model. Three main indices are used for determination (Dubrule, 1983; Chang, 2006; Oliver and Webster, 2014): (1) the root mean squared error (RMSE) is a direct indicator, the smaller this value, the more accurate it performs; (2) an accurate model should have the root mean square standardized error (RMSDE) close to one; (3) the mean error (ME) reflects the average difference between measured and predicted values, the smaller difference between the estimated and observed values the better. In following equations, $\hat{z}\left(x_i\right)$ represents the observed value of a point, and $\hat{\sigma}^2$ is the variance. N is the number of observed data or the predicted data in the dataset.

$$\left.\begin{aligned} \mathrm{RMSE} &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\hat{z}\left(x_i\right) - z\left(x_i\right)\right]^2} \\ \mathrm{RMSDE} &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\frac{\hat{z}\left(x_i\right) - z\left(x_i\right)}{\hat{\sigma}\left(x_i\right)}\right]^2} \\ \mathrm{ME} &= \frac{1}{N}\sum_{i=1}^{N}\left[\hat{z}\left(x_i\right) - z\left(x_i\right)\right] \end{aligned}\right\}. \quad (5)$$

3 Results

Table 1 shows the parameterization that used in performing interpolation procedures. Results of cross-validations within each dataset is summarized in Table 2. Kriging generates the smallest RMSE (1.139 8) in autumn and has the RMSDE (1.243 0) closest to 1 in spring; IDW outperforms in winter, the RMSE (0.853 4) is the smallest with the RMSDE (0.837 2) closest to 1; while in summer, LPI gives the smallest RMSE (1.341 6) as well as the RMSDE (1.422 0) is the closest to 1. Although kriging in this case is not always the best interpolation method, it generates the smallest mean errors, which means predicted values are closer to measured values (except in winter). Hence, the research group chose the optimum interpolator to generate results but used kriging to make spatial variability analyses.

As shown in Table 3 and Fig. 2, in summer the binned values are more scattered with the largest sill value. Likewise, the semivariogram of autumn is scattered, but the range of semivariances and the sill are smaller compared with that in summer. In winter and spring, sill values are smaller so that the binned values are more concentrative. The variability ratio is 11.83%, 42.98% and 74.91% in winter, spring and summer, respectively, and the nugget accounts for 100% for the total variation in autumn, but the standard deviation (SD) of swimming crabs is the highest in summer (1.57), then in winter (1.38), and the SD in autumn is 1.28, which is close to that in spring (1.22). As for the range, it is the largest (1.10°) in autumn, much higher than those in winter and spring (0.48°), and that in summer (0.51°). Examining biomass data, the average weight in spring (94.52 g/ind.) is the heaviest followed by that in winter (59.26 g/ind.), and crabs in summer and autumn are smaller, the average is 42.74 g/ind. and 40.85 g/ind., respectively. However, the catch rate (around 7.9 g/h)

Table 1. Summary of parameters used in each interpolation method

Method	Parameterization
Ordinary kriging	neighbours = 5 length of semi-axis = 2.26 lags = 12 lag size = 0.188 3 semivariogram = exponential (differences of results generated by applying different models are very little)
Inverse distance weighted	neighbours = 10 length of semi-axis = 1.29 power = 2
Local polynomial interpolation	neightbours = 10 length of semi-axis = 1.29 polynomial order = 2 kernel function = constant

Table 2. Cross-validation results for IDW, LPI and kriging for the spring, summer, autumn, winter datasets

Dataset	Interpolation	RMSE	RMSDE	ME
Autumn	IDW	1.252 4	1.786 4	0.121 9
	LPI	1.204 0	**1.567 3**	0.014 4
	Kriging	**1.139 8**	1.886 9	**0.001 6**
Winter	IDW	**0.853 4**	**0.837 2**	−0.073 9
	LPI	0.921 7	0.769 1	**0.049 4**
	Kriging	0.945 7	0.769 8	−0.088 7
Spring	IDW	1.061 9	1.294 5	−0.034 3
	LPI	**1.001 7**	1.278 7	0.127 5
	Kriging	1.028 3	**1.243 0**	**0.002 1**
Summer	IDW	1.395 4	1.544 5	0.015 6
	LPI	**1.341 6**	**1.422 0**	−0.053 8
	Kriging	1.381 2	1.628 4	**0.000 6**

Note: Figures in bold are the optimum values of the statistics.

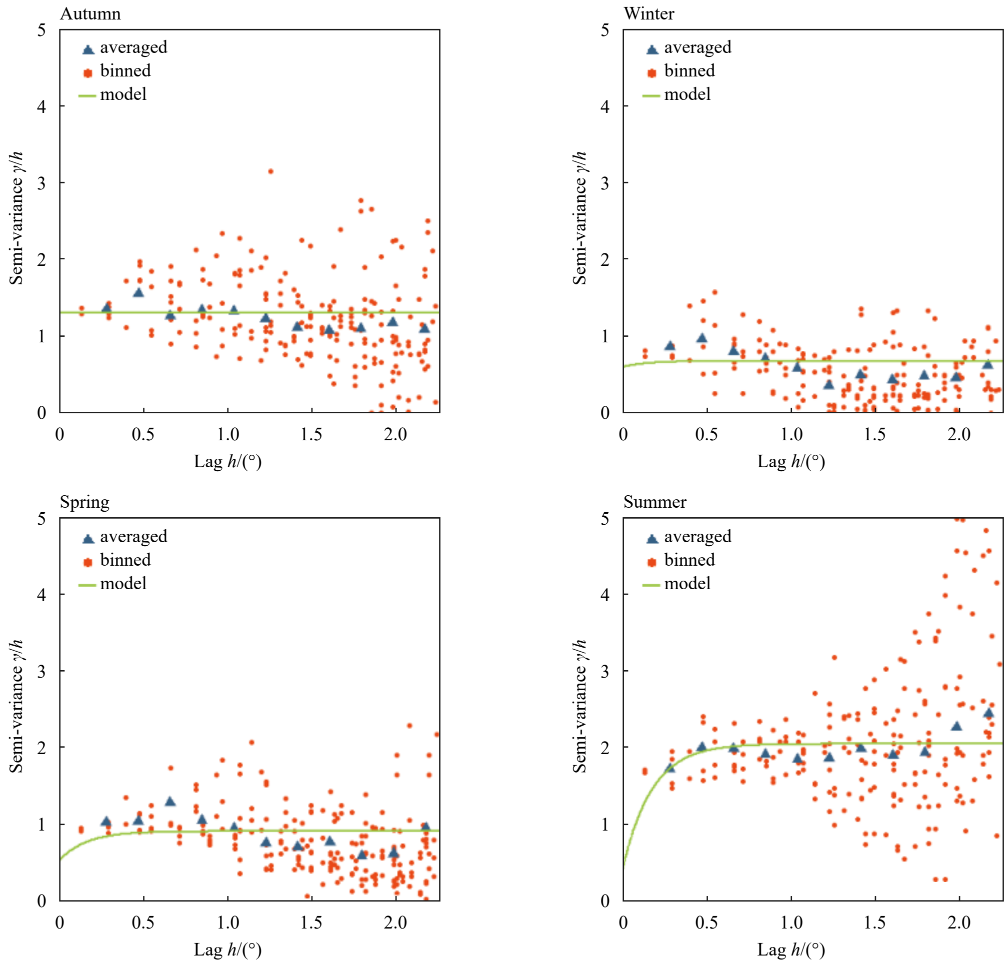

Fig. 2. Semivariograms of each dataset. Red dots represent the semivariance between any pair of points which are binned values grouped by distance (also known as the lag). Conventionally, the lag size (0.094°) multiply the number of lags (12) should be equal to around half of the largest distance (around 2.26° in this study) among pairs of sampling stations. Blue triangles are the averages of each bin, which are used to fit the exponential model.

in autumn and summer is higher than that in winter and spring (5.57 g/h and 5.97 g/h, respectively).

The distribution patterns (Fig. 3) illustrate that most swimming crabs overwintered in distant waters especially in the south, and they were only caught in 35 sampling stations. From winter to spring, it shows a trend of migration to the near shore waters, where they distributed more evenly, and showed up in 62 stations. During the summer, swimming crabs again distributed widely in coastal waters (appeared in all stations). Likewise, the distribution patterns in spring show crabs widely inhabit in coastal waters, mainly in southwest and northeast areas.

4 Discussion

Interpolation techniques enable the spatial distribution patterns to be mapped to elucidate underlying spatial dependence (Maravelias and Haralabous, 1995; Kamble and Aggrawal, 2011), so distribution patterns can be examined on a large scale, which is more intuitive. By knowing distribution patterns, migration behaviors could be inferred so that researchers can learn how swimming crab resource status changes from season to season.

Distribution features of swimming crabs can be explained by biological behaviors. Usually speaking, juvenile swimming crabs inhabit in inshore waters due to poor swimming ability, and adult ones live in more distant waters (Song et al., 1989, 2005; Zhang et al., 2013). In autumn, swimming crabs forage and gain weight in the coastal waters (the average weight was 42.74 g/ind. heavier than that in summer); when the weather becomes cold, they begin to migrate to warmer waters (Song et al., 2005, 2012; Zhang et al., 2013). A small proportion of crabs are hatched in autumn as well (Gao et al., 2012), but they enter a slow-growing state in winter (Liao et al., 2008). In the following spring, they grow up with the newly hatched generation (Song et al., 2012; Zhang et al., 2013). In the summer, the distribution showed that the species were more spatial heterogeneous (the variability ratio was 74.91%). There are two possible reasons: on the one hand, summer moratorium offers a better protection for fishery resources because fishing activities are strictly forbidden, swimming crabs migrated to inshore waters to get fed; on the other hand, juvenile swimming crabs are usually released in June in some spots (Cong et al., 2015; Wu et al., 2016; Xu et al., 2018). Because of poor swimming ability, juvenile crabs mainly inhabit in surrounding waters of releasing spots, so releasing activities may have influences on the stock composition especially in the following August (Zhang et al., 2013; Xie et al., 2014), so it may result in swimming crabs gathering in a certain area in the summer as shown in Fig. 3.

In the winter and spring, distributions of swimming crabs show patchy patterns. In Figs 2 and 3, swimming crabs during these two seasons were more homogenous and more spatially dependent (variability ratio was 11.83% and 42.98%, respectively). It may be influenced by changing marine environment. A large number of swimming crabs spawn in spring in the northern Zhejiang coastal waters, especially near the Changjiang River Estuary, where different water masses are mixed, including the diluted water from the Changjiang River, the coastal water, the Yellow Sea water, as well as the warm currents coming up from the Taiwan Strait; as a result, the sea area becomes abundant with plankton species (Li et al., 2007), forming an ideal feeding ground for spawning and foraging. In the wintertime, crab resources plunged to the lowest level, but the semivariogram looks more concentrated. Figure 3 shows that swimming crabs in winter mainly inhabited in southern Zhejiang offshore waters. Because swimming crabs are temperature sensitive species (Zheng et al., 2012; Cong et al., 2015; Liang et al., 2016; Wu et al., 2016), they overwinter in warmer and deeper waters, migrating from coastal shallower waters to offshore deeper waters and from north to south when the weather gets cold (Yuan et al., 2016; Xu et al., 2018). In addition, the high-temperature and high-salinity Taiwan Strait current flows northward in a converse direction during winter, bringing with abundant nutrients (Zhu et al., 2004; Chen and Sheu, 2006; Liang et al., 2016), which offers a better environment for overwintering. Additionally, a tongue of warm water strongly intrudes into the Yellow Sea in the winter (Teague and Jacobs, 2000; Xu et al., 2009), and the warm water is drawn southward to the northern Zhejiang waters by the coastal current (Mask et al., 1998; Xu et al., 2009), thereby attracting a small number of swimming crabs to overwinter there.

This study demonstrate that geostatistical analysis is applicable in studying swimming crabs; it could be adopted to study other crab fisheries or even other crustacean species. However, there are some limitations in this study. Firstly, the research group lacks sufficient financial support. This study is a derivative of other supported programs; thus, the group failed to get environmental data to explore the relationship between stocks and the environment, plus the group is unable to obtain consecutive year-round biomass data to get more reliable results. Secondly, sophisticated models are not taken into account in this study, such as anisotropic modelling can be used to elaborate the interpolations, and different models could be tested and compared to get more accurate predictions. In future studies, researchers could implement more detailed distribution behavior studies depending on sex, maturity, or egg-bearing condition of stocks, from which distribution and migration features could be better learnt.

Geostatistical analysis helps researchers learn how species distributes and migrates at a broad view. Better understanding of swimming crab resources will be critical for the government and fishery practitioners to make and revise related fishery policies

Table 3. Model parameters plus basic statistics of biomass data within each dataset

Category	Statistics	Autumn	Winter	Spring	Summer
Kriging parameters	nugget	1.29	0.59	0.52	0.36
	range/(°)	1.10	0.48	0.48	0.51
	sill	1.29	0.67	0.91	2.04
	partial sill	0	0.08	0.39	1.68
	variability ratio/%	0	11.83	42.98	74.91
Crab resource (catch rate in natural logarithm form)	mean	7.89	5.57	5.97	7.86
	standard deviation	1.28	1.38	1.22	1.57
	average weight/(g·ind.$^{-1}$)	42.74	59.26	94.52	40.85
	occurrences (87 in total)	73	35	62	87

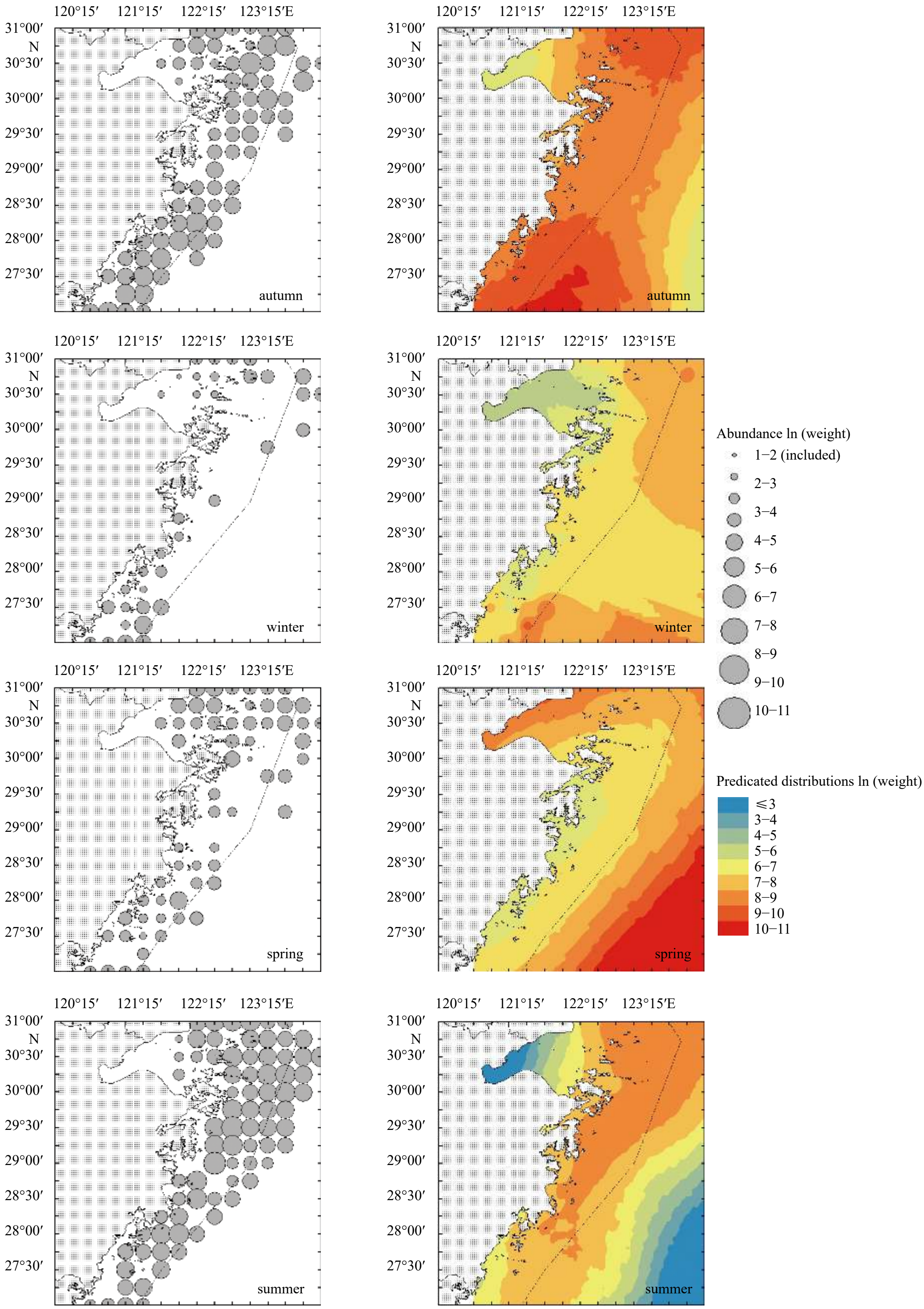

Fig. 3. Distributions of swimming crabs performed by the ordinary kriging interpolation technique. Catch rate is transformed into logarithm form so that the data approximately in normal distribution. According to distribution patterns, the migration behaviors can be inferred.

and to involve stakeholders to contribute to the advancement of sustainable fishery in Zhejiang, even in China. This work provides a reference for researchers to study swimming crab fishery using geostatistical methods, which means it could also be useful in other crab studies or even other crustacean species. Another finding is that geostatitical analysis turns discrete sample points into a continuous surface to show the trend, hence systematic survey design can be further optimized so that researchers could set fewer sample stations to still obtain sufficient data to get accurate results, which is the bonus work the researchers would work out in the near future.

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