Caderno de Estudos Geoambientais
CADEGEO

USE OF INTERPOLATION TO DESCRIBE THE SPATIAL DISTRIBUTION OF BENTHIC ORGANISMS IN COASTAL AREAS

Uso de interpolação para descrever a distribuição espacial de organismos bentônicos em áreas costeiras

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Resumo

As modelagens das distribuições espaciais da biota marinha em zonas costeiras possuem extrema importância, pois podem ser usadas como ferramentas importantes para o gerenciamento de uma área protegida e também são essenciais para identificar quaisquer mudanças no espaço após um monitoramento ambiental. No entanto, para produzir mapas confiáveis, a partir de modelagens de distribuição, a escolha do melhor método de interpolação dos dados amostrados é crítica. Este estudo objetivou avaliar a viabilidade do uso da modelagem para prever a distribuição do bentos na região subtidual de costões rochosos. Além disso, este estudo compara o poder de previsibilidade entre os métodos geoestatísticos de krigagem e cokrigagem, usando a batimetria como covariável. O estudo também avalia um método determinístico, também conhecido como inverso da potência das distâncias (IDW). As variáveis modeladas incluem grandes grupos como macroalgas e corais, assim como um de seus representantes em cada grupo (algas coralinas e o coral Siderastrea stellata, respectivamente). Os resultados indicam que, apesar do método de krigagem apresentar boa previsibilidade para algumas variáveis, o uso da batimetria como covariável no método de cokrigagem produz mapas mais precisos, especialmente quando se utiliza o modelo gaussiano. Os mapas modelados por IDW são mais precisos quando se utiliza o peso 3, no entanto, os mapas produzem muitas isolinhas indesejáveis. Conclui - se que o uso da cokrigagem com dados batimétricos é o método de interpolação mais adequado para os organismos marinhos bentônicos das regiões subtidais de costões rochosos.
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Palavras-chave: Krigagem, Cokrigagem, Benthos, Costão Rochoso, Macroalga, Coral, Modelagem espacial.

Abstract

Modeling spatial distributions of marine biota in coastal areas is extremely important, as they can be used as important tools for managing a protected area and are also they are essential to identify any changes in the space after environmental monitoring. However, to produce reliable maps from distribution models, choosing the best interpolation method from the sampled data is critical. This study to assess the feasibility of using modeling to predict the distribution of benthos in the subtidal regions of rocky shores. In addition, this study compares the power of predictability between the geostatistical methods of kriging and the cokriging, using bathymetry as a covariate. Furthermore, it also evaluates a deterministic method, also known as

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Inverse Distance Weighting (IDW). The modeled variables include large groups such as macroalgae and corals, as well as one of their representatives in each group (coralline algae and the coral Siderastrea stellata, respectively). The results indicate that although kriging method presents good predictability for some variables, the use of bathymetry as a covariate in the cokriging method produces more accurate maps, especially when using the Gaussian model fit. The maps modeled by IDW are more accurate when using weight 3, however, the maps produce many undesirable isolines. It is concluded that the use of cokriging with bathymetric data is the interpolation method most suitable for benthic marine organisms of the subtidal regions of rocky shores.
Keywords: Kriging, Cokriging, Benthos, Rocky shores, Macroalgae, Coral, Spatial modeling.

INTRODUCTION

The coastal environment is subject to constant human pressure that threatens the stability of the marine ecosystem (HARLEY et al., 2006; HAWKINS et al., 2002; HUGHES et al., 2003; ISLAM e TANAKA, 2004; SANGIL et al., 2013; SYVITSKI et al., 2005). In this regard, great efforts have been taken in recent decades to increase environmental protection areas, to protect marine ecosystems from human action (BELGRANO et al., 2015; GAINES et al., 2010). For the inclusion of new marine environment protection areas, it is necessary to carry out geomorphologic studies of the areas to be preserved, as well as understand the geological processes, mainly on the biota spatial distribution, by mapping the organisms arranged in these space. According to REISS et al. (2014), spatial distribution modeling in the benthic environment can be used as: monitoring tool for invasion of exotic species; assessment of species and areas to be protected, such as the creation of a Marine Protected Area (MPA); in addition to allowing better management of ecosystems over time. However, to produce reliable distribution maps, choosing the best interpolation method from the sampled data is critical (MELLO, CR DE et al., 2003; SILVA et al., 2010; SOUZA et al., 2010).

The creation of maps with biological and physical variables can be made from geostatistical tools and other methods such as interpolation by the inverse distance weighted (IDW). A geostatistical study can be considered as a branch of spatial statistics, developed by MATHERON (1963), and can be applied in the mining studies, for example, ecological studies of marine biota (e. g. GIANCARDO et al., 2014; JANSEN et al., 2016), topographic studies of the marine floor (JEROSCH, 2013; HILLMAN et al., 2015) and spatial distribution of fish (LITTLE et al., 1997; THORSON et al., 2015). This technique evaluates the variables of interest that have a spatial dependence (GUERRA e SALLES, 1988), which can be used to predict regions that have not been sampled. The basic concept of geostatistics is based on the assumption that, in general, the samples close to each other in space are more similar to each other than samples that are distant (ISAAKS e SRIVASTRAVA, 1989).

The geostatistical power to explain the spatial correlation between sampled values in space is given by a semivariogram function γ (h), described by Equation 1. This function expresses the spatial behavior of the variable and is able to quantify the variation of a regionalized phenomenon (LANDIM, 2003; MELLO, JOSÉ MARCIO et al., 2005). However, the sensitivity of the method is dependent of the best adjustment of the data sampled with a theoretical model semivariogram (ISAAKS e SRIVASTRAVA, 1989).

$$\gamma(\mathrm{h}) = \frac{1}{2n}\sum_{i=1}^{n}\left[\mathrm{z}(x+h)-\mathrm{z}(x)\right]^{2} \qquad \text{Equation (1)}$$

Where, z(x) is a random variable at point x in the space, separated by a distance h from a second point. The differences are calculated with n pairs of scattered points in space.

The geostatistical interpolators most often used in literature are the kriging and cokriging methods (e. g. ADAMS et al., 2008; ASSUMPÇÃO et al., 2013; BERVEGLIERI et al., 2001; CUNHA et al., 2013; GIOVANI et al., 2014; GIRALDO et al., 2011; HAIBIN et al., 2015; JEROSCH et al., 2006; KNUDBY et al., 2013; MELLO, CR DE et al., 2003; MOURA, OLGA e FERNANDES, 2009; RIOS-LARA et al., 2007; SANGIL et al., 2013; SOUZA et al., 2010). The ordinary kriging method uses the spatial dependence between neighboring samples, in other words, the estimation of a value at a point not sampled results from the linear combination of the values found in the sampled neighboring points without tendency and with minimum variance, thus is a great (CARVALHO e ASSAD, 2005; GREGO e VIEIRA, 2005). This model, as well as the cokriging model, are considered more robust than other interpolators as the IDW, because they provide measures of uncertainty associated with the estimator (SOARES e COELHO, 2006).

The cokriging method uses the same basic principle of kriging, however, it is considered a multivariate extension of the method, where for each sampled point in space a vector of values is obtained instead of one, as in the kriging. Thus, several regionalized variables can be estimated together from a spatial correlation. This method is generally used when obtaining more than one variable simultaneously, wherein, one is subsampled and the other is oversampled with the existence, necessarily, of any correlation between them. In this case, one can use the oversampled variable for improving the estimate of the subsampled variable (ISAAKS e SRIVASTRAVA, 1989).

In the marine environment, the kriging method can be used to estimate the biomass or percentage coverage of both benthic organisms (e. g. ADDIS et al., 2012; MOURA, RODRIGO LEÃO et al., 2013; WOESIK et al., 2012) and pelagic organisms (GEORGAKARAKOS e KITSIOU, 2008; KARNAUSKAS et al., 2012; e. g. RUEDA, 2001). In addition, the kriging method is very useful for predicting abiotic variables in the marine environment (e. g. GILBY et al., 2015; GOROSPE e KARL, 2011; RACHELLO-DOLMEN e CLEARY, 2007). While the distribution modeling of marine organisms by cokriging can use several correlation factors, such as temperature and Chlorophyll-a content (e. g. GEORGAKARAKOS e KITSIOU, 2008), type of substrate or other associated living organisms (e. g. MAZIÈRES e COMLEY, 2008). Thus, depending on the organism of interest to have its distribution modeled, many cofactors present in the marine environment can be used. In the study of GEORGAKARAKOS e KITSIOU (2008), using a hydroacoustic instrument to determine fish density, they observed that bathymetry was the most important covariate to explain pelagic distribution patterns. Considering that benthic organisms such as algae and corals are light dependent to survive due to photosynthetic productivity, the bathymetry suggests to be an important cofactor to be used in cokriging models.

Interpolation by IDW method predicts the point values from the weighted linear combination of the sampled points. The weight of each point is the inverse of a function of the Euclidean distance raised to an exponent. IDW models can be used to model benthic organisms. PRESTON (2002) used IDW model to predict the biodiversity of benthic macroinvertebrates in Chesapeake Bay, USA. This method of interpolation can also be applied to pelagic organisms (e. g. NYE et al., 2009). However, SAHLIN et al. (2014) obtained better results using ordinary kriging to estimate the temperature distribution in southeastern Beaufort Sea (Arctic Ocean) compared to modeling by the IDW method. Thus, depending on the chosen variable, other methods such as geostatistical modeling may provide better results.

MATERIALS AND METHODS

The study area chosen to evaluate the best interpolation method was the rocky shore and its projection to the subtidal zone of the Bardot beach, in Armação dos Búzios municipality, Rio de Janeiro State (Fig. 1). Spatial analysis was limited to the perimeter of the marine environmental protection area of Armação dos Búzios.

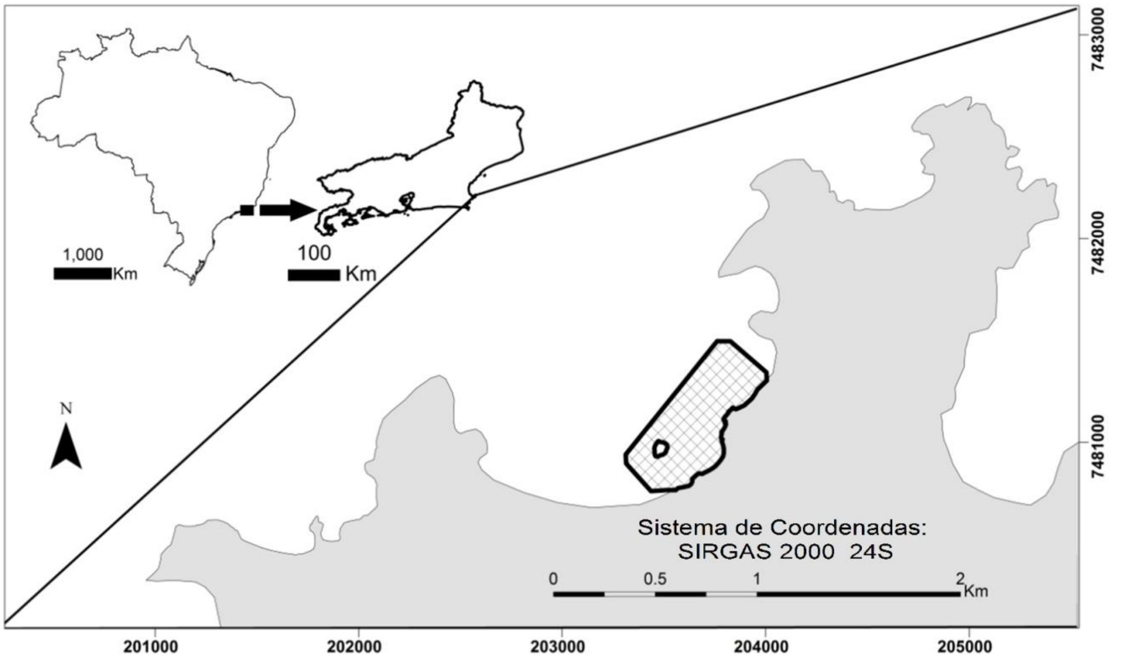

Figure 1. Study area. The marine protected area modeled by interpolation is represented on the map by the checkered area.

The variables selected to carry out the interpolation were based on the major benthic groups described in the region, including the macroalgae and corals (OIGMAN-PSZCZOL e CREED, 2004; OIGMAN-PSZCZOL et al., 2004). Inside, the grouping of macroalgae are represented by the red, brown, and green algae, whereas, the group generally classified as corals includes not only the true corals, such as the species S. stellata (Verril, 1868), but also false corals such as hydrocoral Millepora alcicornis (Linnaeus, 1758) and the gorgonian Phyllogorgia dilatata (Esper, 1806).

To assess whether the interpolation applies to different grouping scales, two smaller groups were selected as additional variables, the first was composed of red algae (coralline coralline) and the second of the true coral S. stellata.

For interpolation, a regular sampling grid with internodes spaced at 60 m was used. The points (n=76) were established previously and identified with support of a device provided by the global positioning system (GPS). Interpolations were carried out with the coverage percentage data of each variable, by identification and quantification of the photos (n=25) by intercept point method in each node of the grid featuring non-destructive sampling.

The spatial variation analysis was performed determining the spatial correlation model of the regionalized variable. For this, the sampling points were adjusted by the theoretical models to the semivariogram Equation 1, described by (VIEIRA et al., 2000).

The spatial correlation calculation is given by the relationship of the ratio between the nugget effect and the sill of the semivariogram (CAMBARDELLA et al., 1994), known as the spatial dependence index (SDI), described in Equation 2, in which CAMBARDELLA et al. (1994) proposed three categories: SDI ≤ 25% (strong); 25% > SDI < 75% (moderate); SDI ≥ 75% (weak).:

$$SDI = \frac{C_0}{C_0 + C} \qquad \text{Equation (2)}$$

Where, Co is the nugget effect and co + c is the sill.

The theoretical models chosen to evaluate the best variogram adjustment and result in a smaller error: the circular model (Equation 3); spherical model (Equation 4), exponential model (Equation 5), and Gaussian model (Equation 6). These models are known as the best to explain the majority of spatial phenomenon (YAMAMOTO e LANDIM, 2015).

$$\gamma(h) = c_0 + c\left(1 - \frac{2}{\pi}\cos^{-1}\left(\frac{h}{a}\right) + \sqrt{1 - \frac{h^2}{a^2}}\right)$$ Equation (3)

$$\gamma(h) = c_0 + c\left[1,5\frac{h}{a} - 0,5\left(\frac{h}{a}\right)^3\right]$$ To h < a

Equation (4)

$$\gamma(h) = c_0 + c$$ To h ≥ a

$$\gamma(h) = c_0 + c\left[1 - \exp\left(-\frac{h}{a}\right)\right]$$ Equation (5)

$$\gamma(h) = c_0 + c\left[1 - \exp\left(-\left(\frac{h}{a}\right)^2\right)\right]$$ Equation (6)

The predictive power of the model was tested by the cross-validation method (ISAAKS e SRIVASTRAVA, 1989). After performing this procedure for all the sampled points, the error between the predicted and sampled values and the determination coefficient (R2) are calculated (BAILEY e GATRELL, 1995), which indicates how the model can explain the observed values.

The criteria for choosing the best model were the SDI values, R2, and SSres, in this order of importance. The mean trend of the errors between the sampled values and the predicted values and their intervals with 95% of confidence were also evaluated.

To check whether the adjusted model has resulted in satisfactory expected values, especially with regard to the spatial dependence index (SDI), the prediction can be performed by interpolation using stochastic models, such as, the ordinary kriging (KO) and cokriging methods (YAMAMOTO e LANDIM, 2015).

Interpolation by the cokriging method was also used for the same set of interpolated samples by the ordinary kriging, from bathymetric profile of the interpolated (no publish), to compare the effectiveness of interpolating and generating maps more adherent to the real distribution of the variables.

In addition, the deterministic method known as the inverse distance weighted (IWD) was compared to the mentioned geostatistical models, and described by Equation 7.

$$\hat{Z}_i = \frac{\sum_{i=1}^{n}\left(\frac{1}{d_i^{\lambda}}.Z_i\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i^{\lambda}}\right)}$$ Equation (7)

Where, $\hat{Z}_i$ is the interpolated value, Zi is the sampled value, di is the Euclidean distance between the sampled and the estimated points, n is the number of neighboring points used in the interpolation, and λ is the exponent weight of the Euclidean distance, this is applied to the weights 1, 2, 3. When the weight increases the analysis emphasizes the nearest points and reduces the prediction error; however modeling generates more isolines with less smooth spreading.

The geostatistical analyses and interpolations were executed in the geographic information system ArcGIS® 10.2 software.

Therefore, This study aims to evaluate the best interpolation method for the variables of the cover percentage of the main benthic organisms from the rocky shores in the subtidal area, from maps scale of 1:5000.

RESULTS

The distribution analysis of the variables showed a strong positive asymmetry (Fig. 2). Even after transformations to log (X + 1), the square root or arc sine had not obtained normality of the data (Table 1). However, there was a small reduction in the asymmetry of the data transformed to log (X + 1), and therefore, this transformation was adopted for estimating and generating maps. After interpolation, the logarithmic values were transformed back to the original scale.

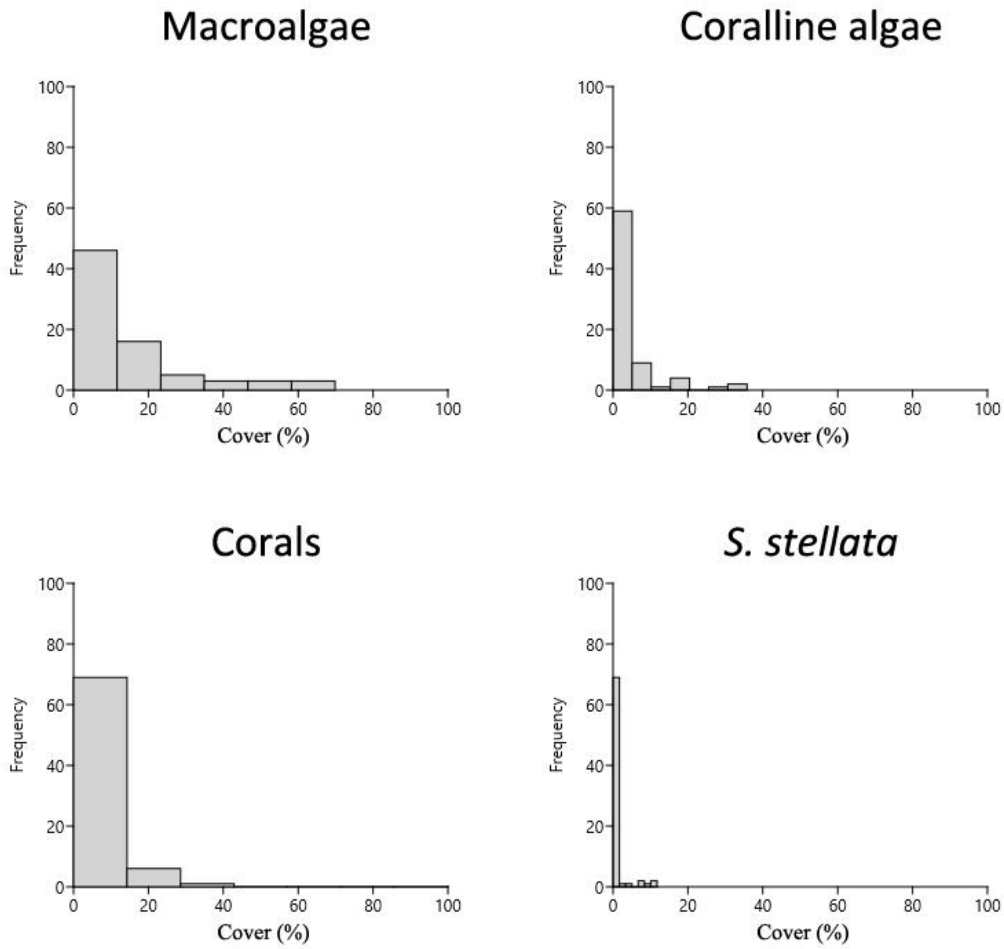

Figure 2. Histogram of distribution of the coverage percentages across the mapping area.

The first method applied was the kriging. Statistical analysis of the semivariograms generated indicated that all variables presented spatial dependence (Table 2). Thus, the use of a stochastic method could be adopted.

The variograms to kriging showed considerable variations in the spatial dependence index (SDI) between variables using the same theoretical model of adjustment, from strong dependence

(SDI ≤ 25%) to weak dependence (SDI ≥ 75%). Acoording to references mentioned, In general, the exponential model that generated higher spatial dependence, except for the variable "coralline algae", was considered moderate by the SDI classification.

Table 1. Kolmogorov–Smirnov normality test with original and transformed data. n, number of samples; p<0.05.

	N	Mean	standard deviation	p - Value
Macroalgae*	76	0.122	0.17751	**< 0.05**
Log (X+1)	76	0.0453	0.06246	**< 0.05**
square root	76	0.2283	0.26614	**< 0.05**
arc sine	76	0.2439	0.29196	**< 0.05**
Coralline algae*	76	0.0358	0.07324	**< 0.05**
Log (X+1)	76	0.0143	0.02831	**< 0.05**
square root	76	0.1033	0.15967	**< 0.05**
arc sine	76	0.106	0.16584	**< 0.05**
Corals*	76	0.0296	0.0687	**< 0.05**
Log (X+1)	76	0.0118	0.02691	**< 0.05**
square root	76	0.0787	0.15402	**< 0.05**
arc sine	76	0.081	0.15964	**< 0.05**
*S. stellata**	76	0.0072	0.02466	**< 0.05**
Log (X+1)	76	0.003	0.0102	**< 0.05**
square root	76	0.0273	0.08114	**< 0.05**
arc sine	76	0.0277	0.08244	**< 0.05**

*data without transformation.

Table 2. Setting parameters of the models to the semivariogram. The comparison between the spatial dependence index (SDI), sum of square of the residuals (SSres) and determination coefficient (R2) indicate better results with the cokriging method.

		Macroalgae			Coralline algae			Corals			*S .Stellata*		
	Model	SDI (%)	SSres	R^2 (%)	SDI (%)	SSres	R^2 (%)	SDI (%)	SSres	R^2 (%)	SDI (%)	SSres	R^2 (%)
Kriging	Circular	81.86	1.83	20.8	33.14	0.26	49.18	26.64	0.29	10.28	0	0.03	19.95
	Spherical	58.55	1.85	17.68	28.92	0.25	36.26	27.53	0.29	11.76	0	0.03	24.29
	Exponential	41.97	1.88	19.8	0	0.26	21.81	0	0.35	2.95	0	0.04	8.82
	Gaussian	86.71	1.84	20.07	47.44	0.24	44.67	42.57	0.3	8.07	0.1	0.03	17.44
Cokriging	Circular	0	1.79	48.82	0	0.23	51.35	0	0.3	46.59	0	0.03	40.03
	Spherical	0	1.66	39.86	0	0.22	40.27	0	0.28	32.69	0	0.03	28.33
	Exponential	0	1.51	28.09	0	0.23	32.85	0	0.28	16.33	0	0.04	16.55
	Gaussian	64.84	2.04	74.55	0.1	0.27	80.78	0	0.31	73.24	0	0.03	58.03
IDW	Weight 1		2	13.44		0.31	9.61		0.34	2.75		0.04	4.31
	Weight 2		1.94	20.09		0.28	18.67		0.31	6.96		0.04	8.77
	Weight 3		1.98	28.59		0.26	30.32		0.29	13.77		0.04	15.6

After the cross-validation test was obtained the determination coefficient (R2) for each interpolation was fitted to several models. Although the exponential model had submitted the best spatial dependency index, as the references indicates, and it was considered a little explanatory compared to the coefficients of the other models. The best results were observed when they were adjusted to the spherical or circular model coefficients. Although it was not very satisfactory, the coefficient values reached from 10 to 49%.

Because of the similarity between the results obtained with regard to the degree of spatial dependence and the determination coefficient, the error measures associated to the method were also evaluated to justify the choice of the best model, besides the criteria already described. However, in Table 3, it can be seen that the prediction errors are also very similar, and in all cases, the range between the upper and lower limits of the errors include a zero, as desired.

Improvement of the prediction accuracy at points not sampled on the map was obtained by the cokriging method, using the densely sampled data, by bathymetry. Even as 80 points referring to the benthos variables (secondary variable) were sampled, 1.969 sample points related to depth (primary variable) were obtained in the study area, with a ratio of around 1:24. Prior to the interpolation, the correlation between the primary and secondary variables was evaluated. The Pearson correlations between the benthos coverage percentages and depth were low (ρ ranging from 0.106 to 0.264), because of the large variation found in shallower areas. However, for all correlations a pattern of decrease in the percentage of coverage with increasing depth was observed.

Table 3. Descriptive statistics of the interpolations errors. Comparison between the interpolation methods of the variables of macroalgae and coralline algae. Emean, mean errors; SD, standard deviation; SE, standard error; l m, limits of errors (95% confidence).

		Macroalgae					**Coralline algae**				
	Model	Emean	SD	SE	upper lm	lower lm	Emean	SD	SE	upper lm	lower lm
Kriging	Circular	0.008	0.156	0.018	-0.027	0.043	0	0.058	0.007	0.013	-0.013
	Spherical	0.009	0.157	0.018	-0.027	0.044	0	0.057	0.007	0.013	-0.012
	Exponential	0.008	0.158	0.018	-0.027	0.044	0.001	0.059	0.007	0.014	-0.012
	Gaussian	0.008	0.156	0.018	-0.027	0.043	0	0.057	0.006	0.013	-0.013
Cokriging	Circular	0.005	0.155	0.018	-0.03	0.039	0	0.056	0.006	0.013	-0.012
	Spherical	0.006	0.149	0.017	-0.028	0.039	0.001	0.054	0.006	0.013	-0.011
	Exponential	0.005	0.142	0.016	-0.026	0.037	0	0.055	0.006	0.013	-0.012
	Gaussian	0.002	0.165	0.019	-0.036	0.039	0	0.06	0.007	0.014	-0.014
IDW	Weight 1	0.008	0.163	0.019	-0.028	0.045	0.002	0.064	0.007	0.016	-0.013
	Weight 2	0.006	0.161	0.018	-0.03	0.042	0.001	0.061	0.007	0.015	-0.013
	Weight 3	0.004	0.162	0.019	-0.033	0.04	0	0.059	0.007	0.013	-0.013

The use of a covariate in the interpolation, in general, significantly increased the spatial dependence index (SDI) between the sampled points (Table 2), resulting in models adjusted to the variogram without any nugget effect. In this improvement, the use of the cokriging method was more effective in producing more accurate maps than the kriging method and increased the explanatory power of the all tested model. In Gaussian models the R2 reached about 50%, and in some cases, such as coralline algae group, reached over 80%.

Using the determination coefficient as a criterion of greater importance, because the spatial dependence index was practically the same for all conditions, and unlike the kriging method, the best theoretical model indicated for the studied variables by cokriging was the Gaussian model. This model also showed a lower mean error in the variables of macroalgae / coralline algae (table 3) and corals S. stellata (Table 4) when compared to the others. In this latter variable, it was observed that the mean error of the cokriging method was about five times lower compared to the kriging method.

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The last interpolator evaluated was the IDW, with weights 1, 2, and 3. From the geostatistical analysis, it was found that the determination coefficient as similar that obtained with the kriging method when using weight 3 to weigh the distances between points (Table 2). Furthermore, the sum of squares of the residuals (SSres) also showed similar values to the ones obtained with the kriging method. Comparing the weights adopted for interpolation from the error measurements, weight 3 was confirmed to be the best fit, with a lower average error, although the standard errors were slightly higher than in the kriging method.

Table 4. Descriptive statistics of the interpolations errors. Comparison between the interpolation methods of the variables Corals and S. stellata. Emean, mean errors; SD, standard deviation; SE, standard error; l m, limits of errors (95% confidence).

		Corals					*S. stellata*				
	Model	Emean	SD	SE	upper lm	lower lm	Emean	SD	SE	upper lm	lower lm
Kriging	Circular	0	0.063	0.007	0.014	-0.014	0	0.021	0.002	0.005	-0.005
	Spherical	0	0.062	0.007	0.014	-0.014	0	0.02	0.002	0.004	-0.005
	Exponential	0	0.069	0.008	0.015	-0.016	0	0.023	0.003	0.005	-0.005
	Gaussian	0	0.063	0.007	0.014	-0.014	0	0.021	0.002	0.005	-0.005
Cokriging	Circular	-0.001	0.063	0.007	0.013	-0.015	0	0.02	0.002	0.004	-0.005
	Spherical	-0.001	0.061	0.007	0.013	-0.015	0	0.02	0.002	0.004	-0.005
	Exponential	-0.001	0.061	0.007	0.013	-0.015	0	0.022	0.002	0.005	-0.005
	Gaussian	0	0.064	0.007	0.015	-0.014	0	0.019	0.002	0.005	-0.004
IDW	Weight 1	-0.001	0.067	0.008	0.014	-0.016	0	0.024	0.003	0.005	-0.006
	Weight 2	-0.001	0.064	0.007	0.014	-0.015	0	0.023	0.003	0.005	-0.005
	Weight 3	-0.001	0.063	0.007	0.013	-0.015	0	0.022	0.003	0.005	-0.005

As the three interpolation methods are feasible in spite of the cokriging demonstrating better results, comparisons of the maps produced by the three methods were performed using the best models adjusted to each one. Thus, for kriging interpolation the spherical model was chosen, and the Gaussian model was used for interpolation with the cokriging method, and for the IDW, the weight of 3 was used.

The maps produced by using the kriging method did not have a good representation of the real environment (Fig. 3). It is observed through the overlap of the points and their actual values on the predicted maps. The kriging sometimes overestimated or underestimated some points in relation to the true values. In contrast, the maps produced by using the cokriging method proved more reliable to the real environment for all variables tested. Comparing the actual values and the predicted map, the cokriging resulted in no overestimation. Only one point was underestimated, for the variable "macroalgae" (Universal Transverse Mercator coordinate system - 204002 E 7481307 N, 24 S), in the cokriging method. Results similar to those from the cokriging were observed in the interpolation by the IDW, however, the maps presented various isolines with less smooth spreading.

DISCUSSION

This study demonstrates that the use of interpolation to estimate the percentage of coverage of benthic organisms in the coastal subtidal regions is feasible. However, due to the heterogeneity of the studied rocky shore (OIGMAN-PSZCZOL et al., 2004), the normal condition of distribution of the sampled values becomes difficult when the grid has large spaces between the sampled points. In this study, there was no intention to obtain the exact positions of the benthic groups, since the objective was to model the distribution of the main groups and to locate the regions of greater and smaller concentration in a scale of tens of meters. So, this study opted for a regular grid with 60 m between nodes. In addition, this spacing reduces the cost and time taken for completion of the sampling throughout the study area. The distribution with positive asymmetry observed in the variables studied here is because of the sampled points farthest from the coast's margin. These points are located on sandbanks, absent of both macroalgae and corals. Thus, the large number of quantized points equal zero, even after transformation, and result in a non-normal distribution. Positive asymmetry can lead to overestimation, on account of the influence of a few higher values near the lower values (YAMAMOTO e LANDIM, 2015), as noted by the low determination coefficients and the overlap of real points on the predicted maps, in the kriging method. Although not a requirement of the geostatistical analysis, the method works best when the distribution approximates the normal (ISAAKS e SRIVASTRAVA, 1989). Therefore, the interpolations have been carried out with the processed data.

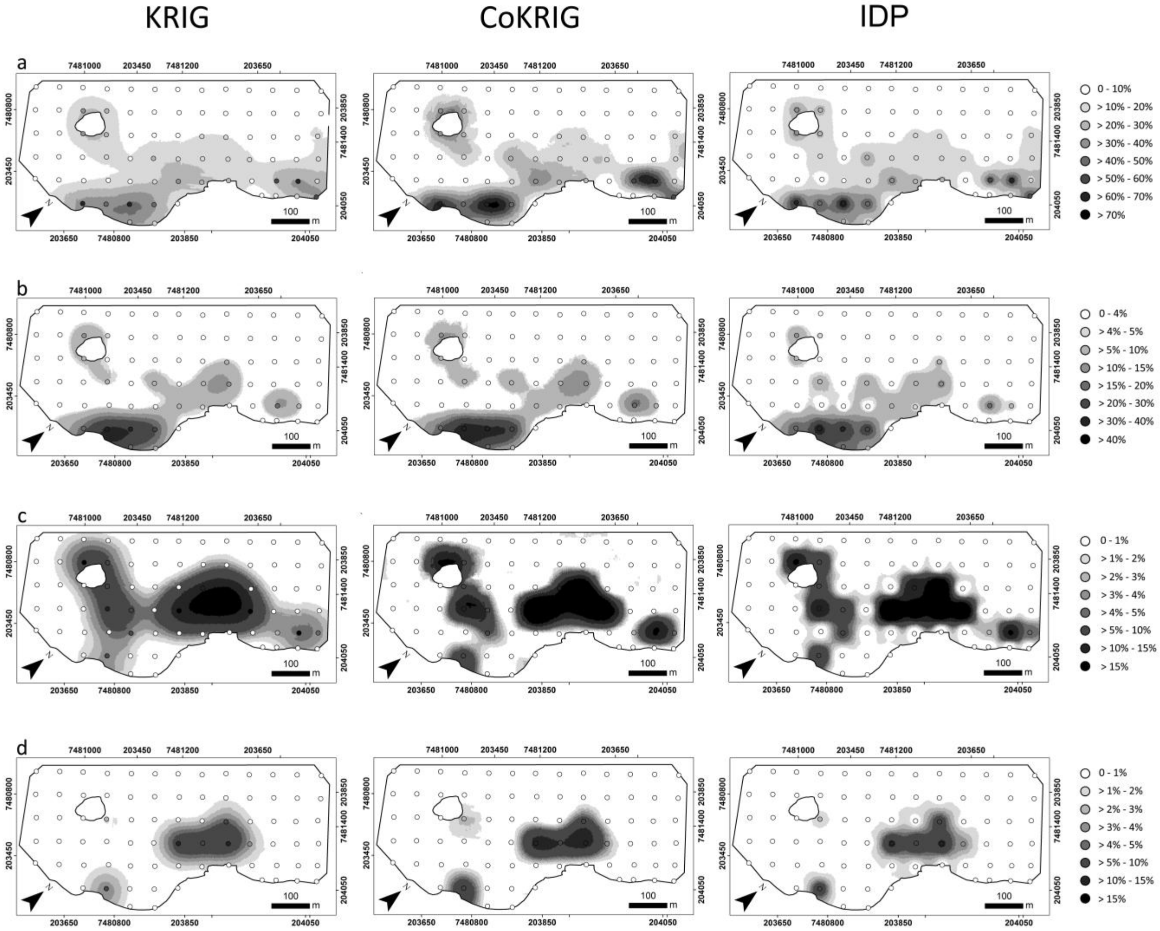

Figure 3. Distribution maps of coverage percentages from modeling by kriging, cokriging and inverse distance weighted (IDW). The sampling grid overlay shows the actual coverage percentage found at each collection point on the scale of legend. The clearest spots predicted on the map indicate overestimation of the method, spots with the same tone indicate correct predictions, and darker spots indicate underestimation of the method. a, b, c, and d represent variables: Macroalgae, coralline algae, coral, and S. stellata, respectively.

The increased predictive power of the unsampled points was achieved in this present study using the bathymetry data as a second most densely sampled variable in relation to the benthic coverage rate. In the correlation, it was found to be inversely related to the variables studied, because autotrophic organisms such as macroalgae and photosynthetic holobionts, associated with other organisms, such as coral, depend on light to produce organic compounds such as energy source (SHEPPARD et al., 2009). However, the penetrating power of the light dims with increasing depth (CASTRO e HUBER, 2012) and the presence of suspended particulate matter in the water column (AIROLDI, 2003; SHEPPARD et al., 2009). According to GODIVA et al. (2010) and TAVARES et al. (2011), the region studied in this study is greatly influenced by the sediment in suspension rising up from rivers at Macaé, São João, and Una, located 40, 20, and 11 km away, respectively. Thus, the absence of seaweed and coral sampled at points more than 4 m deep can be due to reduction of light, besides the lack of rocky shores. The depth, although it has not shown strong correlations, is sufficient for improving the interpolation, by the cokriging method, greatly increasing the determination coefficient (R2), as showed in the Table 2, and the spatial dependence. In addition, the correlation with depth avoided the overestimation of regions with very low or missing values, especially when the Gaussian adjustment model was used with the variogram.

Although interpolation by no geoestatistic method (IWD) has shown good findings, the cokriging method was the best to produce maps with more smoothed dispersion. The quality of the maps was evaluated from the overlap of the real values of the sampled points on the prediction maps of the spatial distribution made by interpolation. This analysis is purely visual and there is no statistical value. It differs from the determination coefficient analysis because a comparison is made with all the sampling sites and it is not intended to assess the power of predictability, but objectively confirm the value predicted by interpolation for the real value of the sample point. The cokriging besides being a more robust method, it can take into account measures of uncertainty (YAMAMOTO e LANDIM, 2015). CUNHA et al. (2013), in a comparative study on distribution of rainfall, utilizing both the kriging and cokriging methods, showed that the best results came from the cokriging method and it can be used in conjunction with subsampled variables. In the marine environment, MAZIÈRES e COMLEY (2008) obtained good results of predictability in distribution maps of reef fish communities, using the habitat characteristics as a covariate. Thus, the cokriging seems to be the best method for construction of distribution maps of benthic organisms dependent directly or indirectly from photosynthetic processes when correlated with bathymetry. Therefore it can be seen that the suggested method allows more accurate estimates.

The method suggested can be applied in both coastal areas, such as rivers and lakes. However, it is necessary to take into account that for each region a priori tests must be carried out to determine the sampling spacing according to the scale of resolution of the models that one wishes to obtain.

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