- 1 Predicting the distribution of a Portunid crab in Patagonian coastal waters: an SDM
- 2 approach
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- 14 Running page head: Predicting the distribution of Portunid crab

15 Abstract

Ovalipes trimaculatus is a cosmopolitan Portunid crab that is comercially important.
However, environmental conditions that drive its distribution have never been studied.
Thus, we aimed to assess the habitat preferences of the species in northern Patagonia
by developing a species distribution model. We obtained spatial quantitative data of the
crab and its prey species from a benthic survey performed prior to commercial fishing
in the area. We used measurements of environment condition, biomass, richness and
evenness of its prey as predictors, and modeled the density of *O. trimaculatus* through

1 a delta-gamma model and produced a map of its predicted biomass. Prey biomass, 2 depth and substrate type were the most important variables for predicting O. 3 trimaculatus' distribution. The model predicts a restricted depth range, with maximum 4 crab density at 10 m (the shallowest depth sampled) in bottom substrates of relatively 5 fine granulometry, as silty sand and silt. Prey biomass does not determine the crab 6 presence, but, where the crab is present, higher prey biomass correlates with higher 7 crab abundance. Our results accurately predicted one of the two actual fishing grounds, 8 hence, the model may be a useful tool for local fishers and managers.

9 Key words: Ovalipes trimaculatus, biotic predictors, San Matías Gulf, Species

10 distribution model

11

12 **1. Introduction**

13 Marine systems management is changing, with an increasing use of tools that depend 14 on spatial information such as marine protected areas, spatial planning and ecosystem-15 based management (Freitag et al. 2018, Janßen et al. 2018). As a consequence, the need 16 for species and habitat distribution maps has also been on the rise (Maxwell et al. 2009). 17 However, the need for assessing the status of a fishery is generally not acknowledged 18 until after the system has already been impacted, making it difficult to understand to 19 what extent it has changed. For this reason, it is relevant to recover information 20 generated before the system has been impacted (Pauly 1995), that may be modeled, 21 and with novel methods, reconstruct the past of a stock or system, and thus understand its present status. This information will be especially useful if it was systematically
 gathered.

3 The use of Species Distribution Models (SDMs) has successfully predicted the 4 distribution of several economically important species (e.g. Jones et al. 2015, 5 Weatherdon et al. 2016). However, few studies have used SDMs to predict the 6 distribution of crustaceans, notwithstanding the economic relevance of this taxonomic 7 group (FAO 2018), even though marine benthic invertebrates present several attributes 8 well suited for this technique (Robinson et al. 2011). In the available models, bathymetry 9 and substrate characteristics have shown to be good predictors of the presence and 10 abundance of marine invertebrate species (e.g. Serrano et al. 2008, Pierrat et al. 2012) 11 and crustaceans species in particular (Gogina and Zettler 2010, Drewnik et al. 2017). In 12 a recent study, sea bottom temperature, sea bottom salinity and sediment type were 13 important predictors of the distribution of three portunid crab species (Luan et al. 2018). 14 Environmental variables are clearly important drivers of the distribution of marine 15 macroinvertebrates such as crabs, but biological variables are rarely evaluated (Reiss et 16 al. 2014), even though calls have been made for the inclusion of interspecific 17 interactions as predictors (Paine 2010, Zarnetske et al. 2012). Trophic interaction is a 18 good candidate in this sense (Reiss et al. 2014).

The portunid crab *Ovalipes trimaculatus* (De Haan 1833) occurs in temperate waters of the Atlantic (Vinuesa 2005, Melo 2010), Pacific (Retamal 1981) and Indian Oceans (Schoeman & Cockcroft 1993). As with other portunid crabs, *O. trimaculatus* is commercially fished in Chile (Haye et al. 2012) and Argentina (Boschi 1997, de la Barra et al. 2019). Despite the economic importance of the species, the variables that drive its

distribution have never been specifically studied. It has been observed to occur in sandy
bottoms (Fenucci & Boschi 1975), ranging from 3 to 100 m depth at different latitudes
and regions (Boschi et al. 1992, Retamal and Arana 2000). However, the probability of
occurrence within a depth range or in different substrates has never been systematically
studied. Moreover, its preference for other environmental variables, relevant for the
distribution of benthic species such as seabed slope (e.g. Compton et al. 2013, Basher et
al. 2014), has not yet been described.

8 In the San Matías Gulf (41° S, Argentina), a fishery for O. trimaculatus has existed since 9 2007 (de la Barra et al. 2019). Although the fishery has been growing since its inception, 10 after 10 years it is still fairly small in terms of activity, size of vessels (around eight 11 fiberglass motor boats of 6.5–9.5 m), number of fishers and catch levels (de la Barra et 12 al. 2019). It is a surface-supplied diving fishery in which divers fish on previously baited 13 areas, shallower than 20 m (de la Barra et al. 2019). Crabs are picked up by hand and 14 stored in a net bag. The fishery occurs in the north-western coast of the gulf, in two 15 distinct fishing grounds (hereafter referred to as eastern and western according to their 16 relative positions in the gulf, Figure 1). Each fishing ground is associated with a landing 17 point on the coast (Figure 1) with no specific infrastructure (ports or marinas, de la Barra 18 et al. 2019). To launch the vessels, fishers have farm tractors parked on the beach. The 19 fishery takes place throughout the year, with the effort depending mainly on the wind 20 conditions (de la Barra et al. 2019).

Adequate management of this fishery requires an understanding of the biological and
 ecological aspects of the target population, but because of its small scale, along with

political decisions, there are neither specific management measures for the fishery, nor
 monitoring of the population.

3 As Ovalipes trimaculatus has a generalist carnivore diet (de la Barra et al. 2018), we 4 expect the biomass of prey species to be a good predictor of the distribution of O. 5 trimaculatus, independently of prey identity. However, locations with higher prey 6 abundance may not be necessarily the more energetically profitable (Elner & Hughes 7 1978) or offer all the nutrients that adult O. trimaculatus need (Pulliam 1975). 8 Environments with a high variety of prey species could represent high profitability and 9 a broad offering of different nutrients. For this reason, the richness and evenness of prey 10 species could also be good biological predictors of the distribution of *O. trimaculatus*.

11 Given this background, the aim of our study was to assess the distribution of O. 12 trimaculatus in the north of the San Matías Gulf taking advantage of information 13 gathered before the beginning of the crab fishery, during a systematic survey of the 14 benthic community. These surveys were independent of the crab fishery and thus 15 provide information about the system before it was impacted by fishing. We tested the 16 hypothesis that O. trimaculatus' distribution depends on depth, substrate type, seabed 17 slope, water temperature, and the biomass, richness and evenness of its prey. Through 18 the use of SDMs we aim to generate a baseline of spatial information about the species 19 in the San Matías Gulf and identify the variables that may drive its distribution during 20 the cold season.

21

22 **2.** Materials and Methods

23 2.1 Study area

The San Matías Gulf is a temperate system located in the Patagonian Shelf Large Marine Ecosystem (Argentina). The seabed of the gulf is mainly composed of sediment of different grain size (Servicio de Hidrografía Naval Argentino 1974). The Gulf does not receive sufficient freshwater input to have any noticeable effect on salinity. During the survey, salinity remained relatively homogeneous throughout the study area ranging from 33.92 to 34.45‰.

7 2.2 Species distribution model

During June and July 2006 (approximately one year before the beginning of the crab fishery) 200 stations (survey hauls) were sampled in the north of the San Matías Gulf using a 1.6 m wide-mouth dredge (maximum weight of 50 kg, more details in Narvarte et al. 2011) as a means of estimating the abundance of different benthic resources. The survey was performed during the cold season. In other swimming crab fisheries, using dredges during the time of the year when the species is less active has proven to be a better way of estimating abundance (Vølstad et al. 2000).

15

The survey had a quasi-regular design covering different benthic environments between the 10 and 60 m isobaths (depth range that includes most of the described bathymetric distribution of *O. trimaculatus*). The design consisted of groups of 2 to 5 sampling stations each, located along a transect perpendicular to the coast extending between the 10 and 60 m isobaths (Figure 1).

During the survey, each haul was tracked using a GPS to calculate the area swept by the dredge. For each haul, the total weight of each species captured was measured. As Narvarte at al. (2011) observed that the efficiency of the dredge was very high (over 90%

for mussels, sea urchins and ophiuroids), whenever the dredge was lifted empty it was considered that it had not worked correctly (e.g. the dredge must have not touched the ground, or had not been properly deployed), as a result these hauls were not used in the subsequent analysis. Seventy two of the 129 species captured were identified as potential prey of *O. trimaculatus* following de la Barra et al. (2018). These included a selection of: bivalves, gastropods, chitons, cephalopods, crustaceans (mainly decapods), echinoids, ophiuroids, asteroideans and polychaetes (Electronic supplement 1).

8 We obtained a climatological layer of sea surface temperature (SST) for June 9 constructed from AVHRR (NOAA) satellite images for the period 2000 –2008 (processing 10 details of satellite images are found in Williams et al. 2010). The resolution of the SST 11 images (0.01° sides, ca. 1.1 km²) was applied to all the raster layers used in this study for 12 consistency. We constructed a depth map of the area by interpolating bathymetric 13 points from a nautical chart of the Naval Hydrographic Service of Argentina (SHN 2000) 14 using an ordinary Kriging function (all the following statistical analyses and maps were 15 generated in R version 3.5.0, R Core Team 2018, ordinary kriging function of the package 16 "gstat", Pebesma 2004,). The nautical chart had between one and ten in situ measures 17 of depth for each pixel of the map generated by us. From the depth map, we obtained 18 a slope map by assigning, to each pixel, the maximum slope observed between itself and 19 its eight neighboring pixels. A map of the substrate types was obtained by rasterizing a 20 sedimentology map of the area (SHN 1974) using QGIS (QGIS Development Team 2016). 21 The sedimentology map had a coarser resolution (only 65 survey points in the study 22 area) and was used as an indicator of the different large substrate habitats in the area. 23 In 108 stations, covering the full extent of the survey area, in situ measures of water 24 temperature were collected at 10 m depth using a handheld multiparameter probe

1 (YSI556). With this information, we constructed a bottom temperature layer by 2 interpolating these measurements with an ordinary Kriging function. We considered 3 temperature at 10 m a good proxy of sea bottom temperature because during this time 4 of the year the water column is well mixed (Rivas and Beier 1990). Finally, we assigned 5 values of depth, slope, SST and temperature at 10 m depth to each haul using the 6 coordinates of the beginning of each haul and the raster layers of the variables using the 7 R package "raster" (Hijmans 2019).

8 For each haul three estimators of the availability of O. trimaculatus' prey were calculated: biomass, richness and evenness of prey species. Biomass was calculated as 9 10 the aggregated biomass of all the prey species per area swept by the dredge (g m⁻²). 11 Richness was derived via the Chao species estimator for abundance data (Gotelli & 12 Colwell 2011) using the Chao1 function in R (Oksansen et al. 2019), and evenness the 13 probability of interspecific encounter (PIE, Hurlbert 1971). The PIE index is a measure of 14 species evenness, but it is also dependent on species richness, and, unlike richness, is 15 not sample-size dependent (Gotelli 2008).

16 Pearson correlation coefficients were calculated among all variables (both 17 environmental and biological) in order to check that they were not highly correlated 18 (r_{pearson} > 0.75). We also checked for collinearity between predictors considering that if 19 the variance inflation factor between two variables was higher than 3 then there was 20 collinearity between these predictors (Zuur et al. 2010) and thus one would be omitted. 21 However, no strong correlation was detected between any pairs of variables (Figure S2) 22 and the variance inflation factor showed that there was also no collinearity between any 23 predictors, thus, all variables were retained in the analyses.

1 We tested the hypothesis that O. trimaculatus' distribution depends on depth, substrate 2 type, seabed slope, temperature at 10 m, SST and the biomass, richness and evenness 3 of its prey through a delta generalized linear model (Shelton et al. 2014). This kind of 4 model is widely used in fisheries studies as it deals with zero inflated continuous 5 distributions, therefore allowing the study of the biomass of a species in addition to its 6 presence - absence patterns (Shelton et al. 2014, Garofalo et al. 2018). For the delta 7 generalized lineal model, the observed catches were divided into two sub-models: one 8 describing the presence or absence of O. trimaculatus (hereafter "Presence sub-9 model"), and one for the distribution of catches conditioned on the presence of O. 10 trimaculatus (hereafter "Biomass sub-model"). We used a logit-link function and a 11 binomial error distribution for the Presence sub-model, and a logarithmic-link with 12 gamma error distribution for the Biomass sub-model, using the biomass per area of O. 13 trimaculatus (g m⁻²) as response variable. Once the parameters of the model were 14 estimated (as described in the next paragraph), we multiplied the Presence sub-model 15 by the Biomass sub-model to obtain the delta generalized linear model that predicts the 16 most likely biomass density of O. trimaculatus (SDM). The spatial autocorrelation of this 17 final model was then tested using Moran's *I* coefficient (Moran 1950).

To evaluate the global and nested models for the Presence sub-model and the Biomass sub-model we used an information theoretical approach. This was done independently for each sub-model (i.e. the analysis of the Presence sub-model did not affect the analysis of the Biomass sub-model). For each case, we analyzed 512 nested models (Table S1 and S2). Akaike's information criterion corrected for small sample size (AICc) was calculated for all the nested models (Burnham & Anderson 2002). Then, the nested models were compared through Δ AICc, which is the difference between the lowest AICc

1 value of the suit of all models (i.e. best of suitable models) and the AICc of each nested 2 model. The AICc weight of a model (w_i) is the relative likelihood that a specific model is 3 the best of a suit of models. Hence, we evaluated the support for each explanatory 4 variable by summing w_i from the models where the variable was included (parameter 5 likelihood, Burnham & Anderson 2002). Finally, parameter estimates were calculated 6 using model-averaged parameter estimates through the R package "MuMIn" (Barton 7 2018), based on w_i from the top-ranked models ($\Delta AICc < 2$). To supplement parameter-8 likelihood evidence of important effects, we also calculated 95% confidence interval 9 limits (CL).

10 The Presence sub-model was trained using 70% of the data, while the remaining 30% 11 were used to test its predictive performance through the area under the receiver 12 operating characteristic curve (AUC) using the R package "pROC" (Robin et al. 2011). The 13 AUC is a threshold independent measure representing the relationship between 14 sensitivity and the corresponding proportion of false positives. It varies between 0 and 15 1; values greater than 0.9 represent an excellent prediction, between 0.7 and 0.9 a good 16 prediction, between 0.7 and 0.5 a weak prediction and below 0.5 prediction comparable 17 to random outcomes (Hosmer et al. 2013).

To generate a predictive map of the density of *O. trimaculatus*, we used the raster layers of the explanatory variables for the entire area (Figure S1) as input for the delta generalized linear model. Raster layers of prey biomass, richness, and evenness (Figure S1 A-C) were developed through kriging (ordinary kriging of the package "gstat" in R, Pebesma 2004). For depth, slope, SST, temperature at 10 m depth and substrate type

1 we used the raster layers previously mentioned in this section (Figure S1 D-H). All rasters

2 had the almost the same extent as the survey (between 1 and 60 m isobaths).

We also constructed response curves of the biomass per area of *O. trimaculatus* to all the explanatory variables. To achieve this, we calculated the mean value of each of the numeric explanatory variables and used them together with the estimated parameters (Table 1) to construct the curve of the mean predicted density of *O. trimaculatus* relative to each predictor.

8

9 **3.** Results

10 From the 200 hauls performed during the survey, 13 presented no catch and 4 had an 11 area swept that was smaller than the expected (less than 100 m²) and were discarded 12 due to likely deployment error. The hauls occurred on six types of substrate: sand, silt, 13 silty-sand and gravel. In total, we analyzed 183 hauls with an area swept of 343.8, 107.2 14 m² (mean, SD). In 40 of these hauls at least one individual of *O. trimaculatus* was caught 15 (Figure 1). The depths of the analyzed hauls ranged between 12 and 58 m, seabed slope 16 ranged between 0.03 and 1.55°, SST between 12.81 and 14.58 °C and temperature at 10 17 m depth ranged between 11.7 and 12.97 °C. Ovalipes trimaculatus' prey were found in 18 all the hauls analyzed and its biomass ranged from 0.11 to 45.3 g·m⁻², its species richness 19 ranged from 1 to 54 and the PIE ranged from 0 to 0.83.

For the Presence sub-model six models had $\Delta AIC < 2$ (Table S1) and were therefore averaged. The averaged Presence sub-model included substrate type, depth, richness and SST as explanatory variables (Table 1. a). Specifically, depth and substrate type had a higher likelihood of explaining presence (Table 1. a). This model obtained an AUC of

0.74, with 95% CL ranging from 0.51 to 0.97, we considered the model to have
acceptable predictive power on the presence of *O. trimaculatus*. The Presence submodel explained 26.15% of the deviance of the presence-absence data.

4 For the Biomass sub-model, five models were averaged to explain the density of O. 5 trimaculatus conditioned on its presence (Table S2). The variables included in the 6 averaged Biomass sub-model were depth, prey biomass, SST, evenness and slope, the 7 latter three having a lower likelihood to explain the Biomass sub-model (Table 1. b). The 8 Biomass sub-model explained 30.54% of the deviance of the biomass data. 9 Through the multiplication of the averaged Presence and the averaged Biomass sub-10 models we obtained the SDM (Figure 2). Between 10 and 60 m depth the SDM predicted 11 an average biomass density of *O. trimaculatus* of 0.30 g m⁻², with a maximum density of 12 1.29 g m⁻². The higher densities of *O. trimaculatus* were predicted at the lower depths 13 of the north coast of the gulf (Figure 2). The model did not present spatial 14 autocorrelation (Moran test P = 0.15).

15 Depending on substrate type, the response curve of the SDM showed clear differences: 16 silt and silty sand presented a higher density of O. trimaculatus, compared to sand or 17 gravel (Figure 3 A-F). Depth and prey species richness showed a negative relationship 18 with O. trimaculatus' density (Figure 3 B, C), while prey biomass presented a positive 19 relationship (Figure 3 F). However, their effect was much lower when the substrate type 20 was sand (Figure 3 B, C, F). Evenness, slope and SST had a very small effect on O. 21 trimaculatus' density (Table 1, Figure 3 A, D, E), and in situ temperature at 10 m depth 22 was not retained in the final model.

4. Discussion

2 Our model suggests that the distribution of Ovalipes trimaculatus in the north of San 3 Matías Gulf is likely influenced by substrate type, depth and prey biomass. Seabed 4 slope, SST, prey species richness and prey species evenness were retained in the model 5 but confidence in their importance was lower as confidence intervals included zero. 6 Before this study we are aware of only one published paper modeling of the 7 distributions of portunid crabs (Luan et al. 2018). Unlike that study, our work was 8 conducted over a smaller area but at a much higher spatial resolution. Furthermore, our 9 study includes proxies of trophic interactions as predictors of the distribution of these 10 crabs for the first time, shedding new light on how they may be modulating the 11 population's distribution.

12 Depth has been found to be a reliable predictor of crustaceans' distribution (Gogina & 13 Zettler 2010, Drewnik et al. 2017). In this study, we determined that the depth range 14 within the studied area was quite restricted, with the maximum predicted density of 15 crabs at 10 m (the shallowest depth sampled). Moreover, in bottom trawl surveys 16 carried out in deeper areas of the San Matías Gulf between 30 and 170 m depth, in 17 different years and seasons, O. trimaculatus has never been found (Ocampo-Reinaldo 18 2005a,b, Ocampo-Reinaldo et al. 2008, Maggioni et al. 2010). This may be because depth 19 may be an indirect estimator of different environmental variables, such as substratum, 20 temperature, light, wave energy and salinity (Reiss et al. 2014). While we tested 21 substrate type and temperature, we did not consider salinity because the spatial 22 variation of this variable in the north of San Matías Gulf is minimal (Rivas and Beier 23 1990), with no appreciable freshwater input (i.e. there are no stream flows into the

Gulf), and the extent of the study area is quite small. In our study, depth might only be
an indirect driver of *O. trimaculatus'* distribution. However, the structuring nature of
bathymetry makes it difficult to replace depth in distribution modelling (Reiss et al.
2014).

5 Our model predicts that, in the San Matías Gulf, O. trimaculatus mainly occurs in bottom 6 substrate of relatively fine granulometry, such as silt and silty sand. Until now, it was 7 assumed that O. trimaculatus mainly occurs in sandy bottoms (Fenucci and Boschi 1975). 8 We found that contrary to some literature, sandy bottoms were the least favorable for 9 O. trimaculatus, indeed, even less favorable than gravel. This is probably because sandy 10 bottoms occur in the western area of the gulf (Figure S1 B), and O. trimaculatus was only 11 caught in two hauls from that area. However, an important fishing ground occurs there, 12 thus it is likely that the SDM has underestimated the density of *O. trimaculatus* in sandy 13 bottoms. As substrate type may influence the efficiency of the dredge, it is also possible that the low biomass of O. trimaculatus in sandy bottoms is due to a lower catchability 14 15 of the species in that type of substrate. Trawling gear may have a different efficiency in 16 catching crustaceans depending on the kind of gear, the substrate type and the species' 17 habitat preference (e.g. Reiss et al. 2006, Somerton et al. 2013). However, for Callinectes 18 sapidus, another portunid crab, the efficiency of dredges is the same in muddy and 19 sandy bottoms during winter as crabs present a quasi-hibernation behavior – they spend 20 most of the time buried in the sediment (Zhang et al. 1993). Given the similarity in 21 season and bottom substrate type, we do not expect our case to be too different.

Sea bottom temperature was one of the main predictors of portunid crab distributions
in a big bay of China (Luan et al. 2018). In our models *in situ* bottom temperature was

1 not a good predictor for crab presence or density and climatological SST provided only 2 a moderate contribution to the final model (Figure 3). Because in situ temperature did 3 not influence the distribution of O. trimaculatus, we do not consider that water 4 temperature directly constrains its distribution in the gulf through influencing 5 physiology or behavior. Instead, the correlation with SST may be indicating a preference 6 of this crab for the water mass of San Antonio Bay which is very productive and during 7 this time of the year is colder than the adjacent waters of the gulf (Figure S1 G, Esteves 8 et. al 1996).

9 Although environmental variables (substrate type, depth and SST) were the most 10 important for predicting the distribution of O. trimaculatus, biological variables (prey 11 biomass, richness and evenness) where all retained in the SDM and therefore, we can 12 affirm that they improved the prediction of the crab's distribution. Co-occurrence of 13 predators and their prey is commonly observed in terrestrial (e.g. Fernández et al. 2003), 14 freshwater (e.g. Godin & Keenleyside 1984), and benthic marine environments (e.g. 15 Stewart & Jones 2001). However, benthic invertebrates are considered to be more 16 dependent on environmental variables than marine apex predators, which have a wider 17 span of homeostasis and are therefore more capable of moving among different 18 environmental conditions to find their prey (Robinson et al. 2011). Moreover, some 19 authors suggest that in the soft sedimentary benthos, environmental variables dominate 20 over biological interactions in driving the distribution of macroinvertebrates (i.e. 21 predation, Woodin 1983, Wilson 1990). Hence, the effect of prey on the distribution of 22 marine macroinvertebrates is generally not evaluated (e.g. see review by Snickars et al. 23 2014), particularly in sedimentary environments. Portunid crabs are benthic

macroinvertebrates, but also are active predators and thus, need to at least partially
 share their distribution with their prey.

3 Using prey biomass as a predictor of predator abundance assumes that energy 4 availability is the main constraint to the predator's diet and that access to prey is equal 5 across the study area (Trainor & Schmitz 2014). In our SDM, biomass of prey species was 6 retained as a predictor in the Biomass sub-model, but not in the Presence sub-model. 7 This means that the amount of prey biomass does not determine the presence of O. 8 trimaculatus, but, given that the species is present, higher prey abundance will correlate 9 with higher biomass of O. trimaculatus (Table 1). As O. trimaculatus is a generalist 10 consumer, it makes sense that prey biomass is not a limiting factor to its presence, it is 11 likely that individuals will find prey in most places. This conclusion is supported by the 12 fact that every haul of the sampling survey presented some amount of prey biomass. 13 However, this was not always the case for consumers that prey upon benthic 14 invertebrates. Hines (1997) and Schwemmer (2016) observed, in eagle rays and wader 15 birds respectively, that prey density must reach a certain limit for it to be a good 16 predictor of predator presence. Using prey biomass as a predictor of predator 17 abundance also assumes that accessibility to prey is the same in every area where 18 predator and prey co-occur (Trainor & Schmitz 2014). This assumption may not be 19 realistic when the abundance of prey species does not reflect the likelihood that a 20 predator finds and successfully captures one of them (Trainor & Schmitz 2014). As 21 mentioned before, crab's predation rate may be affected by substrate type, in particular 22 larger particle size diminishes crab's foraging efficiency (Liu et al. 2019). The results of 23 the SDM suggest that something similar could be happening in the San Matías Gulf. We 24 observed a positive effect of prey biomass mainly within substrate types that favored

the distribution of *O. trimaculatus* (silt and silty sand), but, a lower effect of prey biomass
in suboptimal substrate types (sand, Figure 3 F).

3 The metabolic system of a consumer requires different proportions of key nutrients, 4 hence, the food items that maximize energetic intake may not satisfy the rest of the 5 nutritional needs of the consumer (Pulliam 1975). In a wide variety of taxa, including 6 arthropods, a mixed diet enhances various fitness indicators in comparison with a mono 7 specific diet (Lefcheck et al. 2013). Therefore, patches where various prey species occur 8 should have a higher biological value for a generalist consumer than areas with high 9 dominance of one or a few prey species. However, according to the SDM, higher 10 evenness and richness negatively affect the distribution of O. trimaculatus (Figure 3 A, 11 C), the latter having a larger effect. In coastal sedimentary environments, at a larger 12 scale, benthic species richness positively correlates with depth (Gray 2002, and 13 references therein). However, species richness has a low correlation with depth in our 14 study area (Figure S2). Therefore, we estimate that species richness in San Matías Gulf 15 may be affected by an un-measured variable that negatively affects the distribution of 16 O. trimaculatus. For example, species richness has been observed to be positively 17 correlated with habitat complexity (Gratwicke & Speight 2005) and it is possible that O. 18 trimaculatus prefers simpler habitats with large sedimentary plains, where it can bury 19 itself. Birch (1981) observed that in sedimentary habitats, dominance and richness are 20 positively correlated as well. Gray (2002), on the other hand, proposes that the patterns 21 of species richness in benthic marine sedimentary environments reflect complex 22 processes: a combination of the availability of food resources (i.e. patches of microbial 23 communities) and the spatial and temporal heterogeneity in a given area. However, it is 24 not clear how said processes may affect the distribution of O. trimaculatus.

Our results accurately predicted one of the two fishing grounds, as the highest biomass values for *O. trimaculatus* were obtained within the eastern fishing ground. This was in spite of the relatively low explained deviance obtained, and that no sampling stations occurred inside this fishing ground. The prediction for the western fishing ground, on the other hand, showed very low biomass of *O. trimaculatus*, likely due to the lower sampling effort in that area, or due to a lower efficiency of the dredge in that substrate type, as discussed before.

8 The correlative approach used in this study prevents us from establishing causal 9 relationships between O. trimaculatus' distribution and the environmental and 10 biological variables studied. More complex approaches would be required to adequately 11 deal with this causation. Mechanistic niche modelling, for example, allows integration 12 of mechanistic links between functional traits of organisms and their environments into 13 SDMs (Kearney and Porter 2009). Hybrid datasets combine the inferential power of 14 experiments with the large scales (spatial and temporal) of observational studies 15 (Benedetti-Cecchi et al. 2018). Nonetheless, in many cases it is not possible to carry out 16 an experimental approach (Mac Nally 2000). The difficulty in accessing certain 17 environments, as well as the scarce economic resources available for research 18 throughout the majority of the world, underline the importance that correlative 19 approaches have and will have for some time in our understanding of the natural world. 20 Although unable to indicate causality, correlative approaches are a useful tool to select 21 and refine candidate variables for experimental approaches to progress our 22 understanding of potential mechanisms (Kearney and Porter 2009).

1 In conclusion, the present model of O. trimaculatus' distribution achieved acceptable 2 predictive power for the north of the San Matías Gulf, where a fishery has recently been 3 established targeting this species. Considering the cosmopolitan nature of the species, 4 the environmental and biological variables that constrain its distribution in the San 5 Matías Gulf could also be relevant in other regions, and thus, substrate type, depth, SST, 6 and prey biomass, evenness and richness may be useful candidate variables in future 7 studies. In terms of fishery management, considering the low scale of the fishery, the 8 exploration of the gulf with the objective of understanding the distribution of O. 9 trimaculatus would impose an unaffordable economic cost. Not even the fishers afford 10 to invest time in finding new fishing grounds (de la Barra et al. 2019). Hence, a map of 11 the species distribution may be a useful tool for managers (Maxwell et al. 2009) as a 12 reference of the areas where they should focus their efforts.

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4 **References**

5 Alberts-Hubatsch H, Lee S Y, Meynecke, J O, Diele K, Nordhaus I, Wolff M (2016) Life-6 history, movement, and habitat use of *Scylla serrata* (Decapoda, Portunidae): 7 current knowledge and future challenges. Hydrobiologia 763, 5–21. 8 Alonso R B, Romero M A, Ocampo Reinaldo M, Bustelo P E, Medina A I, Gonzalez R (2019) 9 The opportunistic sense: The diet of Argentine hake *Merluccius hubbsi* reflects 10 changes availability. 27, 100540. in prey Reg Stud Mar Sci

11 https://doi.org/10.1016/j.rsma.2019.100540

- 12 Archambault P, Bourget E (1996) Scales of coastal heterogeneity and benthic intertidal
- 13 species richness, diversity and abundance. Mar. Ecol. Prog. Ser. 136, 111–121.
- 14 https://doi.org/10.3354/meps136111

15 Barton K (2018) MuMIn: Multi-Model Inference. R package version 1.42.1.

Basher Z, Bowden D A, Costello M J (2014) Diversity and distribution of deep-sea shrimps
in the Ross Sea region of Antarctica. PLoS One 9, e103195.

18 Benedetti-Cecchi L, Bulleri F, Dal Bello M, Maggi E, Ravaglioli C, Rindi L (2018) Hybrid

- datasets: integrating observations with experiments in the era of macroecology
 and big data. Ecology 99, 2654–2666.
- Benoit-Bird K J, Battaile B C, Heppell S A, Hoover B, Irons D, Jones N, Kuletz K J,
 Nordstrom C A, Paredes R, Suryan R M, Waluk C M, Trites A W (2013) Prey Patch

1	Patterns Predict Habitat Use by Top Marine Predators with Diverse Foraging
2	Strategies. PLOS ONE 8, e53348. https://doi.org/10.1371/journal.pone.0053348
3	Birch D W (1981) Dominance in marine ecosystems. Am Nat 118, 262–274.
4	Boschi E E (1997) Las pesquerías de crustáceos decápodos en el litoral de la República
5	Argentina. Investig Mar 25, 19–40.
6	Boschi E E, Fischbach C E, Iorio M I (1992) Catálogo ilustrado de los crustáceos
7	estomatópodos y decápodos marinos de Argentina.
8	Branch T A, Hilborn R, Haynie A C, Fay G, Flynn L, Griffiths J, Marshall K N, Randall J K,
9	Scheuerell J M, Ward E J, others (2006) Fleet dynamics and fishermen behavior:
10	lessons for fisheries managers. Can J Fish Aquat Sci 63, 1647–1668.
11	Buck T L, Breed G A, Pennings S C, Chase M E, Zimmer M, Carefoot T H (2003) Diet choice
12	in an omnivorous salt-marsh crab: different food types, body size, and habitat
13	complexity. J Exp Mar Biol Ecol 292, 103–116. https://doi.org/10.1016/S0022-
14	0981(03)00146-1
15	Burnham K P, Anderson D R (2002) Model selection and multimodel inference: a
16	practical information-theoretic approach, 2nd ed. ed. Springer, New York.
17	Compton T J, Bowden D A, Roland Pitcher C, Hewitt J E, Ellis N (2013) Biophysical
18	patterns in benthic assemblage composition across contrasting continental
19	margins off New Zealand J Biogeogr 40, 75–89.
20	Cornell H V (1999) Unsaturation and regional influences on species richness in ecological
21	communities: a review of the evidence. Ecoscience 6, 303–315.
22	Cruz-Rivera E, Hay M E (2001) Macroalgal traits and the feeding and fitness of an
23	herbivorous amphipod: the roles of selectivity, mixing, and compensation. Mar
24	Ecol Prog Ser 218, 249–266. https://doi.org/10.3354/meps218249

1	Cruz-Rivera E, Hay M E (2000a) Can quantity replace quality? Food choice, compensatory				
2	feeding, and fitness of marine mesograzers. Ecology 81, 201–219.				
3	Cruz-Rivera E, Hay M E (2000b) The effects of diet mixing on consumer fitness:				
4	macroalgae, epiphytes, and animal matter as food for marine amphipods.				
5	Oecologia 123, 252–264.				
6	de la Barra P, Botto F, Iribarne O, Narvarte M (2018) Patterns of habitat partitioning for				
7	the portunid crab Ovalipes trimaculatus in coastal Patagonian waters. Estuar				
8	Coast Shelf Sci. https://doi.org/10.1016/j.ecss.2018.08.012				
9	de la Barra P, Iribarne O, Narvarte M (2019) Combining fishers' perceptions, landings				
10	and an independent survey to evaluate trends in a swimming crab data-poor				
11	artisanal fishery. Ocean Coast Manag 173, 26–35.				
12	https://doi.org/10.1016/j.ocecoaman.2019.02.008				
13	Drewnik A, Węsławski J M, Włodarska-Kowalczuk, M (2017) Benthic Crustacea and				
14	Mollusca distribution in Arctic fjord – case study of patterns in Hornsund,				
15	Svalbard. Oceanologia 59, 565–575.				
16	https://doi.org/10.1016/j.oceano.2017.01.005				
17	Du Preez H H (1983) The effects of temperature, season and activity on the respiration				
18	of the three spot swimming crab, Ovalipes punctatus. Comp. Biochem. Physiol.				
19	A Physiol. 75, 353–362.				
20	Eastwood P D, Meaden G J, Carpentier A, Rogers S I (2003) Estimating limits to the spatial				
21	1 extent and suitability of sole (<i>Solea solea</i>) nursery grounds in the Dover Strait. J				
22	Sea Res, Proceedings of the Fifth International Symposium on Flatfish Ecology,				
23	Part I 50, 151–165. https://doi.org/10.1016/S1385-1101(03)00079-0				

Elner R W, Hughes R N (1978) Energy maximization in the diet of the shore crab, *Carcinus maenas*. J Anim Ecol 103–116.

3 Erickson A A, Feller I C, Paul V J, Kwiatkowski L M, Lee W (2008) Selection of an
4 omnivorous diet by the mangrove tree crab *Aratus pisonii* in laboratory
5 experiments. J Sea Res, Mangrove Macrobenthos Special Issue 59, 59–69.
6 https://doi.org/10.1016/j.seares.2007.06.007

7 Esteves J L, Solís M, Sastre V, Santinelli N, Gil M, Commendatore M, González Raies C
8 (1996) Evaluación de la contaminación urbana de la Bahía San Antonio.
9 Fundación Patagonia Natural, Chubut (Argentina) Plan de Manejo Integrado de
10 la Zona Costera Patagónica. Informe Técnico no. 20.

FAO (Ed.) (2018) The State of World Fisheries and Aquaculture 2018 - Meeting the
 sustainable development goals, The state of world fisheries and aquaculture.
 Rome.

Fenucci J L, Boschi E E (1975) Contribución al conocimiento biológico del cangrejo
 comercial de las aguas costeras de la provincia de Buenos Aires *Ovalipes trimaculatus* (De Haan)(Crustacea, Decapoda, Portunidae). Physis A 34, 291–308.

17 Fernández N, Delibes M, Palomares F, Mladenoff D J (2003) Identifying Breeding Habitat

18 for the Iberian Lynx: Inferences from a Fine-Scale Spatial Analysis. Ecol Appl 13,
19 1310–1324. https://doi.org/10.1890/02-5081

Freitag A, Vogt B, Hartley T (2018) Ecosystem-Based Fisheries Management in the
 Chesapeake: Developing Functional Indicators. Coast Manag 46, 127–147.
 https://doi.org/10.1080/08920753.2018.1451729

Fucks E, Schnack E J, Charó M (2012) Aspectos geológicos y geomorfológicos del sector
 N del golfo San Matías, Río Negro, Argentina. Rev Soc Geológica Esp. 25.

1	Garofalo G, Fezzani S, Gargano F, Milisenda G, Ben Abdallah O, Ben Hadj Hamida N,			
2	Jarboui O, Chemmam-Abdelkader B, Khoufi W, Micallef R, Mifsud R, Gancitano			
3	S, Rizzo P, Zgozi S, Ceriola L, Arneri E, Fiorentino F (2018) Predictive distribution			
4	models of European hake in the south-central Mediterranean Sea. Hydrobiologia			
5	821, 153–172. https://doi.org/10.1007/s10750-017-3338-5			
6	Godin J G J, Keenleyside M H (1984) Foraging on patchily distributed prey by a cichlid			
7	fish (Teleostei, Cichlidae): a test of the ideal free distribution theory. Anim Behav			
8	32, 120–131.			
9	Gogina M, Glockzin M, Zettler M L (2010) Distribution of benthic macrofaunal			
10	communities in the western Baltic Sea with regard to near-bottom			
11	environmental parameters. 2. Modelling and prediction. J Mar Syst 80, 57–70.			
12	Gogina M, Zettler M L (2010) Diversity and distribution of benthic macrofauna in the			
13	Baltic Sea: Data inventory and its use for species distribution modelling and			
14	prediction. J Sea Res 64, 313–321. https://doi.org/10.1016/j.seares.2010.04.005			
15	Gotelli N J (2008) A Primer of Ecology, 4th ed. ed. Sinauer Associates, Inc, Sunderland,			
16	MA.			
17	Gotelli N J, Colwell R K (2011) Estimating species richness, in: Magurran, Anne E., McGill,			
18	B.J. (Eds.), Frontiers in Measuring Biodiversity. Oxford University Press, New			
19	York, pp. 39–54.			
20	Gratwicke B, Speight M R (2005) The relationship between fish species richness,			
21	abundance and habitat complexity in a range of shallow tropical marine habitats.			
22	J Fish Biol 66, 650–667. https://doi.org/10.1111/j.0022-1112.2005.00629.x			
23	Gray J S (2002) Species richness of marine soft sediments. Mar Ecol Prog Ser 244, 285–			
24	297. https://doi.org/10.3354/meps244285			

1	Haye P A, Segovia N I, Vera R, de los Ángeles Gallardo M, Gallardo-Escárate C (2012		
2	Authentication of commercialized crab-meat in Chile using DNA barcoding. Food		
3	Control 25, 239–244.		
4	Hedger R, McKenzie E, Heath M, Wright P, Scott B, Gallego A, Andrews J (2004) Analysis		
5	of the spatial distributions of mature cod (Gadus morhua) and haddock		
6	(Melanogrammus aeglefinus) abundance in the North Sea (1980–1999) using		
7	generalised additive models. Fish Res 70, 17–25.		
8	Hijmans R J (2019) raster: Geographic Data Analysis and Modeling. R package version		
9	2.8-19. https://CRAN.R-project.org/package=raster		
10	Hill B J (1980) Effects of temperature on feeding and activity in the crab Scylla serrata.		
11	Mar. Biol. 59, 189–192.		
12	Hines A H, Whitlatch R B, Thrush S F, Hewitt J E, Cummings V J, Dayton P K, Legendre P		
13	(1997) Nonlinear foraging response of a large marine predator to benthic prey:		
14	eagle ray pits and bivalves in a New Zealand sandflat. J Exp Mar Biol Ecol 216,		
15	191–210.		
16	Hosmer D W, Lemeshow S, Sturdivant R X (2013) Applied logistic regression. John Wiley		
17	& Sons.		
18	Hurlbert S H (1971) The nonconcept of species diversity: a critique and alternative		
19	parameters. Ecology 52, 577–586.		
20	Janßen H, Bastardie F, Eero M, Hamon K G, Hinrichsen H H, Marchal P, Nielsen J R, Le		
21	Pape O, Schulze T, Simons S, Teal L R, Tidd A (2018). Integration of fisheries into		
22	marine spatial planning: Quo vadis? Estuar Coast Shelf Sci 201, 105–113.		
23	https://doi.org/10.1016/j.ecss.2017.01.003		

1	Jones M C, Dye S R, Pinnegar J K, Warren R, Cheung W W L (2015) Using scenarios to					
2	project the changing profitability of fisheries under climate change. Fish Fish 16,					
3	603–622. https://doi.org/10.1111/faf.12081					
4	Josefson A B, Hansen J L S (2004) Species richness of benthic macrofauna in Danish					
5	estuaries and coastal areas. Glob Ecol Biogeogr 13, 273–288.					
6	Kangas M I (2000) Synopsis of the biology and exploitation of the blue swimmer crab,					
7	Portunus pelagicus Linnaeus, in Western Australia. Fisheries Research Report N°					
8	121, 2000. Fisheries Western Australia, Fisheries Research Division.					
9	Kearney M, Porter W (2009) Mechanistic niche modelling: combining physiological and					
10	spatial data to predict species' ranges. Ecol. Lett. 12, 334–350.					
11	https://doi.org/10.1111/j.1461-0248.2008.01277.x					
12	Kohl K D, Coogan S C, Raubenheimer D (2015) Do wild carnivores forage for prey or for					
13	nutrients? Evidence for nutrient-specific foraging in vertebrate predators.					
14	BioEssays 37, 701–709.					
15	Lawton J H (1999) Are there general laws in ecology? Oikos 177–192.					
16	Leber K M (1982) Seasonality of macroinvertebrates on a temperate, high wave energy					
17	sandy beach. Bull. Mar. Sci. 32, 86–98.					
18	Lefcheck J S, Whalen M A, Davenport T M, Stone J P, Duffy J E (2013) Physiological effects					
19	of diet mixing on consumer fitness: a meta-analysis. Ecology 94, 565–572.					
20	Li M, Zhang C, Xu B, Xue Y, Ren Y (2017) Evaluating the approaches of habitat suitability					
21	modelling for whitespotted conger (<i>Conger myriaster</i>). Fish Res 195, 230–237.					
22	Liu D, Wang F, Lu Y, Hu N, Su X, Liu J, Zhu B (2019) Behavioral mechanisms of swimming					
23	crab (Portunus trituberculatus) preying on Manila clams (Ruditapes					

1	philippinarum): effects of substrate and competition. Mar Biol 166, 15.				
2	https://doi.org/10.1007/s00227-018-3461-5				
3	Logerwell E A, Hargreaves N B (1996) The distribution of sea birds relative to their fish				
4	prey off Vancouver Island: opposing results at large and small spatial scales. Fish				
5	Oceanogr 5, 163–175.				
6	Luan J, Zhang C, Xu B, Xue Y, Ren Y (2018) Modelling the spatial distribution of three				
7	Portunidae crabs in Haizhou Bay, China. PloS One 13, e0207457.				
8	MacArthur R H, Pianka E R (1966) On optimal use of a patchy environment. Am Nat 100,				
9	603–609.				
10	Mac Nally R (2000) Regression and model-building in conservation biology,				
11	biogeography and ecology: the distinction between-and reconciliation of-				
12	'predictive'and 'explanatory'models. Biodivers. Conserv. 9, 655–671.				
13	Maggioni M, Romero M A, Ocampo-Reinaldo M (2010) Campaña Recursos Demersales				
14	2009 (REDE 09). Estimación de la biomasa y estructura poblacional de la merluza				
15	común (<i>Merluccius hubbsi</i>) en el Golfo San Matías. (Informe Técnico No. N°				
16	01/10). Instituto de Biología Marina y Pesquera "Almirante Storni."				
17	Magurran A E, McGill B J (Eds.) (2011) Biological diversity: frontiers in measurement and				
18	assessment. Oxford University Press, Oxford ; New York.				
19	Maxwell D L, Stelzenmüller V, Eastwood P D, Rogers S I (2009) Modelling the spatial				
20	distribution of plaice (Pleuronectes platessa), sole (Solea solea) and thornback				
21	ray (<i>Raja clavata</i>) in UK waters for marine management and planning. J Sea Res				
22	61, 258–267.				

1	Méléder V, Populus J, Guillaumont B, Perrot T, Mouquet P(2010) Predictive Modelling
2	of Seabed Habitats: Case Study of Subtidal Kelp Forests on the Coast of Brittany,
3	France. Mar Biol 157 (7) 1525–1541.

5 Melo G A S de (2010) The Brachyura (Crustacea: Decapoda) collected by the GEDIP 6 project between Torres, Rio Grande do Sul (Brazil) and Maldonado (Uruguay). 7 Moran P A (1950) Notes on continuous stochastic phenomena. Biometrika 37, 17–23. 8 Narvarte M, González R, Medina A, Avaca M S (2011) Artisanal dredges as efficient and 9 rationale harvesting gears in a Patagonian mussel fishery. Fish Res 111, 108–115. 10 Ocampo-Reinaldo M (2005ª) Campaña Recursos Demersales I 2004 (REDE I – 2004). 11 Informe preliminar: Estimación de biomasa y estructura poblacional de merluza 12 (Merluccius hubbsi). (Informe Técnico No. N° 02-2005). Instituto de Biología 13 Marina y Pesquera "Almirante Storni." 14 Ocampo-Reinaldo M (2005b) Campaña Recursos Demersales I 2005 (REDE I – 2005). 15 Informe preliminar: Estimación de biomasa y estructura poblacional de merluza 16 (Merluccius hubbsi) (Informe Técnico No. N°31/2005). Instituto de Biología

17 Marina y Pesquera "Almirante Storni."

Ocampo-Reinaldo M, Maggioni M, Gavenszky M (2008) Campaña Recursos Demersales
 2007 (REDE 2007). Estimación de biomasa y estructura poblacional de merluza
 común (*Merluccius hubbsi*) en el Golfo San Matías (Informe Técnico No. N°
 08/2008.). Instituto de Biología Marina y Pesquera "Almirante Storni."

- 22 Oksansen J, Blanchet G, Friendly M, Kindt R, Legendre P, McGlinn D, Minchin P R, et al.
- 23 Vegan: Community Ecology Package (version R package version 2.5-6), 2019.
- 24 https://CRAN.R-project.org/package=vegan.

1	Paine R T (2010) Macroecology: Does It Ignore or Can It Encourage Further Ecological		
2	Syntheses Based on Spatially Local Experimental Manipulations? (American		
3	Society of Naturalists Address). Am Nat 176, 385–393.		
4	Pauly D (1995) Anecdotes and the shifting baseline syndrome of fisheries. Trends Ecol		
5	Evol 10, 430.		
6	Pebesma E J (2004) Multivariable geostatistics in S: the gstat package. Comput Geosci		
7	30, 683–691.		
8	Pierrat B, Saucède T, Laffont R, De Ridder C, Festeau A, David B (2012) Large-scale		
9	distribution analysis of Antarctic echinoids using ecological niche modelling. Mar		
10	Ecol Prog Ser 463, 215–230.		
11	Pulliam H R (1975) Diet optimization with nutrient constraints. Am Nat 109, 765–768.		
12	QGIS Development Team (2016) QGIS Geographic Information System. Open Source		
13	Geospatial Foundation.		
14	R Core Team (2018) R: A Language and Environment for Statistical Computing. R		
15	Foundation for Statistical Computing, Vienna, Austria.		
16	Reiss H, Birchenough S, Borja A, Buhl-Mortensen L, Craeymeersch J, Dannheim J, Darr A,		
17	Galparsoro I, Gogina M, Neumann H (2014) Benthos distribution modelling and		
18	its relevance for marine ecosystem management. ICES J. Mar. Sci. 72, 297–315.		
19	Reiss H, Cunze S, König K, Neuman H, Kröncke I (2011) Species distribution modelling of		
20	marine benthos: a North Sea case study. Mar Ecol Prog Ser 442, 71–86.		
21	Reiss H, Kröncke I, Ehrich S (2006) Estimating the catching efficiency of a 2-m beam trawl		
22	for sampling epifauna by removal experiments. ICES J. Mar. Sci. 63, 1453–1464.		
23	Retamal M A (1981) Catálogo ilustrado de los crustáceos decápodos de Chile.		
24	Universidad de Concepción.		

1	Retamal M A, Arana P M (2000) Descripción y distribución de cinco crustáceos				
2	decápodos recolectados en aguas profundas en torno a las islas Robinson Crusoe				
3	y Santa Clara (archipiélago de Juan Fernández, Chile). Investig Mar 28, 149–163.				
4	Rivas A L, Beier E J (1990) Temperature and salinity fields in the north patagonian gulfs.				
5	Oceanol. Acta 13, 15–20.				
6	Robin X, Turck N, Hainhard A, Tiberti N, Lisacek F, Sanchez J C, Müller M (2011) pROC:				
7	an open-source package for R and S+ to analyze and compare ROC curves.				
8	Robinson L M, Elith J, Hobday A J, Pearson R G, Kendall B E, Possingham H P, Richardson				
9	A J (2011) Pushing the limits in marine species distribution modelling: lessons				
10	from the land present challenges and opportunities. Glob Ecol Biogeogr 20, 789–				
11	802. https://doi.org/10.1111/j.1466-8238.2010.00636.x				
12	Schnack E, Aliotta S, Isla F, Lizasoain G (1996) Formas de fondo asociadas a un delta de				
13	reflujo macromareal, San Antonio Oeste, Provincia de Rio Negro, Argentina.				
14	Thalassas 12, 121–135.				
15	Schoeman D S, Cockcroft A C (1993) On the misidentification of a common sandy beach				
16	crab belonging to the genus Ovalipes Rathbun, 1898. Afr Zool 28, 124–125.				
17	Schwemmer P, Güpner F, Adler S, Klingbeil K, Garthe S (2016) Modelling small-scale				
18	foraging habitat use in breeding Eurasian oystercatchers (Haematopus				
19	ostralegus) in relation to prey distribution and environmental predictors. Ecol				
20	Model 320, 322–333.				
21	Serrano A, Preciado I, Abad E, Sánchez F, Parra S, Frutos I (2008) Spatial distribution				
22	patterns of demersal and epibenthic communities on the Galician continental				
23	shelf (NW Spain). J Mar Syst 72, 87–100.				

1	SHN (2000) Carta H-214, De Faro Segunda Barranca a Faro Punta Bajos, Servicio de						
2	Hidrografía Naval Argentino, Buenos Aires.						
3	SHN (1974) Sedimentología de la Plataforma Continental Argentina. Servicio de						
4	Hidrografía Naval Argentino Publ H. 669/1.						
5	Shelton A O, Thorson J T, Ward E J, Feist B E (2014) Spatial semiparametric models						
6	improve estimates of species abundance and distribution. Can J Fish Aquat Sci						
7	71, 1655–1666. https://doi.org/10.1139/cjfas-2013-0508						
8	Snickars M, Gullström M, Sundblad G, Bergström U, Downie A L, Lindegarth M, Mattila J						
9	(2014) Species-environment relationships and potential for distribution						
10	modelling in coastal waters. J Sea Res 85, 116–125.						
11	Somerton D A, Weinberg K L, Goodman S E (2013) Catchability of snow crab						
12	(Chionoecetes opilio) by the eastern Bering Sea bottom trawl survey estimated						
13	using a catch comparison experiment. Can. J. Fish. Aquat. Sci. 70, 1699–1708.						
14	Stewart B D, Jones G P (2001) Associations between the abundance of piscivorous fishes						
15	and their prey on coral reefs: implications for prey-fish mortality. Mar Biol 138,						
16	383–397.						
17	Svendsen G M, Romero M A, Williams G N, Gagliardini D A, Crespo E A, Dans S L, González						
18	R A (2015) Environmental Niche Overlap between Common and Dusky Dolphins						
19	in North Patagonia, Argentina. PLOS ONE 10, e0126182.						
20	https://doi.org/10.1371/journal.pone.0126182						
21	Torres L G, Read A J, Halpin P (2008) Fine-scale habitat modeling of a top marine						
22	2 predator: do prey data improve predictive capacity. Ecol Appl 18, 1702–1717.						

1	Trainor A M, Schmitz O J (2014) Infusing considerations of trophic dependencies into
2	species distribution modelling. Ecol Lett 17, 1507–1517.
3	https://doi.org/10.1111/ele.12372
4	Turner H V, Wolcott D L, Wolcott T G, Hines A H (2003) Post-mating behavior, intramolt
5	growth, and onset of migration to Chesapeake Bay spawning grounds by adult
6	female blue crabs, Callinectes sapidus Rathbun. J. Exp. Mar. Biol. Ecol. 295, 107–
7	130.
8	Van Engel W A (1958) The Blue crab fishery and its fishery in Chesapeake Bay. Part 1 -
9	Reproduction, early development, growth, and migration. Commer. Fish. Rev.
10	20, 6–17.
11	Van Hoey G, Degraer S, Vincx M (2004) Macrobenthic community structure of soft-
12	bottom sediments at the Belgian Continental Shelf Estuar Coast Shelf Sci 59, 599–
13	613.
14	Vinuesa J H (2005) Distribution of decapod and stomatopod crustaceans from San Jorge
15	Gulf, Argentina. Rev Biol Mar Oceanogr 40, 7.
16	Vølstad J H, Sharov A F, Davis G, Davis B (2000) A method for estimating dredge catching
17	efficiency for blue crabs, Callinectes sapidus, in Chesapeake Bay.
18	Weatherdon L V, Ota Y, Jones M C, Close D A, Cheung W W L (2016) Projected Scenarios
19	for Coastal First Nations' Fisheries Catch Potential under Climate Change:
20	Management Challenges and Opportunities. PLOS ONE 11, e0145285.
21	https://doi.org/10.1371/journal.pone.0145285
22	Williams G, Sapoznik M, Ocampo-Reinaldo M, Solis M, Narvarte M, González R, Esteves
23	J L, Gagliardini D (2010) Comparison of AVHRR and SeaWiFS imagery with fishing
24	activity and in situ data in San Matías Gulf, Argentina. International Journal of

1	1 Remote Sensing, 31: 17,	4531	—	4542.				
2	https://doi.org/10.1080/01431161.2010.485218							
3	Wilson W H (1990) Competition and Predation in Marine Soft-Sediment Communities.							
4	4 Annu Rev Ecol Syst	21,	:	221–241.				
5	https://doi.org/10.1146/annurev.es.21.110190.001253							
6	Woodin S A (1983) Biotic interactions in recent marine sedimentary environments, in:							
7	Biotic Interactions in Recent and Fossil Benthic Communities. Springer, pp. 3–38.							
8	Zainal K, Noorani A (2019) Temperature Dependence of the Heart Rates in the Blue							
9	9 Swimming Crab <i>Portunus segnis</i> (Forskal, 1775). Arab	Swimming Crab <i>Portunus segnis</i> (Forskal, 1775). Arab. J. Sci. Eng. 1–7.						
10	10 Zarnetske P L, Skelly D K, Urban M C (2012) Biotic multipliers	s of climate	e change	. Science				
11	11 336, 1516–1518.							
12	12 Zhang C I, Ault J S, Endo S (1993) Estimation of dredge sampl	ling efficier	ncy for b	lue crabs				
13	13 in Chesapeake Bay. Korean J. Fish. Aquat. Sci. 26, 369	9–379.						
14	14 Zuur A F, Ieno E N, Elphick C S (2010) A protocol for data ex	ploration t	o avoid	common				
15	15 statistical problems. Methods Ecol. Evol. 1, 3–14.							
16	16 Tables							
17	17 Table 1: Parameter likelihoods, estimates and 95% confide	ence interv	al limit	s (CL) for				
18	18 explanatory variables describing variation in (a) proba	explanatory variables describing variation in (a) probability of presence of O.						
19	19 <i>trimaculatus</i> , and (b) biomass density given that it is present	trimaculatus, and (b) biomass density given that it is present. Explanatory variables with						
20	CL excluding zero are in bold.							

Response	Explanatory	Parameter	Parameter estimate ±	CL	
variable	variable	likelihood	SE	Lower	Upper
(a)					
Presence of	Intercept		5.22 ± 7.44	-9.37	19.81

O. trimaculatus	Substrate (Sand)	1	-19.04 ± 1679.76	-3311.31	3273.24
	Substrate (Gravel)	1	-1.07 ± 0.71	-2.47	0.32
	Substrate (Silt)	1	-0.57 ± 0.57	-1.69	0.56
	Depth	1	-0.04 ± 0.02	-0.08	-0.00
	Richness	0.59	-0.04 ± 0.05	-0.16	0.01
	SST	0.38	-0.28 ± 0.55	-2.06	0.59
(b)					
Biomass of	Intercept		-2.60 ± 4.07	-10.58	5.37
O. trimaculatus	Depth	1	-0.03 ± 0.01	-0.06	-0.01
	Prey biomass	1	0.04 ± 0.02	0.01	0.07
	SST	0.47	0.23 ± 0.31	-0.06	1.02
	Evenness	0.46	-0.42 ± 0.56	-1.87	0.06
	Slope	0.11	0.04 ± 0.14	-0.27	0.93

2 Figures



Figure 1: Sampling stations analyzed. Circles indicate hauls where at least one *O. trimaculatus* was captured; their size is proportional to the biomass of *O. trimaculatus*

captured per area swept. Crosses indicate hauls where *O. trimaculatus* were not
 captured. Areas enclosed by dashed lines are fishing grounds used between 2008 and
 2013. Empty circles on the coast indicate where the vessels are launched.



Figure 2: Predicted biomass density of *O. trimaculatus*. The SDM model was
extrapolated between 0 and 60 m depth. Areas enclosed by dashed lines are fishing
grounds used between 2008 and 2013.



Figure 3: Averaged response curves of the SDM to the predictors. A Response curve to
Evenness (PIE), B response curve to depth, C response curve to prey species richness, D
response curve to seabed slope, E response curve to SST, F response curve to prey
species biomass. Grey ribbons represent standard errors.