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Spatial assessment of benefits of a coastal Mediterranean Marine Protected Area

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ABSTRACT

Marine reserves are increasingly advocated not only as conservation but also as fisheries management tools to safeguard the decline of coastal fishing resources. Still, conclusive evidence of their functioning is lacking, amongst others due to the influence of spatio-temporal variations in fish populations and habitat heterogeneity which could hamper a sound data interpretation. We conducted a spatial analysis of the benefits of the Medes Island Marine Reserve by combining geostatistical and Geographic Information System (GIS) tools. Concurrently, we analysed effects of trends reflecting habitat heterogeneity and spatial structuring of data on spatial predictions of fish catch per unit effort (CPUE) and length. Predicted spatial patterns showed the complexity and simultaneous action of trend factors leading to mostly non-linear gradients in CPUE and length data. CPUE of total fish and CPUE and length of common pandora (*Pagellus erythrinus*) increased close to the Integral Reserve due to direct and indirect reserve effects. CPUE and length of striped red mullet (*Mullus surmuletus*) slightly increased also near the Integral Reserve, but distinct reserve effects could not be identified due to the strong influence of artificial reefs. We conclude that the spatial dimension of the Buffer Zone, where artisanal fisheries are allowed, permits in general protection only for target species, favouring a habitat with no discontinuities from the reserve outwards. Our spatial approach to assess reserve benefits provides major insights into complex systems like coastal marine reserves in the northwestern Mediterranean. In addition, it contributes to a crucial aspect of marine conservation, viz. the decision on the spatial dimension of protected areas.

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1. Introduction

Coastal protected areas throughout the world, and in the Mediterranean in particular, are no longer seen only as nature conservation instruments but also as safeguard against declining coastal fish resources and tourist attractions (Claudet and Pelletier, 2004; Diréach et al., 2004; Claudet et al., 2006). Accordingly, an increasing number of studies deal with the use and functioning of marine reserves ("no take areas") or marine protected areas (MPAs) as fisheries management

tools (Harmelin, 2000; Fraschetti et al., 2002; Ashworth and Ormond, 2005; Boudouresque et al., 2005; Abesamis et al., 2006; Claudet et al., 2006; Floeter et al., 2006). Coastal MPAs located in the northwestern Mediterranean can be characterized as small areas (usually <10 km²) mostly located around or adjacent to islands managed with no-take or partial-take regulations (Francour et al., 2001). Commercial fishing is restricted to types of fishing gears and fishing boats that are typical for the artisanal fisheries: trammel nets, gillnets or longlines. Artisanal fishery are often coastal and involve small

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capital investment and boats than 12 m (Colloca et al., 2004). In the Mediterranean, the artisanal fishery is characterized by highly diverse fishing gear and target species, as well as by a marked seasonality, determined by the fishermen local knowledge on the species behavior and abundance throughout the year. The artisanal fishing activity, although contributing 80% to the EU Mediterranean fleet (more than 30000 artisanal vessels) and generating more than 100000 jobs (COM, 2002), shows a clear decline in many coastal areas (Gómez et al., 2006). For this reason, studies on coastal fisheries are also of special interest in terms of conservation of regional traditions and lifestyle.

In contrast to tropical regions (Russ and Alcala, 1996; Russ et al., 2004; Abesamis et al., 2006) only a few studies of temperate (Murawski et al., 2003; Blyth-Skyrme et al., 2006) and Mediterranean MPAs demonstrate clear fisheries benefits like increased catches or yield (Goñi et al., 2006), that could be explained by a “spillover” of biomass from the reserve into the surrounding waters (Rowly, 1994). The lack of evidence for MPA effectiveness might be caused by several factors: (i) inappropriate sampling designs (Fraschetti et al., 2002; Guidetti, 2002), (ii) lack of data covering the period before and after the creation of the MPA (Fraschetti et al., 2002), (iii) use of methods merely capable to detect linear biomass gradients (Murawski et al., 2003), (iv) neglecting the effect of spatio-temporal variations of fish populations and/or habitat heterogeneity (García-Charton and Perez-Ruzafa, 2001; García-Charton et al., 2004).

Systems like marine reserves are spatially heterogeneous, which results in various spatial patterns of fishing activities depending on the distribution of the target species (which in turn depends on habitat and interspecific interactions). Spatial heterogeneity is often accounted for through the standardization of catch per unit effort (CPUE) data (Babcock et al., 2005). However, CPUE data standardization does not eliminate the influence of spatial autocorrelation (Legendre, 1993) on biomass estimates or spatial assessments (Simard et al., 1992; Babcock et al., 2005). Spatial autocorrelation is caused by spatial structuring of CPUE data, i.e. statistical non-independence of nearby samples, and can be analysed and modelled mathematically by geostatistics (Cressie, 1991).

In fisheries, geostatistics is employed to optimise sampling strategies (Petitgas, 1996), to estimate fish biomass and corresponding variances, taking into account the existence of spatial structures (Maynou, 1998; Rivoirard et al., 1998), as well as to map estimated distributions and spatial patterns of organisms (González Gurriarán et al., 1993; Maravelias et al., 1996; Stelzenmüller et al., 2004a,b; Jensen and Miller, 2005). Further, geostatistical tools can be used to assess the effects of trends on catch data (Rufino et al., 2006), the importance of factors like habitat association of species and spatial survey scale (Stelzenmüller et al., 2005a) or type of fishing gear (Stelzenmüller et al., 2006) on spatial estimations of distribution patterns of marine resources.

Our study area comprises the Medes Island Marine Reserve, a coastal MPA located in the northwestern Mediterranean. Ever since, the creation of the reserve a number of studies have been carried out to assess its performance and to evaluate reserve effects on fish populations (García-Rubies and Zabala, 1990; Macpherson et al., 2000), ichthyoplankton

(Sabatés et al., 2003), crustaceans (Díaz et al., 2005) and sea urchins (Hereu et al., 2005). Significantly higher abundance of commercial and non-commercial fishes was reported in the Integral Reserve zone compared to nearby non-protected control areas (García-Rubies and Zabala, 1990). Still, evidence that this increased abundance of commercial fish species enhances the local fishery by biomass exportation is lacking.

In this study, we assessed reserve benefits by predicting spatial pattern of CPUE data from an artisanal fleet and by analysing the impact of spatial factors: presence of the MPA, artificial reefs, a river, *Posidonia* meadows, depth, and combined effects applying universal kriging with an external trend approach (UK with ET) (Webster and Oliver, 2001). Our study was focused on two target species characteristic of the artisanal Mediterranean fishery, the common pandora (*Pagellus erythrinus*) and the striped red mullet (*Mullus surmuletus*).

We combined geostatistical and Geographical Information System (GIS) tools to account concurrently for the influence of spatial trend variables and the effect of spatial structuring on spatial predictions of CPUE and fish length. Thus, we propose a complementary novel approach to assess reserve benefits in heterogeneous coastal MPAs.

2. Methods

2.1. Study and onboard sampling

This study took place in the northwestern Mediterranean, in the adjacent waters to the Medes Islands Marine Reserve, a

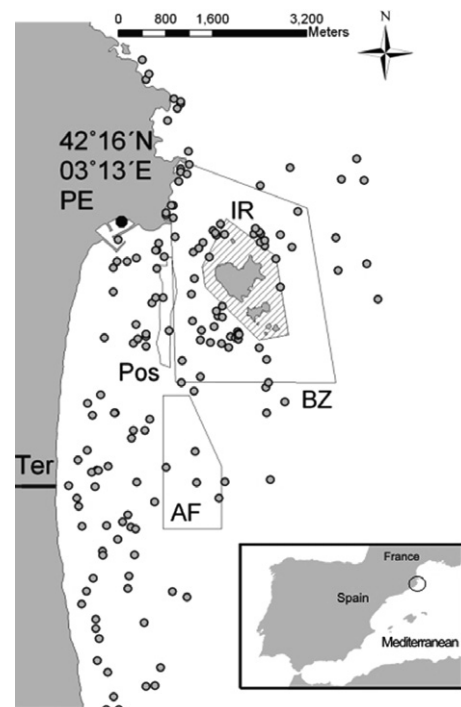


Fig. 1 – Study area with the Medes Islands Integral Reserve (IR), the Buffer Zone (BZ), the river Ter (Ter), the artificial reefs zone (AF), *Posidonia* meadows (Pos), the port L'Estartit (PE) and the positions of all sampled fishing gears (indicated by the midpoint).

small archipelago located 1 km offshore of the town of L'Estac-tit (42°N, 03°E, Fig. 1). The reserve, established in 1983 to pre-serve its marine habitat, but not explicitly to enhance local fisheries, consists of an Integral Reserve (IR; 91 ha) where all fishing activity was banned in 1991, and a Buffer Zone (BZ, 418 ha) where only artisanal fisheries are allowed. Thus, with-in the study area no industrial fleet is operating. The study area encloses the MPA, a zone with artificial reefs (AF, imple-mented to ban trawlers from the adjacent waters to the re-serve), and *Posidonia oceanica* meadows (Pos). The Medes Islands Marine Reserve represents a rocky-littoral fish assem- blage and houses all major Mediterranean benthic communi- ties (Garrahou et al., 1998; Díaz et al., 2005; Hereu et al., 2005).

The artisanal fishing fleet operating in the vicinity of the reserve can be characterized by a small number of fishing boats (24) with a mean length of 6.5 m and a mean fishing power of 31.41 (HP). The most often employed fishing gears are trammel nets, gillnets, and longlines. Fishing takes place all year round with alternating seasons for the main target fish species: striped red mullet (*M. surmuletus*), common pan- dora (*P. erythrinus*), gilthead seabream (*Sparus aurata*), Euro- pean hake (*Merluccius merluccius*), European seabass (*Dicentrarchus labrax*), striped seabream (*Lithognathus mormy- rus*), and common sole (*Solea vulgaris*).

We obtained daily data on catch composition, fish length, catch positions (using GPS), type of fishing gear, local depth and type of bottom in March–December, from 2003 to 2005 (fishing activity is lower in the winter due to weather

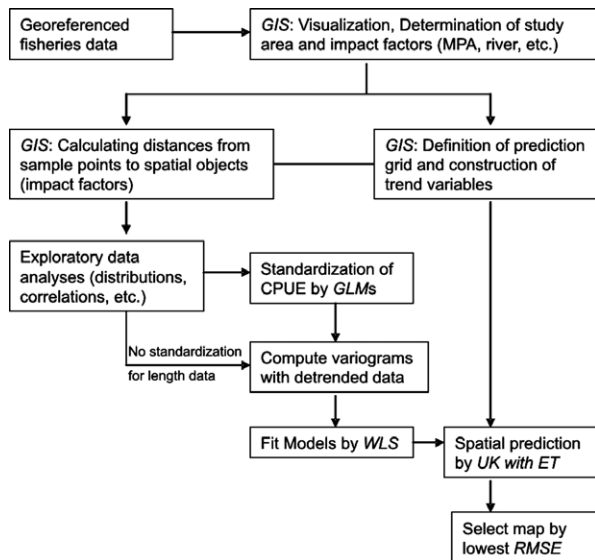


Fig. 2 – Conceptual model for spatial prediction of fisheries data. GIS, Geographic Information System; GLM, generalized linear model; WLS, weighted least squares; UK with ET, universal kriging with external trend; RMSE, root mean squared error derived from cross validation.

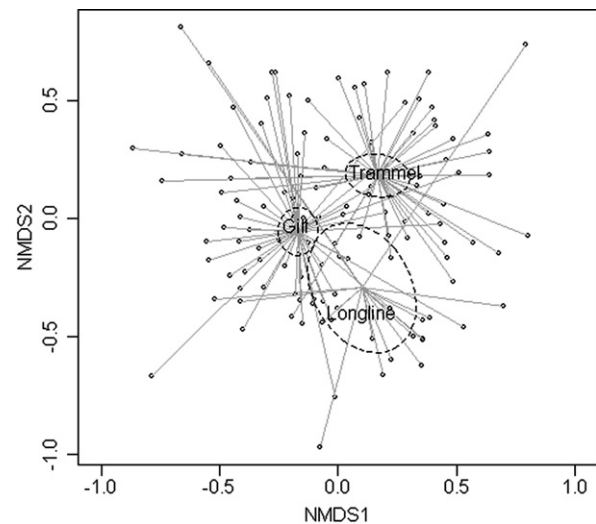


Fig. 3 – Non-metric multidimensional scaling (NMDS) computed with CPUE of total fish (TC; kg boat⁻¹), aggregated for 2003–2005, showing a clear separation by fishing gear. Items were combined based on the centre of the class.

Table 1 – Results of the calibration analyses (GLMs)

Data	Model	Dev.	Res. df	Res. deviance	F	Pr (>F)	Deviance ex. (%)	AIC	Power coeff.
TC	Null		126	177.14			33.3	387.6	
	Gear	14.96	123	162.17	4.52	0.005			Gillnet: 1
	Vessel	20.57	119	141.59	4.66	0.002			Longline: 0.55
	Quarter	2.37	116	139.22	0.72	0.544			Trammel: 0.51
	Bottom type	21.14	107	118.07	2.12	0.544			Tram–Gill: 1.65
PC	Null		64	88.99			29.2	196.4	Gillnet: 1
	Gear	23.55	61	65.43	7.35	<0.01			Longline: 1.05
	Quarter	2.44	59	62.99	1.14	0.326			Trammel: 0.26
MC	Null		27	75.07			78.7	93.8	Tram–Gill: 0.25
	Gear	19.56	25	55.58	8.56	0.004			Trammel: 1
	Vessel	22.40	21	33.08	4.90	0.011			Gillnet: 0.18
	Month	17.07	14	15.99	2.14	0.108			Tram–Gill: 2.02

TC: CPUE of total fish (kg boat⁻¹); PC: CPUE of *P. erythrinus* (kg boat⁻¹); MC: CPUE of *M. surmuletus* (g boat⁻¹); Dev. = deviance; Deviance ex.: deviance explained; AIC: Akaike information criterion (AIC); Power coeff.: power coefficients; GLMs = generalized linear models.

conditions). We sampled the seven vessels that conduct a continuous fishery, resulting in representative information on catches and fishing activities in the vicinity of the Medes Island Marine Reserve.

2.2. Data standardization

We converted numbers of fish to biomass per boat (CPUE: kg boat^{-1}) on the basis of length–weight relationships ($W = aL^b$; with a and b from the literature). We analysed the CPUE of total fish (TC), *P. erythrinus* (PC) and *M. surmuletus* (MC; CPUE: g boat^{-1}) two of the most abundant species in the catches (contributing 10% to the total catch in weight), with distinct habitat preferences (*P. erythrinus*: rock, gravel, sand, and mud; *M. surmuletus*: sand and soft bottoms). Additionally, we investigated the mean total length (cm) of *P. erythrinus* (PL) and *M. surmuletus* (ML) caught per fishing haul. In general, aggregated CPUE is potentially confounded by differences in catchability, caused by variation in vessel characteristics, fishing gears, and fishing seasons (Hilborn and Walters, 1992; Maunder and Punt, 2004). This is especially true for CPUE data coming from an artisanal fleet, due to the high diversity of fishing gears used (Colloca et al., 2004).

We visualized the confounding effect within the CPUE using non-metric multidimensional scaling (NMDS), based on a Bray–Curtis dissimilarity matrix (Bray and Curtis, 1957). We only considered species, which occurred more than once in the catches of trammel nets, gillnets and longlines.

In order to standardize the CPUE among the different fishing gears for each variable (TC, PC, MC) we used generalized linear models (GLM), the most common method for standardizing catch and effort data (Maynou et al., 2003; Maunder and Punt, 2004; Venables and Dichmont, 2004; Murawski et al., 2005). For GLM computations, we considered the following initial set of explanatory variables: fishing gear (trammel net, gillnet, longline and combined trammel–gill net), year, month, quarter, length of net, fishing boat (seven boats) and type of bottom (sand, mud, gravel, and rock; representing distinct fishing grounds). We fitted models with a stepwise backward selection procedure by exact Akaike Information Criterion (AIC; Akaike, 1974), with catches equal to 0 eliminated from the analysis. In cases where a temporal variable was not significant, we incorporated it in the model anyway, as one of the objectives of standardizing CPUE data is to detect trends over time in biomass indices (Maunder and Punt, 2004). Then, we derived calibration coefficients by back-transforming the parameter estimates (Quinn and Deriso, 1999) and transformed CPUE data by dividing the raw CPUE by the appropriate power coefficient. Hence, we conducted the subsequent spatial analyses of catch patterns with standardized CPUE.

2.3. Definition of trend variables

One main objective of this study was to assess spatial patterns in CPUE and length data in relation to various factors constituting habitat heterogeneity and potentially affecting the spatial distribution of effort. We defined spatial trend variables in ArcGIS v8.0 by calculating the shortest linear distance (m) from the spatial position of the samples (midpoints of fishing haul) to the spatial objects defined by their bound-

aries. Consequently, the constructed trend variables were “Distance to the MPA”, “Distance to the River”, “Distance to AF”, and “Distance to Pos”. Further on, we considered also “Depth” as a trend variable for the spatial analyses of CPUE and length data of common pandora and striped mullet. In contrast, we stratified CPUE of total fish in TC₁ (local depth <30 m) and TC₂ (local depth ≥ 30 m), as in the study area the general habitat characteristic changes from a sandy bottom at depth <30 m to a muddy or rocky bottom at depth ≥ 30 m.

To detect co-linearity among the trend variables and between the standardized CPUE and the spatial trend variables, we computed pseudo-likelihood ratio tests to verify

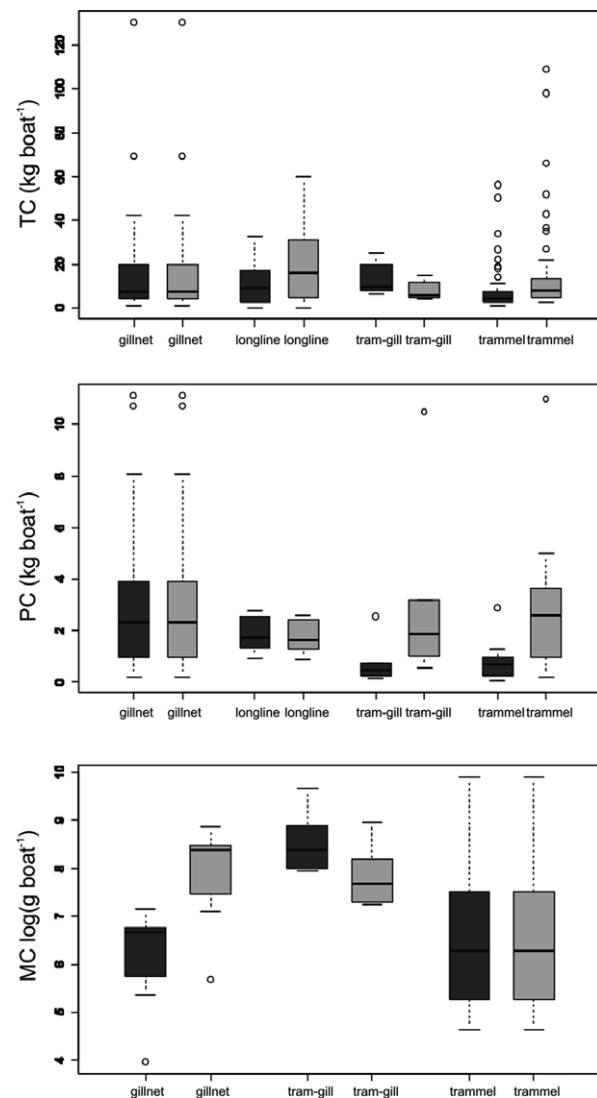


Fig. 4 – Boxplots of CPUE of total fish (TC; kg boat^{-1}), *P. erythrinus* (PC; kg boat^{-1}), and *M. surmuletus* (MC; g boat^{-1}). Dark and light gray boxes indicate raw and standardized CPUE, respectively. Mid lines, boxes and whiskers represent median, lower and upper quartiles and smallest and largest observation within an interquartile range of 1.5. Circles indicate observations beyond an interquartile range of 1.5. Fishing gears employed were gillnet, trammel net, longline and trammel net–gill net combined (tram–gill).

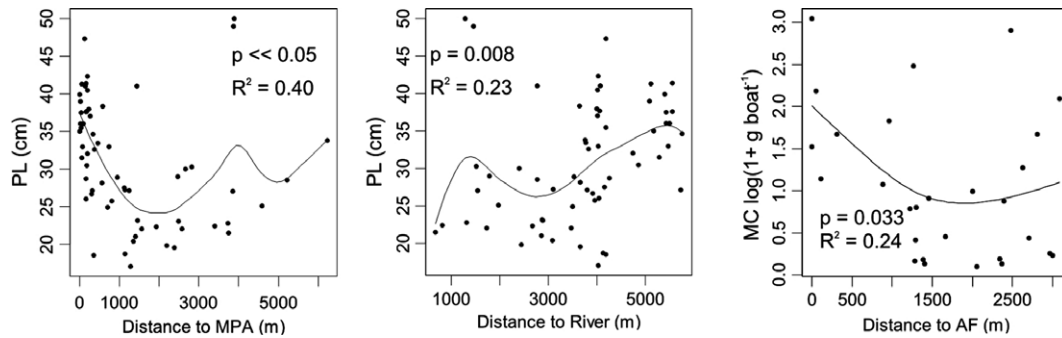


Fig. 5 – Plots of *P. erythrinus* mean length (cm) vs. distance to the MPA (m), vs. distance to the river (m) as well as standardized *M. surmuletus* ($\log(1 + \text{g boat}^{-1})$) vs. distance to the artificial reef zone (m) with fitted non-linear regression models showing a significant deviation from the tested null-hypotheses: “Trend variable has no effect on catch or length data”.

regression models (Bowman and Azzalini, 1997) and Spearman rank correlation tests (Best and Roberts, 1975).

For each variable under study, we drew 50 m by 50 m grids over the study area and repeated distance measures for each grid cell midpoint. For all prediction grids of common pandora and striped red mullet, we modeled geostatistically the variable “Depth” to derive estimates of depth at each grid cell. These derived prediction grids served as base maps for spatial modeling and mapping.

2.4. Spatial analyses

The aim of this study was to predict spatial patterns of fisheries data and to assess possible conservation and fisheries benefits around the Medes Islands Marine Reserve in relation to impacts of habitat heterogeneity and spatial structuring of fisheries data. One necessary condition indicating fisheries benefits in terms of resource spillover from a marine reserve is a density gradient declining from the border of the MPA to the surrounding waters (McClanahan and Mangi, 2000). Thus, in numerous studies linear regressions are applied to measure this density–distance relationship (Chapman and Kramer, 1999; McClanahan and Mangi, 2000; Murawski et al., 2003). Plots of catch data vs. distance to MPA can show complex relationships at multiple distance scales due to the confounding effects of environmental factors (like habitat heterogeneity) and behavioural adaptations to seasonally varying environment (Murawski et al., 2003). This makes interpretation of reserves and their spillover effects by linear statistical models difficult. Therefore, we conducted a com-

bined geostatistical/GIS analysis, where we used secondary spatial information (constructed trend variables) to predict spatial patterns of CPUE and length data using universal kriging with an external trend (Webster and Oliver, 2001). This method has been successfully applied in soil science to enhance estimates of soil properties (Goovaerts, 1997; Mueller and Pierce, 2003), but its application to fisheries data is still uncommon (Rufino et al., 2004).

We interpolated CPUE and length data with universal kriging with external trend on the 50 m by 50 m grids with the help of the trend variables according to Cressie (1991) and Goovaerts (1997). For the preceding structural analyses, we detrended data with individual trend variables, combinations of two of them (not showing a co-linearity), and additionally the combinations: depth + MPA + AF (only combination possible in terms of the presence of co-linearity) and depth² (for PC, PL, MC and ML) (Cressie, 1991; Kaluzny et al., 1998). For variogram computations, we aggregated sampling data (2003–2005), assuming a stable spatial distribution of fish populations through time. We computed omnidirectional experimental semivariograms of the variables TC₁, TC₂, PC, PL, MC and ML with the robust “modulus” estimator (Cressie and Hawkins, 1980) and estimated parameters of spherical, exponential and Gaussian variogram models by a weighted least squares procedure, as recommended by Cressie (1991).

We validated spatial models (maps, derived with universal kriging with external trend) by cross validation (Deutsch and Journal, 1998), using the fitted variogram model.

From the cross validation results we calculated: bias (ME), mean squared deviation ratio of the predictions vs. samples

Table 2 – Spearman rank correlation coefficients with significant correlations ($p < 0.05$) indicated in bold

External trend	$\log(1 + \text{TC})$ (kg boat ⁻¹)	$\log(1 + \text{TC}_1)$ (kg boat ⁻¹)	$\log(1 + \text{TC}_2)$ (kg boat ⁻¹)	$\log(\text{PC})$ (kg boat ⁻¹)	PL (cm)	$\log(\text{MC})$ (g boat ⁻¹)	ML (cm)
Depth	0.14	-0.13	0.14	0.12	0.26	0.36	0.06
MPA	0.01	0.13	-0.02	-0.19	-0.25	-0.29	-0.28
River	-0.02	-0.23	0.18	0.10	0.30	0.15	0.14
AF	0.00	-0.15	0.19	-0.01	0.25	-0.33	0.00
Pos	0.04	0.05	0.03	-0.08	0.04	-0.20	-0.28

MPA: distance to the MPA; River: distance to the river; AF: distance to AF; Pos: distance to Pos; TC: CPUE of total fish caught; TC₁: CPUE of fish caught at <30 m depth; TC₂: CPUE of fish caught at ≥30 m depth; PC: CPUE of *P. erythrinus*; MC: CPUE of *M. surmuletus*; PL: mean length of *P. erythrinus*; ML: mean length of *M. surmuletus*.

(MSDR) and root mean squared error (RMSE) as diagnostic measures to evaluate precision and quality of the spatial models (Mueller and Pierce, 2003). We used the RMSE to compare map quality for the interpolations and to select the best spatial model with/without the corresponding trend variable. Finally, to detect the areas of most rapid changes in CPUE or length data, we computed the maximum rate of change between each cell and its eight neighbours with the slope function, available within the Spatial Analyst extension for ArcGIS. A conceptual model for the spatial prediction of CPUE and length data can be found in Fig. 2. For geostatistics, we used the R environment (R Development Core Team, 2005) with the package geoR, while for mapping we used ArcMap v8.0 (ESRI Corp., Redlands, California).

3. Results

3.1. Data standardization

The NMDS plot, based on aggregated raw CPUE data, showed a clear separation of the catches by fishing gear, thus demonstrating the necessity of CPUE standardization for sound spatial analyses (Fig. 3). General linear models fitted to CPUE data of total fish and the common pandora explained only a small proportion of deviance: 33.3% and 29.2%, respectively (Table 1). This suggests that factors other than gear, vessel, quarter or type of bottom cause most of the variability within

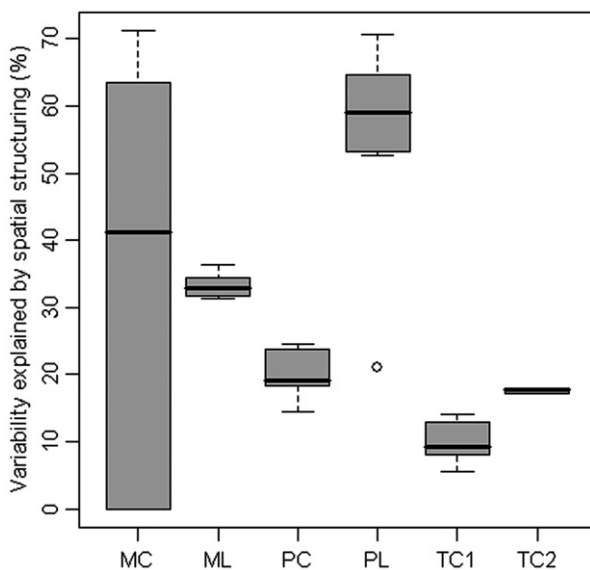


Fig. 6 – Boxplot of the calculated ratios (partial sill/total sill; indicating % of variability explained by spatial structuring) of experimental variograms of CPUE of *M. surmuletus* (MC; g boat⁻¹), mean length of *M. surmuletus* (ML; cm), CPUE of *P. erythrinus* (PC; kg boat⁻¹), mean length of *P. erythrinus* (PL; cm), CPUE of total fish caught at depth <30 m (TC₁; kg boat⁻¹) and at depth ≥30 m (TC₂; kg boat⁻¹). Mid lines, boxes and whiskers represent median, lower and upper quartiles and smallest and largest observation within an interquartile range of 1.5. The circle indicates an observations beyond an interquartile range of 1.5.

the CPUE data. In contrast, the model fitted to the CPUE of striped red mullet explained a great proportion of deviance (78.7%). Power coefficients for the CPUE of total fish indicated that trammel nets and longlines had lower, and mixed trammel-gill nets had higher catchability than gillnets (see Table 1). Power coefficients for CPUE data of *P. erythrinus* showed lower catchabilities for trammel nets and trammel-gill nets than gillnets and longlines. Finally, for *M. surmuletus*, catch-

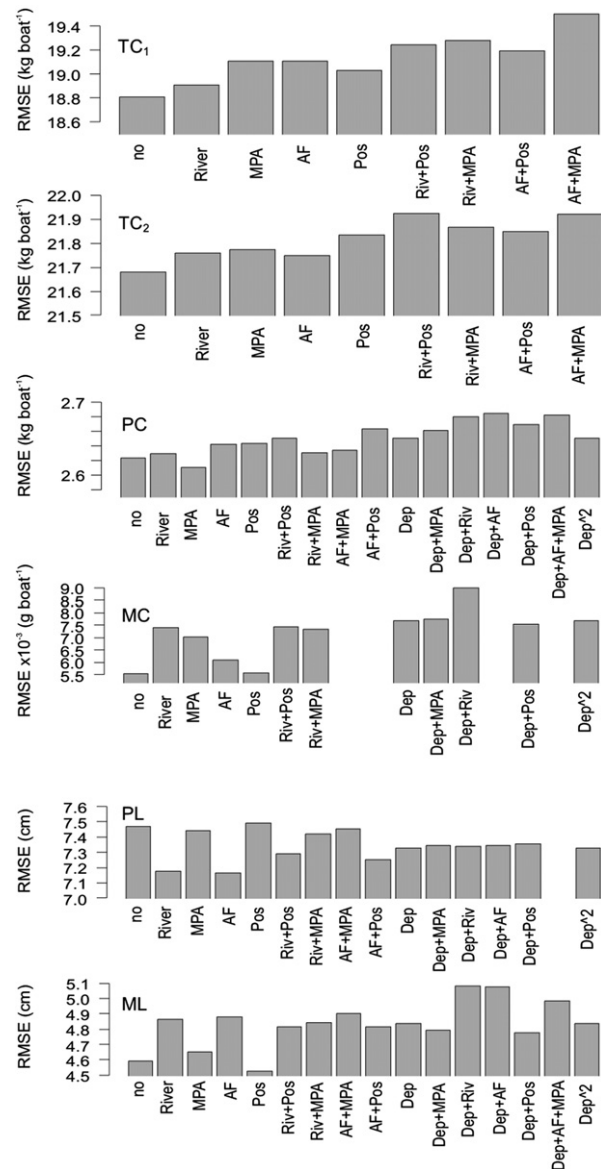


Fig. 7 – Root mean squared error (RMSE) values as criteria of prediction quality of spatial models estimated by universal kriging with external trend for CPUE of total fish caught at depth <30 m (TC₁) and at depth ≥30 m (TC₂), *P. erythrinus* (PC), and of *M. surmuletus* (MC), mean length of *P. erythrinus* (PL) and of *M. surmuletus* (ML). The lowest RMSE values indicate the best estimates and therefore the spatial model to be selected. No = no trend variable, River = distance to the river, MPA = distance to the MPA, AF = distance to AF, Pos = distance to Pos, and Dep = Depth.

ability of gillnets was much lower than trammel and trammel–gill nets. In Fig. 4 the raw and CPUE data (TC, PC and MC) standardized by the obtained calibration coefficients are compared by fishing gear. Great differences between raw and standardized CPUE data correspond to a greater deviation of the corresponding calibration coefficient from one.

3.2. Trend variables vs. standardized CPUE and length data

We tested the effect of an individual trend variable on the mean value of CPUE and length data by employing pseudo-likelihood ratio tests and regression models (Fig. 5). We found significant deviations from the assumed no-effect model (Null-hypotheses: “Trend variables has no effect on CPUE or length data”) for responses of mean length of *P. erythrinus* (PL) to distance to the MPA and to distance to the riv-

er, as well as for CPUE of *M. surmuletus* (MC) to distance to the artificial reef zone. Sizes of common pandora decreased with increasing distance to the MPA and increased with increasing distance to the river, whereas CPUE of striped red mullet decreased with distance to the artificial reef zone.

We detected significant correlations for all data sets between the trend variables “Distance to river” and “Distance to AF”, and between “Distance to MPA” and “Distance to Pos”. Hence, we took this co-linearity of trend variables into account for the subsequent geostatistical analyses. In Table 2, the Spearman rank correlation coefficients calculated between trend variables and CPUE and length data are listed and significant correlations are indicated in bold. In general, correlation coefficients were rather low, but correlation between fish biomass caught at depth level <30 m and “Distance to river” was significant. The mean length of common

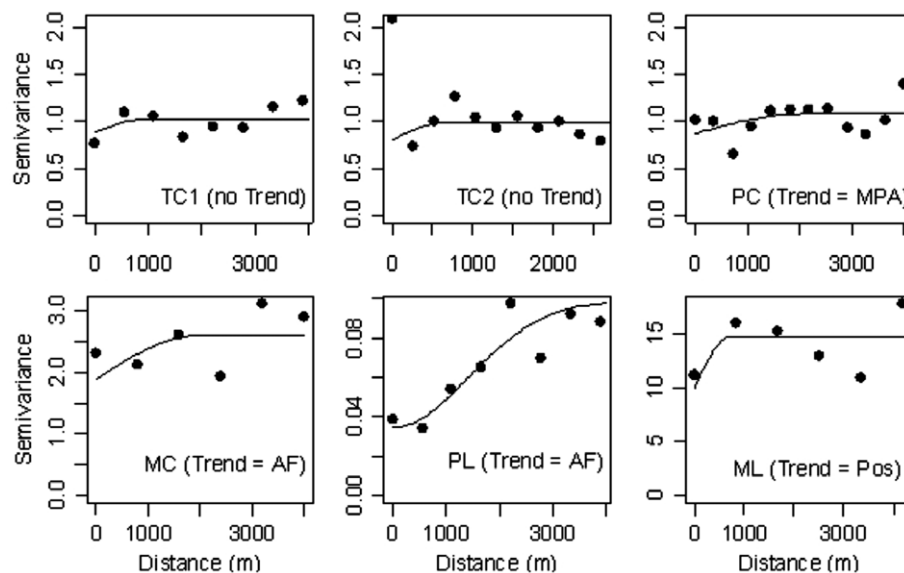


Fig. 8 – Selected experimental variograms computed for CPUE of total fish caught at depth <30 m (TC₁; kg boat⁻¹) and at depth ≥30 m (TC₂; kg boat⁻¹), of *P. erythrinus* (PC; kg boat⁻¹), and of *M. surmuletus* (MC; g boat⁻¹), mean length of *P. erythrinus* (PL; cm) and of *M. surmuletus* (ML; cm) with fitted spherical and Gaussian variogram models.

Table 3 – Selected models fitted with weighted least squares to experimental semivariograms

Data	Spatial trend	Model type	Nugget	Partial sill	Total sill	Ratio (%)	Range (m)	Practical range (m)	MF
TC ₁	No	sph	0.88	0.15	1.03	14.12	1000	1000	39.25
TC ₂	No	sph	0.80	0.18	0.98	17.95	600	600	172.00
PC	MPA	sph	0.85	0.22	1.07	20.09	2000	2000	25.99
MC	AF	sph	1.90	0.71	2.60	27.07	2000	2000	6.60
PL	AF	gauss	0.04	0.07	0.10	65.66	2000	3464	29.53
ML	Pos	sph	10.00	4.68	14.68	31.90	718	718	5.36

TC₁: CPUE of total fish caught at <30 m depth (kg boat⁻¹); TC₂: CPUE of total fish caught at ≥30 m depth (kg boat⁻¹); PC: CPUE of *P. erythrinus* (kg boat⁻¹); MC: CPUE of *M. surmuletus* (g boat⁻¹); PL: mean length of *P. erythrinus* (cm); ML: mean length of *M. surmuletus* (cm); MPA: distance to Integral Reserve; river: distance to river; AF: distance to AF; Pos: distance to Pos; ratio (%): partial sill/total sill, indicating percentage of variability explained by spatial structuring; Practical range (m): indicates mean patch diameter (m); Minimizing function (MF): goodness-of-fit criterion for variogram modelling; sph = spherical model and gauss = Gaussian model.

pandora was significantly correlated with “Depth”, “Distance to MPA” and “Distance to river”.

3.3. Spatial analyses and mapping

In total we computed 83 experimental omnidirectional semi-variograms and spherical, exponential, linear, Gaussian and pure nugget effect models described the data best. All models fitted to standardized CPUE and length data explained 0–71% of the variability, whereas the degree of spatial autocorrelation was highest in length data of *P. erythrinus* and lowest in CPUE of total fish caught at depth <30 m (Fig. 6). The mean level of spatial structuring was highest for mean length of common pandora (60%) and lowest for TC₁ (10%). The great range of ratio values calculated for CPUE data of striped red mullet indicates the most difficult variable to fit. We selected spatial models based on the lowest root mean squared error (RMSE) and considering at the same time that estimated maps should represent the magnitude of sampled values.

In Fig. 7, the calculated RMSE are presented for all computed maps. Estimates were not improved for TC₁ and TC₂ when we used external trend variables for spatial estimations; thus, in these cases we mapped with ordinary kriging. In general, the use of only one trend variable resulted in more precisely estimated maps for CPUE and length data. We achieved best map quality for CPUE data of common pandora with “Distance to the MPA” as trend variable. Although for CPUE data of striped red mullet root mean squared error values were lowest for the spatial models without a trend and

“Distance to Pos”, we rejected these models due to overestimation (several orders of magnitude) of real sample data and selected finally the spatial model incorporating the trend variable “Distance to AF”. The same trend variable led to best spatial predictions for mean length of common pandora. On the contrary, we selected for mean length of striped red mullet the spatial model with the external trend variable “Distance to Pos”. Semivariograms of the selected experimental semivariograms are presented in Fig. 8 and corresponding goodness-of-fit statistics in Tables 3 and 4. Experimental semivariograms were rather erratic, especially at distances smaller than 1 km, resulting in increased nugget effects and small percentages of variability explained by spatial structuring (Fig. 8). In almost all cases spherical variogram models (with the exception of the Gaussian model for PL) were selected revealing a high precision and quality of the spatial estimation (Table 4). We found that corresponding practical ranges spanned from 600 m (TC₂) to 3500 m (PL). Further, we found the lowest ratio value revealing a low level of spatial autocorrelation within the data for CPUE data of TC₁ (14.1%) and the highest (65.7%) for PL (Table 3).

The values of mean CPUE and length, and their standard deviation estimated by the classical and geostatistical approach, are compared in Table 5. In general, we found that classical and geostatistical mean estimates were similar, with the geostatistical standard deviation was consistently lower than the classical.

All selected maps and corresponding calculated slopes are displayed in Fig. 9a (TC₁, TC₂ and PC) and Fig. 9b (MC, PL and

Table 4 – Diagnostic measure of precision and quality of selected maps

Data	Spatial trend	MSE	VSE	RMSE	ME	MSDR
TC ₁	No	0.085	1.099	18.810	1.441	1.094
TC ₂	No	0.140	1.682	21.682	1.754	1.687
PC	MPA	−0.062	0.381	2.611	−0.336	0.379
MC	AF	−0.029	0.231	6096.800	−2154.300	0.223
PL	AF	0.022	1.346	7.166	−0.022	1.324
ML	Pos	−0.001	1.373	4.524	−0.009	1.318

TC₁: CPUE of total fish caught at <30 m depth (kg boat^{−1}); TC₂: CPUE of total fish caught at ≥30 m depth (kg boat^{−1}); PC: CPUE of *P. erythrinus* (kg boat^{−1}); MC: CPUE of *M. surmuletus* (g boat^{−1}); PL: mean length of *P. erythrinus* (cm); ML: mean length of *M. surmuletus* (cm); MPA: distance to the MPA; River: distance to the river; AF: distance to AF; Pos: distance to Pos; Diagnostic measures to evaluate precision and quality of the spatial models obtained by the cross validation procedure: mean standardized error (MSE), variance of standardized error (VSE), root mean squared error (RMSE), bias (ME), mean squared deviation ratio of the predictions vs. samples (MSDR).

Table 5 – Mean CPUE and length, and their standard deviation estimated by classical statistical approach (M_{CL}, SD_{CL}) and by the kriging procedure (M_K, SD_K) based on the selected variogram models

Data	Unit	M _{CL}	M _K	SD _{CL}	SD _K
TC ₁	kg boat ^{−1}	15.16	13.67	19.11	1.97
TC ₂	kg boat ^{−1}	16.84	15.57	21.33	1.29
PC	kg boat ^{−1}	2.97	2.75	2.74	0.72
MC	g boat ^{−1}	3792.10	5015.80	5289.90	1919.70
PL	cm	30.93	28.44	8.03	3.80
ML	cm	21.60	21.62	4.50	0.48

TC₁: CPUE of total fish caught at depth <30 m; TC₂: CPUE of total fish caught at depth ≥30 m; PC: CPUE of *P. erythrinus*; MC: CPUE of *M. surmuletus*; PL: mean length of *P. erythrinus*; ML: mean length of *M. surmuletus*.

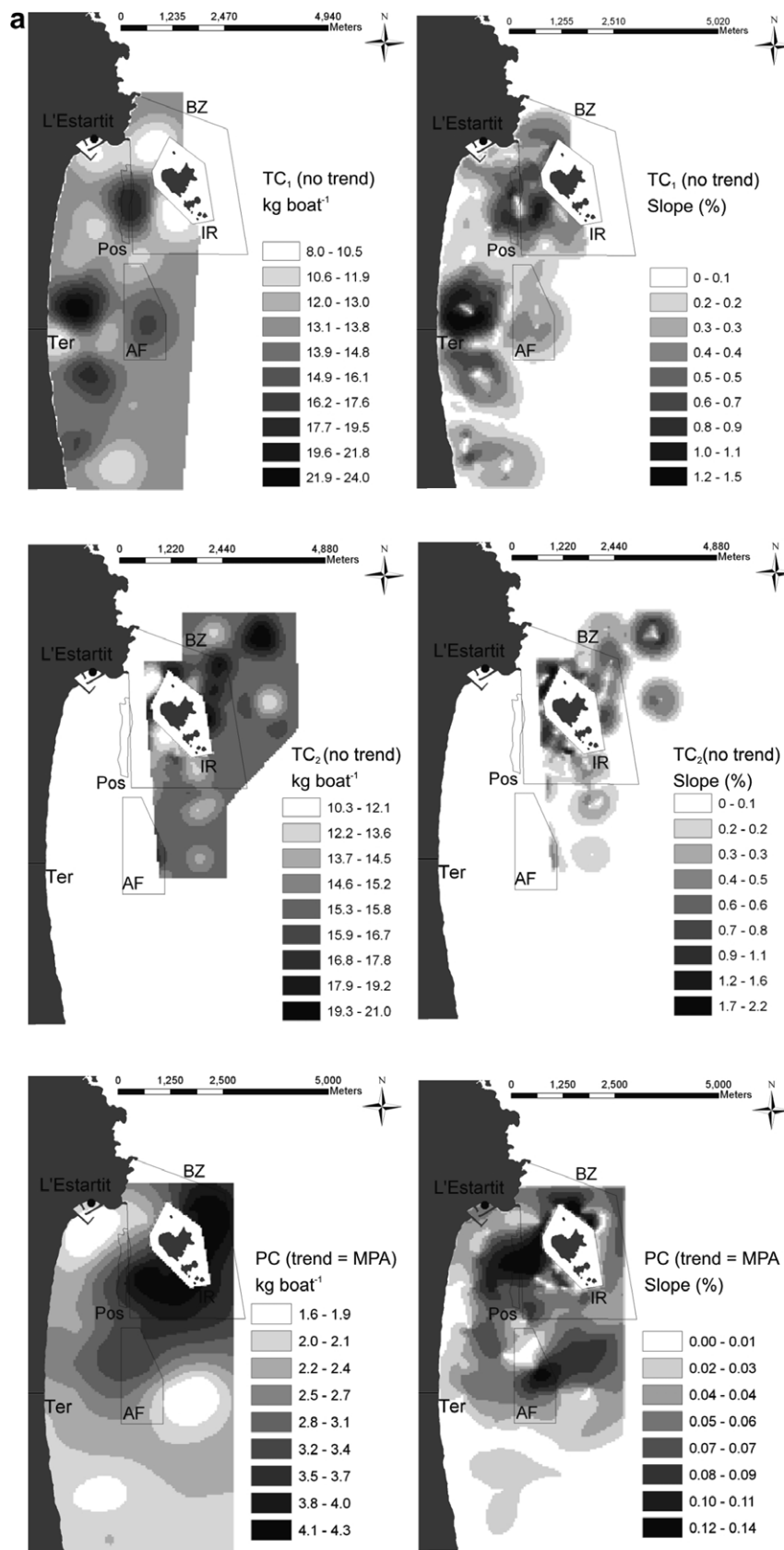


Fig. 9 – (a,b) Maps of CPUE of total fish caught at depth <30 m (TC₁) and at depth ≥30 m (TC₂), of *P. erythrurus* (PC), of *M. surmuletus* (MC), mean length of *P. erythrurus* (PL) and of *M. surmuletus* (ML). These maps were estimated with universal kriging using external trend, based on selected models (left panel) with corresponding maps of estimated slopes, indicating the steepest changes of variable values (right panel).

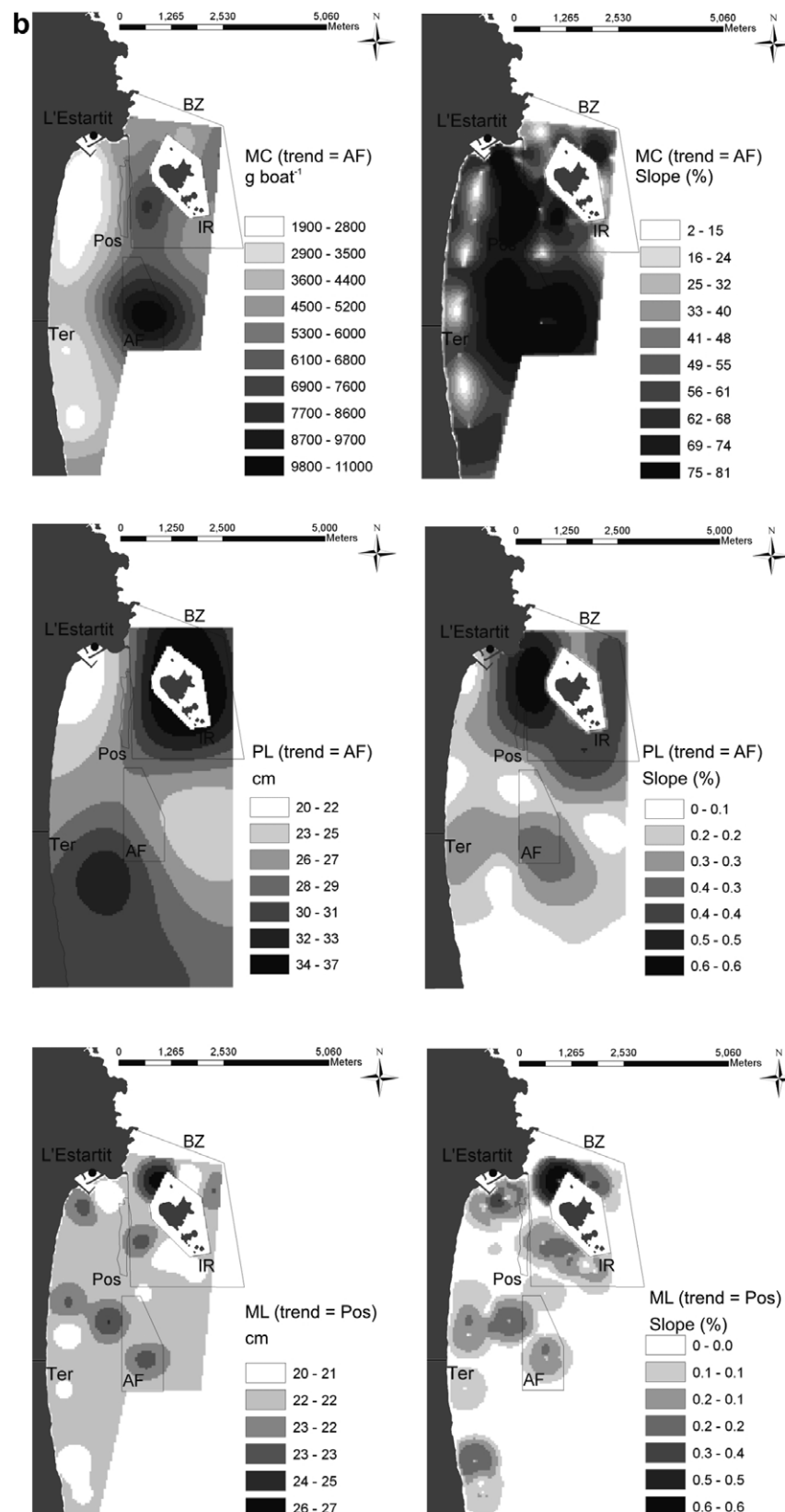


Fig. 9 – continued

ML). We observed increased CPUEs of total fish near the river mouth and the *Posidonia* meadows at depth <30 m and close to the Integral Reserve and 2 km northeast from it at depth ≥ 30 m. Further, we found the most rapid changes of TC_1 values near the river and the *Posidonia* meadows, while we located more rapid changes of TC_2 values very close and 2 km northeast from the Integral Reserve. We discovered highest CPUE of *P. erythrinus* northeast and southwest of the Integral Reserve, demonstrating the strong influence of the variable “Distance to the MPA”. Hence, we found the steepest slopes on the western border of the Integral Reserve and in the artificial reef zone. We observed largest individuals of *P. erythrinus* in the surrounding waters of the Integral Reserve with strongest gradients at the western border of the Medes Islands Marine Reserve. On the contrary, we located highest CPUE of *M. surmuletus* inside the artificial reef zone, which had the steepest slopes. We recovered in the study area a rather uniform distribution of mean lengths of striped red mullet with increased values and strongest gradients at the northern border of the Integral Reserve.

4. Discussion

The aim of this study was to predict spatial patterns of fisheries data and to assess possible conservation and fisheries benefits around the Medes Islands Marine Reserve in relation to impacts of habitat heterogeneity and spatial structuring of fisheries data. We combined geostatistical and Geographical Information System (GIS) tools to account concurrently for the influence of spatial trend variables and the effect of spatial structuring on spatial predictions of CPUE and length data. Even though we detected rather low levels of spatial autocorrelation, our results showed that the latter has to be taken into account for detecting the benefits of marine reserves with better resolution. This low level of autocorrelation was due to the erratic experimental semivariance revealing high nugget effects. This increased variability at small distances can probably be ascribed to small scale heterogeneity due to the uncertain “area swept” by fixed gears and/or local oversampling (Stelzenmüller et al., 2005b).

In none of the cases, results of simple correlations between CPUE and length data and trend variables corresponded well with the final selected spatial trend factors. Either trend variables were not significant or correlation coefficients with other than the selected trend variables were higher, indicating that the constructed secondary spatial information does not sufficiently capture data variability. Presumably, a further temporal and/or spatial stratification of data would improve correlation coefficients in general and their agreement with relevant factors geostatistically selected.

Our findings revealed that for CPUE of total fish caught at depth <30 m and ≥ 30 m no trend component could improve spatial predictions, whereas predicted maps showed increased CPUE values around the Integral Reserve (for TC_1 , TC_2) and the river (for TC_2). Due to the presence of high and low CPUEs at dense locations around the Integral Reserve border, linear regressions or correlations of fish CPUE with the spatial trend variable “Distance to the MPA” were not significant. This demonstrates that linear methods applied

to biomass gradients are insufficient to measure complex reserve effects such as biomass spillover.

Recently more complex statistical models like mixed effect models (Murawski et al., 2003), permutational multivariate analysis of variance (Claudet et al., 2006) or generalized additive models have been used to account simultaneously for environmental effects such as depth and distance to MPA (Goñi et al., 2006). However, assuming statistically independent data these methods do not account for spatial autocorrelation present in fisheries data, which could lead to wrong conclusions. The need of spatial analyses of CPUE data in the context of evaluating MPAs as a management tool is also discussed in Babcock et al. (2005).

We predicted (with “Distance to the MPA” as secondary variable) the highest CPUEs of *P. erythrinus* within the Buffer Zone with an estimated patch of increased biomass with a diameter of 2 km (~practical range of variogram model). These findings correspond well with the estimated spatial distribution of mean length of *P. erythrinus*, which showed a clear aggregation of larger individuals around the border of the Integral Reserve. Thus, higher fisheries yields in terms of number and size can be expected when targeting *P. erythrinus* in the Buffer Zone of the Medes Island Marine Reserve, a species with a relatively high commercial value. Maps of the predicted slopes for CPUE and mean length of *P. erythrinus* showed the most rapid changes in CPUE and length mainly in the Buffer Zone, but also in the surroundings of the artificial reef zone. Hence, *P. erythrinus* is one of the species directly affected by the presence of the Medes Island Marine Reserve.

On the contrary, the predicted map of CPUE of striped red mullet (with “Distance to AF” as secondary variable) indicated increased *M. surmuletus* biomass in the vicinity of the artificial reef zone, with a large patch located in the centre of the artificial reef zone and a much smaller communicating patch in the Buffer Zone. As the spatial distribution of greater individuals of *M. surmuletus* was highly patchy, estimated slopes revealed the steepest changes of *M. surmuletus* length within a vast proportion of the study area. Thus, for *M. surmuletus*, the presence of the reserve has no direct effect as its preferred habitat is located in the surroundings of the artificial reef zone. However, predicted spatial distributions based on aggregated data represent rather a mean picture of CPUE and length gradients (March–December). Thus, seasonal deviations from estimated absolute values and patterns could be expected.

In summary, in applying this combined geostatistical/GIS approach we found increased CPUE and length data at the border of the Integral Reserve, probably due to direct effects (TC_2 , PC) or indirect reserve effects (TC_1) like the protection of *Posidonia* meadows by the restricted use of the Buffer Zone. Our study shows that conservation or fisheries benefits detected in the vicinity of a MPA could also be attributed to other factors, in particular to the river Ter and the artificial reefs. The predicted spatial patterns show the complexity and simultaneous action of various trend factors leading to mostly non-linear directed gradients in CPUEs and length data. Further, spatial models reflect traditional fishing practices based on local knowledge.

Our results suggest that the ad hoc definition of the spatial dimension of the Buffer Zone, where artisanal fisheries are

allowed, would permit the protection of only a few target species, benefiting from a habitat with no discontinuities from the Integral Reserve outwards. However, the size of the Buffer Zone seems to have the potential to enhance local fisheries but other factors, like a decrease of operating fishing boats with time, hamper the evaluation of the Medes Islands Marine Reserve as a fisheries management tool. In fact, the fishing effort applied in the study area is much lower than that allowed by the fishing regulations in force, given that only a small number of vessels based in the fishing port of L'Estartit (7 out of 24) goes fishing all year round.

Finally, we argue that our spatial approach to assess reserve effects can provide major insights into complex systems like coastal MPAs in the northwestern Mediterranean and elsewhere, and may contribute to a crucial aspect of marine conservation, the size of protected areas.

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