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A Bayesian spatial approach for predicting seagrass occurrence

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ABSTRACT

We implement a Bayesian spatial approach to predict and map the probability of occurrence of seagrass *Posidonia oceanica* at high spatial resolution based environmental variables. We found that depth, near-bottom orbital velocities and a spectral pattern of Landsat imagery were relevant environmental variables, although there was no effect of slope or water residence time. We generated a data inventory of *P. oceanica* samples at Palma Bay, NW Mediterranean, from three main sources: side scan sonar, aerial imagery and a customized drop-camera system. A hierarchical Bayesian spatial model for non-Gaussian data was used to relate presence-absence data of *P. oceanica* with environmental variables in the presence of spatial autocorrelation (SA). A spatial dimension reduction method, the predictive process approach, was implemented to overcome computational constraints for moderately large datasets. Our results suggest that incorporating spatial random effects removes SA from the residuals and improves model fit compared to non-spatial regression models. The main products of this work were probability and uncertainty model maps, which could benefit seagrass management and the assessment of the ecological status of seagrass meadows.

1. Introduction

Seagrass meadows provide important ecosystem services including carbon sequestration, nutrient cycling, protection from erosion, and enhanced biodiversity (Hemminga and Duarte, 2000). In the Mediterranean Sea, the dominant seagrass species is the endemic *Posidonia oceanica* (L.) Delile, which forms extensive meadows on both soft and hard bottoms, from sea level down to 40 m (Duarte, 1991; Boudouresque et al., 2009). *P. oceanica* is a long-lived marine clonal angiosperm characterized by very slow growing rhizomes (Marbà and Duarte, 1998) and is sensitive to natural and anthropogenic disturbances (Boudouresque et al., 2009; Grech et al., 2012; Jorda et al., 2012). Monitoring seagrass is particularly important because the European Water Framework Directive (Foden and Brazier, 2007; López y Royo et al., 2009; Montefalcone, 2009) and the Marine Strategy Framework Directive use seagrass as an indicator of ecosystem health and disturbance (Marbà et al., 2013).

Species distribution models (SDM) have been extensively used in conservation planning and management (Peterson et al., 2002). Such models relate species distribution data (e.g., presence–absence) to environmental characteristics in order to improve our understanding of the effects of environment on species distribution (inference) and our ability to predict species distributions (Crase et al., 2012). However, achieving these objectives has proved challenging. One of the most important drawbacks of species distribution data is spatial autocorrelation (SA), that is, observations that are not only related to environmental conditions, but also to one another because of the geographic distance between them. SA may lead to (1) incorrect assessment of the ecological processes causing the observed distribution, and (2) poor predictive capabilities. These two errors are especially relevant to modeling *Posidonia oceanica* because the biology of the species (i.e., clonal reproduction and low growth rate) suggests that SA may be high.

Despite the fact that SA is usually ignored, spatial models are a useful tool for relating seagrass presence with environmental variables and human threats (Bekkby et al., 2008; Leriche et al., 2011; Downie et al., 2013). Bayesian hierarchical models have recently been applied in seagrass research (March et al., 2013). However, it is not feasible to fit large datasets with such models using Markov chain Monte Carlo methods (MCMC) as it results in a problem known as the "big-n problem". This consideration is important when working with large areas and a large number of sampling locations. One solution is the proposed *predictive process approach* (Banerjee et al., 2008; Banerjee and Fuentes, 2012). The *predictive process approach* allows a balance between model richness and computational feasibility, and it has been successfully employed in previous studies (Finley et al., 2009; Latimer et al., 2009; Eidsvik et al., 2012).

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In this work we implement a *predictive process approach* to analyze the spatial distribution of seagrass occurrence from point-based data and a set of environmental variables. This modeling approach allows testing the effects of environmental variables on seagrass occurrence while considering SA, and generates maps of probability of occurrence and its uncertainty. We demonstrate such approach using data of *Posidonia oceanica* at Palma Bay (NW Mediterranean) to assess and map its spatial distribution.

2. Materials and methods

2.1. Study area

The study was conducted in Palma Bay (Mallorca, NW Mediterranean), a large (31 km, 50 m maximum depth) oligotrophic bay (Fig. 1). This area is under ecological pressure from humans because the surrounding municipalities have 44.8% of the population, and are the main targets of tourism in Balearic Islands. Palma Bay contains extensive seagrass meadows of *Posidonia oceanica* (Diaz Del Rio, 1993). Conservation measures in this area include two marine protected areas (Fig. 1), which were declared largely to protect the seagrass meadows from human pressures. The first is a marine area called "Cap de Cala Figuera", located in the western area of Palma Bay, which was declared as a Site of Community Importance (SCI, Natura 2000) in 2006. The other, Palma Bay Marine Reserve, in the eastern area of Palma Bay, was declared a marine reserve in 1982 by the local government, although human activities were not regulated until 1999. In addition, since 1990 several artificial reefs have been deployed in order to deter illegal trawling in the area (Moreno et al., 1994).

2.2. Data collection

Within a study area of ∼100 km^2 (Fig. 1), we determined the presence-absence of *Posidonia oceanica* at Palma Bay using three different methods through a random sampling design (mean distance to the nearest neighbor location was 247 m, $n = 857$ locations). Firstly, we used aerial photography imagery (Instituto Geográfico Nacional) to determine seagrass absence in shallow waters ($n = 19$ locations). Secondly, we used a recent survey conducted at Palma Bay Marine Reserve by side scan sonar (Government of Balearic Islands, http://lifeposidonia.caib.es) to determine the presence-absence of seagrass in the reserve ($n = 153$ locations). Finally, we used an underwater drop-camera system (March et al., 2013) to collect standardized vertical geo-referenced images at 685 locations during expeditions between January 2008 and June 2009. At each location, three images were captured at random sampling positions separated by 2–10 m. Image classification was based on the Braun-Blanquet Cover Abundance (BBCA) scale. The BBCA assesses the cover of *P. oceanica* according to a qualitative scale

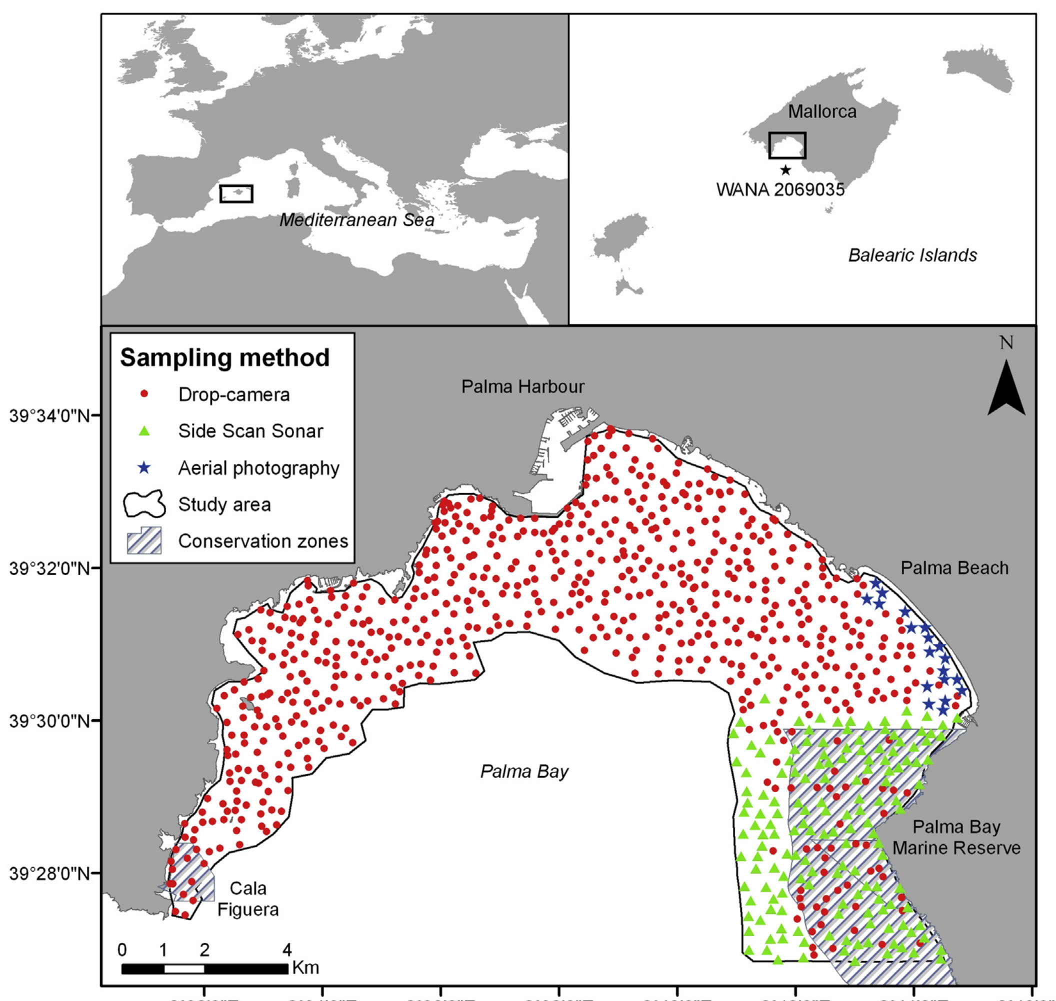

Fig. 1. Palma Bay. Sampling locations classified by observation method: aerial photography, side scan sonar and drop camera.

ranked from 0 to 5. This methodology was previously cross-validated with side scan sonar data and calibrated among observers (see March et al., 2013 for details). This indicator has been previously used for seagrass research (Fourqurean et al., 2001; March et al., 2013). We defined the presence of seagrass at a location when at least 2 out of 3 images had a BBCA score equal to or higher than 1.

2.3. Environmental variables

We generated models of environmental variables that were selected *a priori* as putative explanatory variables of *Posidonia oceanica*. Those environmental variables included geomorphological (depth and slope), oceanographic (near bottom orbital velocity and water residence time), and multispectral data from Landsat bands. All variables were modeled in the study area using a regular grid of 50 × 50 m at Palma Bay.

2.3.1. Geomorphological variables

We used point-data sounding from digitized nautical charts (Instituto Hidrográfico de la Marina, 1:25,000) to generate a digital bathymetric model (DBM) using Multilevel B-spline Approximation (MBA) algorithm (Lee et al., 1997). Then we calculated the slope (SLP), measured in degrees, using a 3 × 3 neighborhood around each cell in the DBM. We used R v.2.9.1 (MBA and spgrass6 packages) for the analysis.

2.3.2. Oceanographic variables

We quantified exposure to waves in the seagrass meadow by calculating near-bottom orbital velocities (U_b) in the study area from wave conditions (Infantes et al., 2009, 2011). The significant wave height (*Hs*), peak period (*Tp*) and direction were obtained from the closest WANA node, located approximately 15 km from the study site at a 50 m depth (Fig. 1, upper-right inset). The WANA node provides wave data from the reanalysis of a third generation spectral WAM model site (see Infantes et al., 2009 for details). Data from the WANA node for the period 1996 to 2010 show that the most energetic waves in the study area are from the SW, with an average H_s of 0.7 m and T_p of 5.5 s. These conditions were propagated to the shore using a numerical model based on the mild slope parabolic approximation (Kirby and Dalrymple, 1983).

The water residence time (WRT) was estimated with a high-resolution ocean circulation model that reproduces the dominant patterns of the observed circulation in the bay (Jordi et al., 2011). The trajectory of virtual Lagrangian particles introduced in the model at each grid point was determined by interpolating the model currents to the particle position. The time lapsed for each particle to travel a distance greater than 5 km from its initial position was used as estimate of the residence time. A new set of particles was released each 12 h during the model run (6 months, May–October 2009). The residence time used in this study was averaged for each set of particles and interpolated to the regular grid of 50 × 50 m.

2.3.3. Landsat enhanced thematic mapper plus (ETM+)

Multispectral data by the Landsat ETM + instrument were obtained from the Earth Resources Observation and Science (EROS) Center (http://eros.usgs.gov/). There are eight multispectral bands with a spatial resolution of 30 m for the six reflective bands, 60 m for the thermal band, and 15 m for the panchromatic band. A total of 72 Landsat ETM+ images were acquired for the study area for the period 1999–2009. Free-of-clouds pixel values were measured at the sea surface for each band, and the images were converted to at-sensor spectral radiance using radiometric sensor calibration (Chander et al., 2009) and interpolated to a regular grid of 50 × 50 m using an optimal statistical interpolation with a cut-off length scale of 500 m. A principal components analysis (PCA) of averaged values was applied to reduce the number of bands into two principal components (PC1 and PC2), which were used as predictor variables. This approach preserves the original spectral patterns while reducing interband correlation in the satellite data (Koutsias et al., 2009).

2.4. Data analysis

We implemented a predictive spatial model for point-referenced data for of seagrass occurrence in Palma Bay. The spatial predictive model was a Bayesian hierarchical model based on a previous work (March et al., 2013) and implemented in the *spBayes* package (Finley et al., 2007). As this study included a large number of observations ($n = 857$ locations), which results in the "big-n problem", we used a *predictive process approach* (Finley et al., 2009; Latimer et al., 2009; Banerjee and Fuentes, 2012; Eidsvik et al., 2012). The steps involved in the analysis workflow were as follows (see Appendix A for details): 1) specifying a logistic regression model to relate environmental variables with seagrass presence-absence; 2) defining a spatial correlation function to incorporate spatial dependence in the model; 3) selecting a reduced number of representative locations (knots) to introduce a second stage in the model and improve the computation speed; 4) assigning prior distributions to set the probability distribution that represents the uncertainty of the model parameters; 5) using Markov Chain Monte Carlo (MCMC) methods to fit the model; 6) selecting the best model from a set of candidate models using the Deviance Information Criterion (DIC); 7) cross-validating the model using the area under curve (AUC) with a randomly selected subset of 15% ($n = 129$ locations) to assess the model accuracy and select a threshold probability (i.e. through an optimization method) to classify probabilities into presence or absence, and 8) sampling the posterior distribution to map the predicted values (ie. the median) and also the associated levels of uncertainty (ie., 95% credible intervals) at a resolution size of 150 × 150 m.

3. Results

3.1. Environmental covariates

Maps of the covariates used for model prediction (Fig. 2) show that the depth (DBM) ranged from 0.3 to 42.7 m (Fig. 2A), with a mean value of 24 m. The east area of the bay was gently sloping in comparison with the west area, which had steep slopes and a maximum value of 4.97° (Fig. 2B). In contrast, the east area presented higher values of U_b because of exposure to the predominant SW wave climate (Fig. 2C). U_b values ranged from 0 to 1.62 m/s. The WRT model results ranged from 2 to 8.96 d, with higher values at the NE area of the bay (Fig. 2D). For the Landsat bands, the first two Principal Components (PCs) from the analysis accounted for 98% of the total variance in the original dataset. PC1 was more closely associated with bands 1–5 and 7–8, whereas PC2 was more influenced by band 6.

3.2. Spatial distribution of Posidonia oceanica

The presence-absence dataset for seagrass (Fig. 3A) show that *Posidonia oceanica* was detected between 2 m and 33 m (maximum sample depth was 42 m depth).

Results of the model selection are detailed in Appendix B (Table B.1). The model that incorporated all variables was selected because of its low DIC value. Parameter estimates of the model are

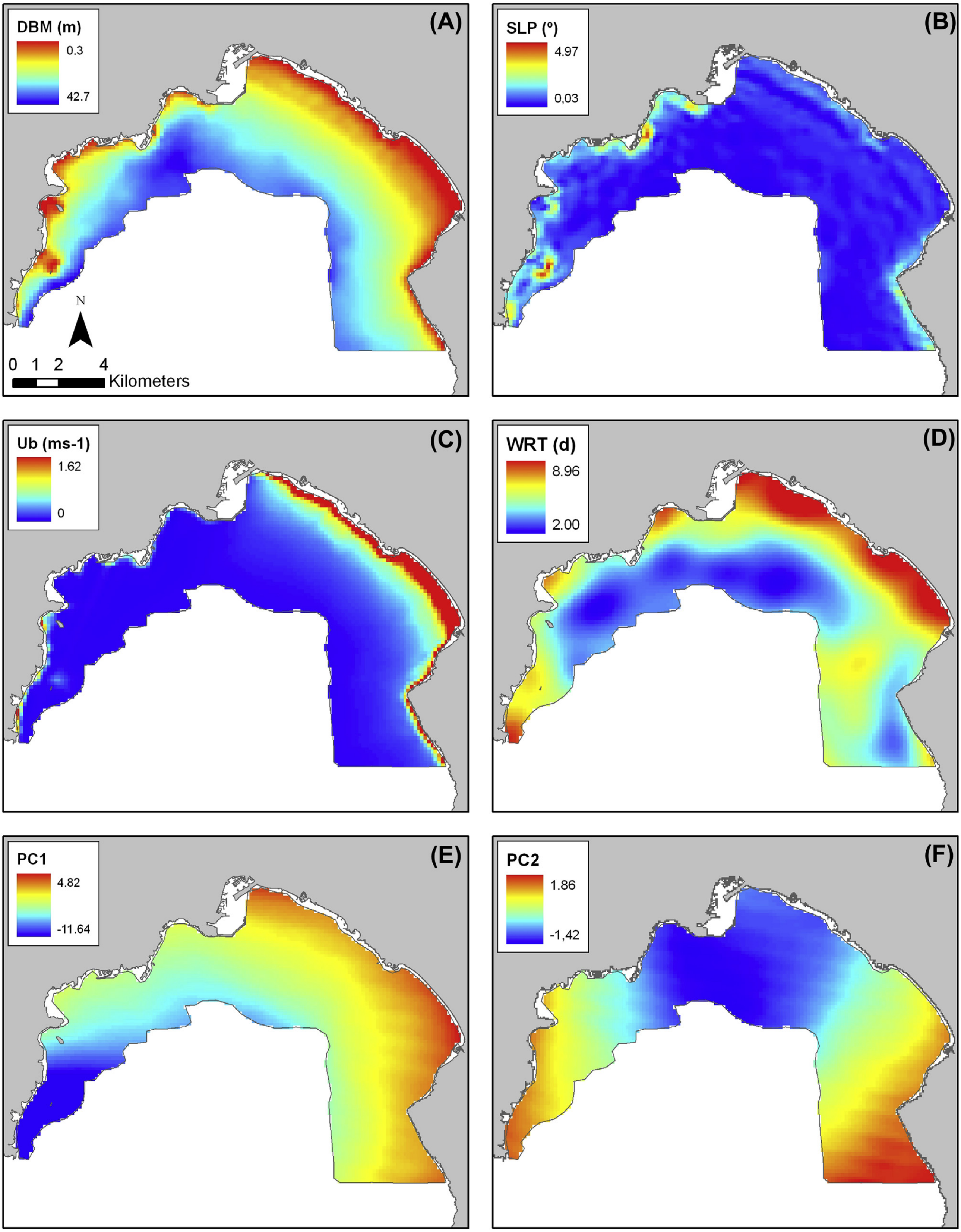

Fig. 2. Environmental covariates (150 × 150 m grid): a) Depth, b) Slope, c) U_b, d) Wrt; e) Landsat PC1, f) Landsat PC2.

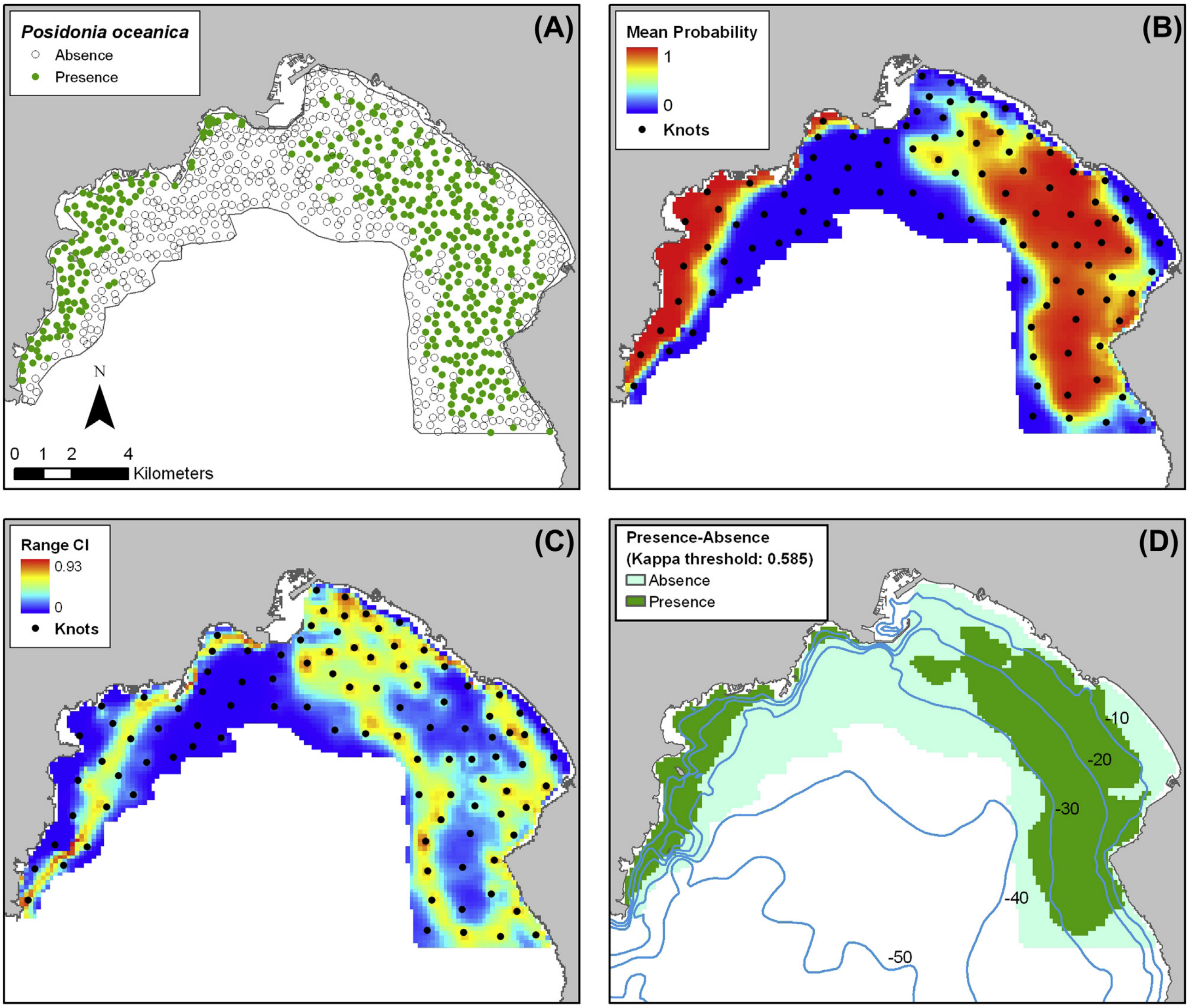

Fig. 3. Spatial prediction of seagrass cover (150 × 150 m grid): a) observed values of presence-absence; b) posterior estimates (median) for predicted response surface Y(s) seagrass cover; c) uncertainty of the prediction represented by the range between the lower and upper 95% posterior predictive intervals, d) classification of presence-absence based on a threshold of 0.585.

detailed in Table 1. The credible 95% intervals (CI) suggested that DBM, U_b and PC2 were relevant because they did not include zero. However, SLP, WRT and PC1 were not relevant in determining *Posidonia oceanica* ocurrence. Concerning the spatial autocorrelation (SA), the median values of spatial parameters were 13.873 for σ^2, and 0.001 for ϕ (see the specification of the spatial effect variance -σ^2- and the spatial decay parameter -ϕ- in Appendix A). The posterior mean of the effective range indicated a decline in the residual spatial autocorrelation at ∼4811 m. This suggests that any observation (presence-absence) would be affected by other observations within 4811 m. Fig. 4A shows how the fitted semivariogram of the residuals of a non-spatial GLM reached an asymptote close to 5000 m, whereas in Fig. 4B the semivariogram of the residuals of the hierarchical Bayesian model remained flat (i.e. spatial independence). This illustrates that the Bayesian approach explicitly accounted for spatial dependence.

Table 1
Parameter estimates of the selected model (posterior median and upper and lower 2.5 percentiles). The first block provides point and credible interval estimates of the intercept and covariates; the second block provides estimates for the variance (σ^2), spatial decay (ϕ), and effective range parameters.

Parameter	Posterior median	0.025 Quantile	0.975 Quantile
Intercept	11.981	6.700	19.888
DBM	−0.419	−0.601	−0.256
U_b	−9.756	−13.806	−6.411
PC2	1.228	0.031	2.773
SLP	−0.844	−1.953	0.195
PC1	−0.301	−0.676	0.272
WRT	−0.383	−1.175	0.181
σ^2	13.873	5.054	24.915
ϕ	6.24×10^{-4}	3.25×10^{-4}	1.20×10^{-3}
Effective range (m)	4811	2503	9224

The probability maps of seagrass cover and the associated error are presented in Fig. 3B and D, respectively. The median value of each pixel posterior distribution serves as the prediction value. The prediction error is presented by the range of 0.025 and 0.975 CI quantiles (Fig. 3C).

Cross-validation performance of the spatial model resulted in an AUC value of 0.90 ± 0.03 (±sd), indicating very good predictive power. Contours indicating the presence of seagrass using the

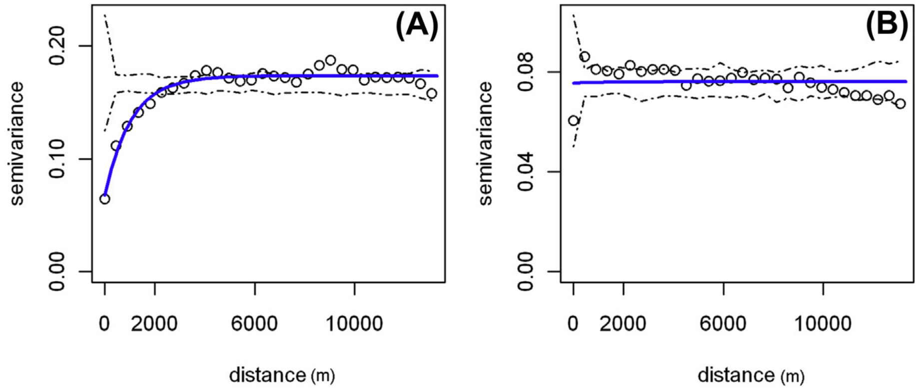

Fig. 4. Empirical semivariograms computed for the residuals from a non-spatial GLM (a) and the residuals from the hierarchical model (b). Dashed lines represent envelopes of 99 permutations.

estimated probability threshold of 0.585 are shown in Fig. 3D. The estimated extent of seagrass based on this threshold in the study area was 47.6 ha.

4. Discussion

4.1. Distribution of Posidonia oceanica in Palma Bay

Posidonia oceanica meadows dominate the seabed of Palma Bay at depths of up to 30 m. Meadows were found in two main patches (Fig. 3D). In the eastern part of the bay, *P. oceanica* was also found in deeper waters, in a patch that occurred partially within the MPA of Palma Bay, where management efforts for seagrass began in 1982. In contrast, two zones that were shallower than 30 m were not covered by *P. oceanica*. The first zone was the area close to Palma Beach, where there was high wave exposure and fine sands were the dominant component. The second zone was near the area of Palma harbor, where significant human pressures are present. (e.g., coastal development, sewage, commercial boat anchoring). In this area, the scattered pattern of *P. oceanica* resulted in high uncertainty estimates.

4.2. Effect of environmental variables

Among the geomorphological variables, bathymetry had the greatest influence on *Posidonia oceanica* distribution at Palma Bay. The relationship of seagrass ocurrence according to bathymetry can be explained by an irradiance gradient (Dalla Via et al., 1998; Duarte et al., 2007). The lower depth limit of 33 m in our dataset is consistent with the findings of previous studies (Marbà et al., 2002; Zupo et al., 2006; Duarte et al., 2007) although slope did not have a relevant role in the spatial distribution of *P. oceanica*. Although slope has been identified as an important factor for the distribution of macrophytes (Duarte and Kalff, 1990; Narumalani et al., 1997; Bekkby et al., 2008), there is sometimes no effect in cases with small slope variation in gentle terrains (Krause-Jensen et al., 2003), which may apply in our case.

A decrease of seagrass cover with increasing exposure to waves has been demonstrated in previous studies (Krause-Jensen et al., 2003; Bekkby et al., 2008; Infantes et al., 2009; Vacchi et al., 2010, 2012). In the present work, U_b was found to affect the distribution of seagrass, although a similar study conducted over a smaller area in the eastern part of Palma Bay did not find a clear effect of U_b (March et al., 2013). In that previous study, the entire study area had the same orientation to wave exposure whereas the present study found a difference in exposure between the eastern and western parts of the bay, highlighting the relevance of scale in interpreting the effects of environmental variables.

The other oceanographic parameter considered in this study, WRT, did not influence the distribution of the meadows at Palma Bay. WRT has been proposed as a good indicator to assess the vulnerability of the ecosystem to pollutants, and proved to have a definite effect on *Posidonia oceanica* in a previous study (Orfila et al., 2005). However, it should be noted that the correlation between areas free of seagrass and WRT was found at values larger than 15 d, whereas the maximum WRT in our study area was only 9 d.

Landsat imagery has been used in previous studies as a direct source of presence-absence data for seagrasses in shallow waters (Roelfsema et al., 2009; Lyons et al., 2013). Although no empirical data were available to calibrate the Landsat imagery and correlate it with turbidity or SST, we used principal components as a proxy. Bands 1 to 3, which have been related with water turbidity and chlorophylls (Erkkila and Kalliola, 2004), were related to PC1. On the other hand, band 6, which has been correlated with SST (Thomas et al., 2002), was related to PC2. This second component seems to present some correlation with the spatial distribution of *Posidonia oceanica* at Palma Bay (Table 1). Looking at Fig. 2F, we can see how PC2 presents a gradient from the northern-center part of the Bay to the east and west.

4.3. The modeling approach

The purpose of this work was not only to map *Posidonia oceanica* at Palma Bay, but also to evaluate the effect of different environmental variables in the presence of spatial autocorrelation. We demonstrated that the modeling framework adopted in this work was able to remove spatial autocorrelation from the model residuals by incorporating a spatial error term (Fig. 4). The flexibility of our modeling approach allowed the inclusion of other environmental variables that, if available, could enhance the richness and predictive power of the model.

Uncertainty provides an important complement to any map of predicted presence-absence probability. This information could be used to identify areas where environmental variables cannot explain the distribution of the species. We found greater uncertainty close to edges of the meadow and in areas with scattered presence of seagrass. This information could be used to identify possible local human-related pressures, or other environmental variables that are not currently considered. As extensive cartographies are now becoming available (eg. EUSeamap), the “big-*n* problem” may become a constraint in modeling of species distribution. The *predictive process approach* appears to be an effective method for overcoming such problem that it could be applied in other systems and has a great potential for being implemented in conservation planning and management.

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Appendix A and B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ecss.2013.08.009.

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