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Original Article

Incorporating landscape metrics into invertebrate fisheries management: case study of the gooseneck barnacle in Asturias (N. Spain)

Antonella Rivera[1]*, Stefan Gelcich[2], Lucía García-Flórez[3], and José Luis Acuña[1]

[1]*Departamento de Biología de Organismos y Sistemas, Universidad de Oviedo, Oviedo, Spain*
[2]*Departamento de Ecología, Center of Applied Ecology and Sustainability (CAPES) & Centro de Conservación Marina, Pontificia Universidad Católica de Chile, Santiago, Chile*
[3]*Centro de Experimentación Pesquera, Consejería de Desarrollo Rural y Recursos Naturales del Principado de Asturias, Gijón, Spain*

**Corresponding author: tel: +34 985 10 6261; e-mail: antonellarivera.p@gmail.com*

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Landscape components can affect all the important biological processes of invertebrate populations, including their harvest quality, yet they are rarely considered in fisheries management frameworks. Here, we explore landscape, economic and ecologic variables to demonstrate that landscape metrics can be a valuable component in the management of sessile invertebrate fisheries. We developed a map-derived model that links landscape variables with the quality of a fishing resource, using five topographical variables—coastal convexity, orientation, complexity, exposure, and distance from the coast—all but the latter were tested at 23 different spatial scales. The model was ground-truthed using the case study of the gooseneck barnacle fishery in Asturias (N. Spain). Distance from the coast, coastal convexity on a scale of 25 km and exposure on a scale of 1 km appear to be driving the quality of the resource. Our model can predict high-quality gooseneck barnacle fishing zones with 72% accuracy. Moreover, we used a 10-year time-series of gooseneck barnacle landings and sales to analyse the impact of quality on the fishery. Fishers have a bias towards harvesting high-quality gooseneck barnacles, which are sold at higher market values. Thus, quality directly affects landings and sales. Our results highlight the interest of incorporating landscape metrics in fisheries management to generate and support spatially explicit conservation and exploitation policies.

Keywords: co-management, fishery, gooseneck barnacle, landscape metrics, quality.

Introduction

Marine and coastal systems are profoundly impacted by anthropogenic activities (Halpern *et al.*, 2008), particularly by overfishing (Jackson *et al.*, 2001). This overexploitation is reducing large long-lived fish while simultaneously increasing invertebrate populations (Pauly *et al.*, 2002). This trend has also been accompanied by increased harvest of invertebrates (FAO, 2012) and the development of new marine invertebrate fisheries (Perry *et al.*, 1999). Nevertheless, invertebrate fisheries have not received the attention they deserve. Stock assessments and management models for invertebrates continue to lag behind those developed for finfish (Orensanz and Jamieson, 1998). Paradoxically, invertebrate demand and market value continue to increase, jeopardizing their sustainability (Castilla and Defeo, 2001). The economic value of invertebrates is generally dependent on morphological traits that determine their market desirability [e.g. mussels (Kunz, 1893; Dolmer and Frandsen, 2002), sea urchins (McBride *et al.*, 2004) and sea cucumbers (Conand and Byrne, 1993)]. These traits can be referred to as *quality of the resource*.

Fisheries managers have recognized the importance of habitat on yield and quality of the resource (Taylor *et al.*, 2002). This is particularly important for invertebrate sedentary species where all the main processes of the fisheries tend to have a spatial component (Caddy, 1989) that influences their distribution, abundance (Underwood and Chapman, 1996), and quality (Caddy and Defeo, 2003). Furthermore, fishing strategy will also be influenced by landscape features, since areas with higher densities (Caddy, 1989) or larger size classes (Caddy, 1972) will receive more fishing pressure. Therefore, the inclusion of landscape ecology in invertebrate fisheries may represent a step towards integrated ocean management (Kappel *et al.*, 2012).

Nonetheless, the incorporation of landscape metrics in the aquatic and coastal realm is not up to par with terrestrial systems (Pittman *et al.*, 2011), particularly in directly linking habitat preferences and landscape effects to fisheries management. The effect of habitat on species abundance, diversity and productivity has been incorporated in fisheries research through typifying habitats, identifying areas of primary productivity, determining oceanographic structures (such as currents, upwelling, and eddies) and identifying the effects of human activity (Taylor *et al.*, 2002). However, due to technological difficulties even typifying these landscapes continues to be a costly endeavour (Zajac, 2008). Thus, it is imperative for researchers to develop simple, low cost tools that can facilitate the incorporation of landscape metrics in fisheries management.

The gooseneck barnacle (*Pollicipes pollicipes*) fishery in Asturias (N. Spain) provides an ideal case study to examine landscape effects on resource quality and its influence on the fishery. The gooseneck barnacle is a cirripede that inhabits intertidal cliffs with high wave exposure (Barnes, 1996). This fishery has been successfully co-managed for the past 20 years (Rivera *et al.*, 2015). Economic returns for high-quality individuals of the species in the area have reached values of over 250 euros/kg (Rivera *et al.*, 2014). Similar high market values have been known to drive luxury species close to extinction (Purcell *et al.*, 2014). Therefore, it is important to assess the effects of quality on the gooseneck barnacle exploitation rate and the drivers for these differences. Population analyses have found no significant genetic differences among low- and high-quality phenotypes (Campo, 2006; Quinteiro *et al.*, 2006). Thus, the source of this variability continues to puzzle scientists. Previous studies in the Cantabrian Sea have observed an effect of wave exposure on gooseneck barnacle biomass (Borja *et al.*, 2006). We hypothesize that landscape metrics can help pinpoint the causes of variability in gooseneck barnacle phenotypes.

We used a simple, map-based, low cost method to measure five landscape properties (coastal orientation, convexity, complexity, distance, and exposure) at 23 different spatial scales and assessed their relationship with the quality of gooseneck barnacles. These data were used to formulate and validate a predictive model of gooseneck barnacle quality. We then examined a 10-year time-series of gooseneck barnacles landings and sales in Asturias to appraise the socio-economic value of quality differences on the fishery. Here, we test the efficacy of landscape metrics in predicting gooseneck barnacle quality and consider the management implications of the results as a way to highlight the importance of landscape metrics in the management of invertebrate fisheries.

Material and methods

Study area

The gooseneck barnacle co-management system in Asturias (N. Spain) is located between the Eo estuary (7.035831 W, 43.529291 N) and Cape Peñas (5.770935 W, 43.689880 N), covering a coastline of roughly 200 km along the Cantabrian Sea (Figure 1). The fishery has been co-managed for the past 20 years by the fishers' associations and the local government (Rivera *et al.*, 2014). The system is divided into seven management regions known as *plans*, which are subdivided into 256 fishing zones categorized according to the quality of barnacles they render (Figure 1).

We used a regional, 1:5000 coastline cartography (*Cartografía base del Principado de Asturias*) to estimate the topographic variables. This cartography was reprojected from the European Datum 1950 (ED50) to the World Geodetic System (WGS 84) using the *rgdal* package (Keitt *et al.*, 2011) in R computing software (R Development Core Team, 2012).

Gooseneck barnacle quality

A characterization of gooseneck barnacle quality and size was given by Molares *et al.* (1987). Barnacles with an elongated peduncle are categorized as a low-quality resource and those with a short and wide peduncle are considered of high quality. Since the inception

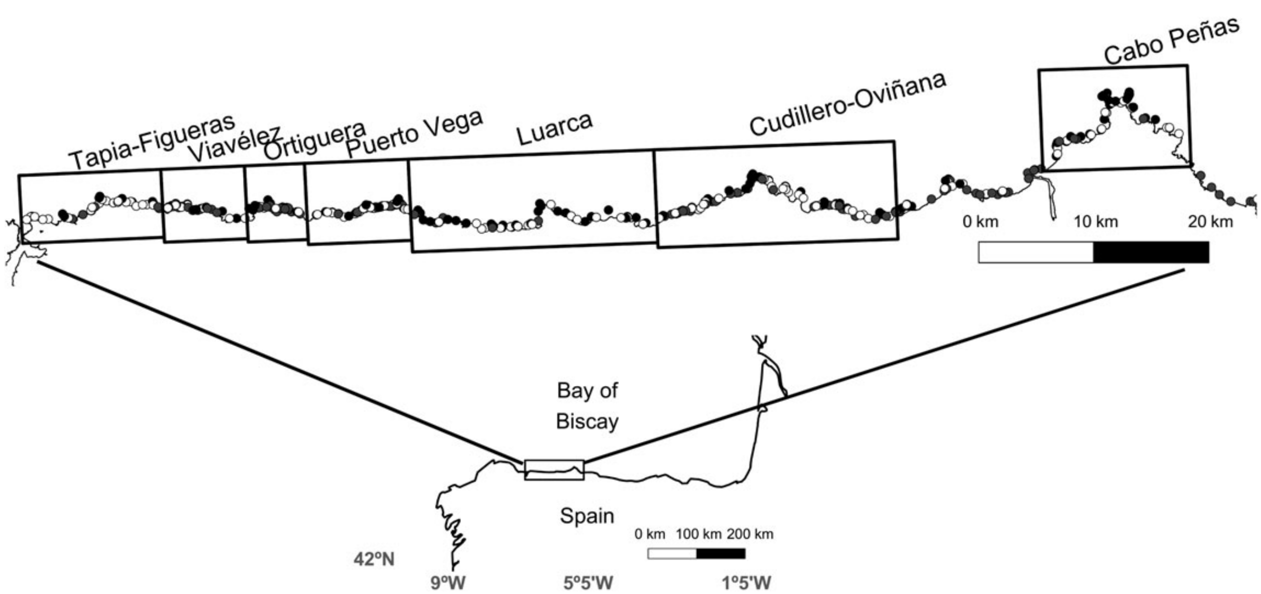

Figure 1. Map of the Asturian gooseneck barnacle co-management system. High-, intermediate-, and low-quality fishing zones are represented by black, light grey, and white circles, respectively. The management regions (*plans*) are represented by squares.

of the gooseneck barnacle fishery in Asturias, the quality for each fishing zone was classified in three ranks (high, intermediate, or low). This classification was determined through fishers' knowledge based on the economic value of the barnacles yielded by each fishing area. Scientists systematized fishers' knowledge of fishing site quality, using a GIS system and information from experts in the area (i.e. fishers and surveillance officers). This was incorporated into the *Principado de Asturias Coastal and Marine Geographic Information System* (Alcázar-Álvarez *et al.*, 2008). We corroborated these differences by sampling 990 individuals of commercial size [13.7 mm rostro-carina length (Cruz *et al.*, 2010)] in high-, intermediate-, and low-quality zones. We used a Kruskal–Wallis one-way analysis of variance by ranks test to detect significant differences in rostro-carina length among qualities. For *post hoc* comparisons, a Dunn's test was applied.

Modelling fishing zone quality

Landscape metrics

Our hypothesis, based on fishers' knowledge, was that wave-beaten areas would render higher quality barnacles. Therefore, we chose to analyse five quantitative, map-derived, coastal topography metrics that affect an areas' exposure to wave action, these are: distance from the coast, orientation, convexity, exposure, and complexity (using the fractal dimension of the coastline as a proxy). These metrics were analysed for the 256 fishing areas. Choosing a fixed spatial dimension to analyse landscape variables can be arbitrary, due to their heterogeneous nature. Therefore, we considered these variables at multiple scales (Wu and Qi, 2000). Thus, orientation, convexity, exposure, and complexity were assessed at 23 different spatial scales: 0.2, 0.3, 0.5, 0.6, 0.75, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 15, 17.5, 20, 22.5, 25, 27.5, and 30 km based on the extent of our study area. The scale with the best fit was incorporated into the full model selection. The first step was to find the centroid (centre of mass) for each area. We calculated the distance from the centroid to its nearest neighbour on the coastline using a *k*d-tree (Arya *et al.*, 1998) and included it as a continuous variable in our analyses. If the area was an island, the nearest point on the mainland was selected (using the same nearest neighbour methodology) to calculate the other landscape metrics. A circle was generated around the centroid, with a diameter corresponding to the scale of choice. Next, we selected the two intersection points between the circumference and the coastline (A and B) and a straight line was drawn between them (line A–B; see Supplementary Figure S1). The orientation of the area is determined by the angle between the perpendicular to line A–B and the E–W line; angles of 180° and 0° indicate a purely westward or eastward orientation, respectively. The convexity of an area is estimated by the difference between the total surface of land above the A–B line minus the total surface of water between the A–B line and the coastline; convex coastlines are indicated by positive values and concave coastlines by negative values. Exposure was estimated as the total area of water surrounding the centroid for each fishing area (considering islands or coastline).

We used fractal dimension as a proxy for coastal complexity. The fractal dimension is a ratio that captures the change in perimeter length and detail in a pattern of an object as a function of the scale of measurement (Mandelbrot, 1967), hence the larger the fractal dimension the greater the complexity of the coast. We determined the fractal dimension of each fragment of coastline through the *box-counting* methodology employed in Wahl *et al.* (1994). First, a 2000 × 2000 matrix was generated from a raster layer of the fragment of coastline at each spatial scale. Second, a regular grid made up of boxes of size R was superimposed on the matrix. We used a matrix instead of a two-dimensional image to ensure reproducibility of our analyses. The number of boxes that include the coastline (N) was counted. The procedure is repeated the maximum number of times admissible for our chosen matrix size (20) with boxes of decreasing size. A linear regression is carried out with the results of our box-counting repetitions using the formula:

$$\log\ N_i = \alpha + \log\frac{1}{R_i}\beta + \varepsilon_i, \quad (1)$$

where N is the number of boxes, R is box size, β is the fractal dimension of our coastline fragment, α is the intercept, and ϵ is the error.

All sampling metrics were continuous variables. These were programmed using R 2.15.3 computing software (R Development Core Team, 2012).

Statistical analyses

Fishing zone quality was analysed using a proportional-odds logistic multiple regression model with R packages *rms* (Harrell, 2013) and *MASS* (Venables and Ripley, 2002). The proportional odds model can be written as

$$\log\left(\frac{P_j^i}{1-P_j^i}\right) = \alpha_j + \beta X^i, \quad (2)$$

where P_j^i is the probability of a fishing site i being in rank category j or lower, α is the intercept which determines the cut-off point between rank categories of j and β is the slope for explanatory variables X, of fishing zone quality, for each fishing site i ($X^i = X_1^i + X_2^i + \cdots + X_n^i$). Thus, intercepts depend on j but slopes are all equal. The proportional-odds assumption was tested by a likelihood ratio test of equal slopes with the package *ordinal* (Christensen, 2012). Multicollinearity between variables was also assessed.

To avoid overfitting, only the most representative scale for each variable was selected. We carried out regression models for each scale, using a single explanatory variable, and a null model that only includes an intercept, which reflects no dependence of gooseneck barnacle quality on the explanatory variable. We explored the fit of the regression models using the estimated generalized R^2 (Nagelkerke, 1991). A Bonferroni correction was applied to avoid type I error. Model selection was performed using Akaike information criterion (AIC) and Akaike weights (AICWt; Burnham and Anderson, 2002). The most suitable scale was then incorporated into a model selection using all explanatory variables. Once the optimal model using all explanatory variables was selected, the spatial autocorrelation of the residuals was analysed using Moran's I coefficient for equal distance classes. The fitted category probabilities (Fox, 2009) of each term in the optimal model were calculated. All graphical displays were plotted using the *ggplot2* package (Wickham, 2009).

Model validation

The apparent performance of our optimal model was assessed by fitting a prediction model with the *rms* package (Harrell, 2013) using the entire dataset. We looked at R^2 and Somers' D_{xy} rank correlation coefficient (Somers, 1962) as summary measures of the model's performance.

To address the predictive accuracy of the model, we employed Ten-fold cross-validation. Ten-fold cross validation (Geisser, 1975) was carried out by splitting our dataset into 10 random groups (folds) that preserved the overall class distribution. In each fold, 90% of the data were used to generate a predictive model and the other 10% were used to evaluate the model estimates. Confusion matrices, a matrix that cross-tabulates information on the actual values against the predicted classifications (Kohavi and Provost, 1998), were generated for each fold using the *caret* package (Kuhn *et al*., 2012). A total confusion matrix was calculated by adding the values in the individual matrices. The total confusion matrix identified the true positive rate (sensitivity), true negative rate (specificity), balanced accuracy (average between sensitivity and specificity for each class), and total accuracy (proportion of correct predictions).

Effects of barnacle quality on the fishery

To understand the effect of quality on landings, yearly landings data for 2001–2011 were analysed for 222 fishing zones in the Asturias gooseneck barnacle co-management system. Landings were separated according to their quality and were standardized based on their coast length. A one-way analysis of variance (ANOVA) was used to test for differences between gooseneck barnacle qualities in landings per kilometre.

Daily gooseneck barnacle sales data for the 17 main fish markets in Asturias were collected from 2001 to 2011. The mean yearly price per kilogram range and its standard error was calculated, considering daily minima and maxima. The spread of daily values in price per kilogram is attributed to the quality of the resource.

Results

Corroboration of gooseneck barnacle's fishing site quality classification

We tested the quality classifications established using fishers' knowledge by analysing the differences in rostro-carina length among qualities. Significant differences related to quality were found (Kruskal–Wallis; χ^2: 14.46, d.f.: 2, $p < 0.0001$). According to *post hoc* Dunn's tests, these differences were more pronounced between the high and low classes and intermediate and low classes (both $p < 0.001$) than between high and intermediate (p: 0.07). Therefore, the classification into three different qualities appears reliable.

Modelling fishing zone quality

We analysed the individual effect of five landscape variables (distance to the coast, exposure, convexity, complexity, and orientation) on gooseneck barnacle quality. The scale on which four of these variables (exposure, convexity, complexity, and orientation) could affect quality was unknown. Thus, we tested their effect at 23 different scales. AIC model selection showed that optimal scales were 1 km for exposure (*AICWt*: 0.38; R^2: 0.21; $p < 0.0001$), 25 km for convexity (*AICWt*: 0.71; R^2: 0.05; p: 0.02), and 30 km for complexity (*AICWt*: 0.78; R^2: 0.06; p: 0.004). For more information on the coefficient of determination for the different scales, see Supplementary Figure S2. There was no effect of orientation over quality since the null model was selected as the best model. We used these three variables at their corresponding scales and distance from the coast for our global model selection.

For the global model selection, 21 models were considered (Supplementary Table S1). The model with the highest explanatory power takes into account distance, convexity, and exposure without any interactions (*AICWt*: 0.31; R^2: 0.39 and $p < 0.0001$). No significant spatial autocorrelation was detected. Exposure at a 1 km scale was very variable and no clear spatial patterns can be observed (Figure 2). Convex zones at a 25 km scale are generally found towards the eastern zone of our study area in Cape Peñas. On the contrary, concave zones were observed in the western and central areas of the coast (Figure 2).

According to our model, areas that are convex, highly exposed and further from the coast will have a greater probability of being in the higher quality rank and concave, protected areas on the coastline are more likely to hold gooseneck barnacle of a lower quality rank (Figure 3; Table 1). The probability of observing intermediate zones decreases in convex, exposed areas separated from the coast but this decrease is not as pronounced as in lower quality areas. Additionally, intermediate areas exhibit concave coastlines (Figure 3A).

The model was supported and statistically significant ($p < 0.0001$) according to cross-validation analysis. The confusion matrix of predicted vs. actual classes is presented in Supplementary Figure S3. The overall accuracy was 0.56 with 95% confidence intervals of 0.5 and 0.62. Sensitivity estimates were higher for the intermediate and high-quality ranks and specificity was higher for the low and high ranks (Table 2). The model displays predictive capacity for all ranks (balanced accuracy >0.6), in particular the high-quality rank (balanced accuracy: 0.72; Table 2).

Effect of barnacle quality on the fishery

Seasonal landings per quality were standardized by kilometre to homogenize the productivity of all areas. Standardized landings were analysed for 222 fishing zones in the Asturian gooseneck barnacle co-management system. Significant differences where found among the three qualities (one-way ANOVA F_2: 103.5, $p < 0.001$;

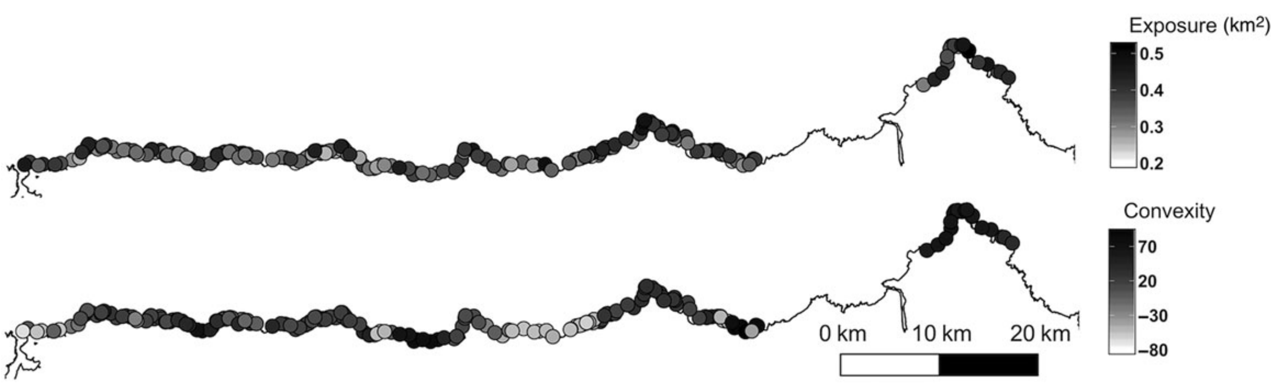

Figure 2. Map of the Asturian coast showing values for exposure at a 1 km scale (upper panel) and convexity at a 25 km scale (lower panel).

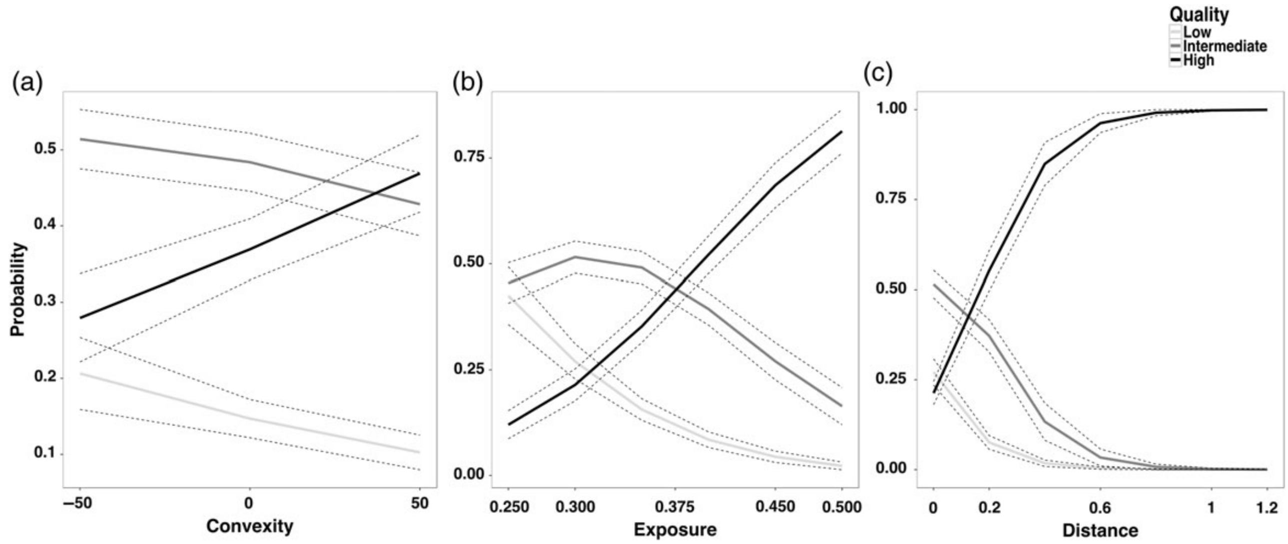

Figure 3. Model estimated fitted category probabilities for convexity at a 25 km scale (a), exposure at 1 km scale (b), and distance to coast (c). Black, grey, and white lines represent high, intermediate, and low classes of barnacle quality, respectively.

Table 1. Predictor variables in the best model with their coefficient and significance.

	Predictor	Coefficient	$P(\chi)$
Quality			
$\alpha_{\text{Intermediate}\mid\text{High}} = 6.50$	Convexity	0.0082	0.022
$\alpha_{\text{Low}\mid\text{Intermediate}} = 4.21$	Distance	7.5893	<0.0001
	Exposure	13.85	<0.0001

The variable α indicates the cut-point between classes.

Table 2. Sensitivity, specificity, and balanced accuracy for each class of fishing zone quality based on the cross-validation of the optimal model.

	Sensitivity	Specificity	Balanced accuracy
Low	0.32	0.92	0.62
Intermediate	0.66	0.54	0.6
High	0.6	0.84	0.72

Figure 4A). Most landings are obtained from high-quality fishing zones, followed by intermediate and low-quality zones, indicating fishers concentrate their effort in high-quality areas. Furthermore, daily landings data for all fish markets showed an ample price per kilogram range, with a daily difference of 147.85€ per kilogram in 2001 up to 265.2€ in 2007 (Figure 4B). Therefore, quality of the resource exerts an effect upon market value and effort distribution.

Discussion

Our results show how gooseneck barnacle quality can be modelled using five landscape metrics, which were assessed at 23 different spatial scales. Our model indicates that higher gooseneck barnacle qualities will be present in areas that are highly exposed at a small, 1 km scale, convex at a 25 km scale, and further away from the coast. Additionally, we analysed a 10-year time-series of gooseneck barnacle landings and sales in Asturias. Both datasets appear affected by the quality of the individual barnacles, indicating the importance of this attribute in the effort placement and revenue of the fishery. These findings may bear important implications for the sustainable management of this and other invertebrate fisheries, such as the need for spatially explicit ban and effort distribution.

Phenotypic plasticity and scale

Our model reflects the influence of landscape variables on gooseneck barnacle quality. There is a 75% probability of encountering high-quality barnacles in exposed and convex areas (Figure 3B). Furthermore, in our study area, fishing zones located at a distance of ca. 700 m or more from the coast will coincide with high-quality gooseneck barnacles. All variables are likely reflecting the effect of wave action on gooseneck barnacle morphology. To our knowledge, this is the first time the effect of topography is directly modelled for gooseneck barnacle quality. Nevertheless, Parada *et al.* (2012) observed a relationship between gooseneck barnacle typologies and type of coastline. It is not uncommon to relate wave exposure to a species' biomass or distribution (Borja *et al.*, 2006; Burrows *et al.*, 2008). Many of these models use complex simulation tools to determine marine climate parameters such as wave propagation, fetch, and wind intensity. Wind direction and intensity were not accounted for in our study, which could improve our model's accuracy. Nonetheless, considering the 1 km scale on which exposure affects an areas' quality it is unlikely that the effect of the wind will have a profound influence on the outcome of the model. Furthermore, wind characteristics are more complex to model and data are not always available. Instead, the use of simple map-derived variables, such as the ones used here, will facilitate the assimilation of landscape metrics in public management agencies for this and other invertebrate fisheries.

The influence of wave action on gooseneck barnacle quality is not surprising considering their quality is determined by the amount of mass in their peduncle (Molares *et al.*, 1987). This would imply that barnacles require short and wide peduncles to withstand wave action. A similar response is observed in alpine plants, which grow shorter when affected by persistent winds (Billings and Mooney, 1968). Furthermore, barnacles develop shorter cirri in wave-beaten areas possibly as a means to prevent damage (Marchinko and Palmer, 2003). According to fishers' knowledge in the Canadian

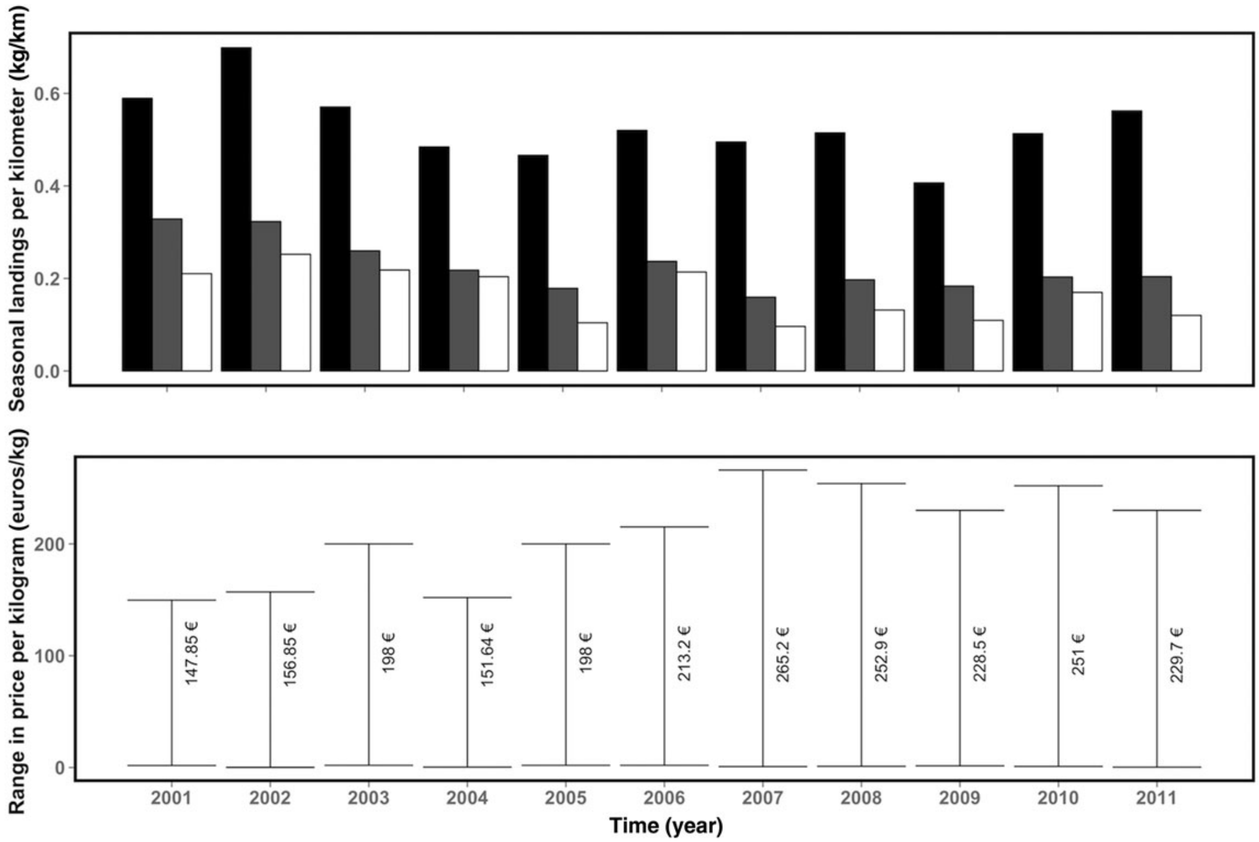

Figure 4. Landings and sales differences in quality for 2001–2011. (a) Seasonal landings per kilometre divided by quality classes high (black), intermediate (grey), and low (white). (b) Range in price per kilogram. Bottom hinge represents the minimum value and top hinge the maximum value. The total difference between these values is presented at the right of each bar.

Pollicipes polymerus fishery, body shape and size in this species could vary with wave exposure. Seeing that no genetic differences among phenotypes were found (Campo, 2006; Quinteiro *et al.*, 2006) this would indicate a phenotypic plasticity in the species, a characteristic which has been linked to the resilience of fished populations (Healey, 2009).

It is important to highlight that exposure and convexity affect the gooseneck barnacle quality at different spatial scales (1 and 25 km, respectively; Figure 2). The 25 km scale coincides with the geographical feature of Cape Peñas (Figure 2). Thus, the effect of the variables in our model may be context specific. Perhaps the magnitude of their effect will differ in other management areas, which is why it is important to test these effects at multiple scales as was performed in this study. A similar multi-scale effect of exposure was observed on reef fish abundance and biomass (Gust *et al.*, 2001). Notwithstanding varying magnitudes, the processes and variables analysed here will likely exert an effect upon gooseneck barnacle quality in other areas.

Ecological phenomena, including the effect of topographic features on a species morphology (Figure 2), do not occur at a single scale (Levin, 1992). Therefore, multi-scale analyses are essential to understand the dynamics of a species. A mismatch in scales between ecological phenomena and management institutions can compromise the resilience of a socio-ecological system (Cash *et al.*, 2006). For example, in areas where gooseneck barnacles are managed at large spatial scales, the small-scale quality variability is not being considered, which could generate a systematic depletion of the high-quality areas. Fortunately, these multi-scale effects can be detected by incorporating landscape metrics through our simple map-based approach for coastal species, or through seabed mapping for benthic species, and scale appropriate policies can be generated.

Effect of barnacle quality on the fishery

Our standardized catch dataset indicates a clear selectivity towards high-quality barnacles (Figure 4A). Considering, barnacles have a maximum population size driven by space-limited recruitment (Roughgarden *et al.*, 1985; Karlson and Levitan, 1990), we standardized landings per fishing site length to ensure they reflect the effort placed in these areas and not yield. Additionally, the gooseneck barnacle fishery in Asturias applies an individual total allowable catch per fisher of either 6 or 8 kg (depending on the management region) per day during the fishing season (Rivera *et al.*, 2014); therefore, landings are independent from the productivity of each area. Thus, the bias towards high-quality individuals is probably linked to the extreme range across qualities in gooseneck barnacle market prices (Figure 4B). The daily spread in gooseneck barnacle prices can vary up to 265.2 € kg^{-1} (Figure 4B). Therefore, by improving the quality of their product, fishers can increase their revenue (Grafton *et al.*, 2000), this can be achieved by focusing their daily catch limit exclusively to high-quality zones.

Management implications

The incorporation of landscape metrics in fisheries management can aid in both economic and conservation objectives, through the development of spatially explicit management policies (Table 3). The

Table 3. Management implications of our map-based landscape metrics model for the gooseneck barnacle and other invertebrate fisheries.

Context	Management implications
Local gooseneck barnacle fishery	Continue to promote the incorporation of fishers' knowledge in management frameworks
	Continue to protect high quality areas from overexploitation through bans and catch limits
	Continue to match the opening of banned high-quality areas with periods of high market demand
	Continue to increase selectivity of high-quality areas to reduce bycatch
	Create a network of no-take MPAs in areas of low economic relevance (low quality)
Regional and global invertebrate fisheries	Use map-based methodology to identify different fishing sites according to quality
	Classify their management area into fine-scale fishing sites
	Match the scale of the topographic effects with the management scale
	Increase selectivity of high-quality areas to reduce bycatch
	Reduce harvesting costs
	Increase value per unit effort
	Establish spatially explicit bans and catch limits in high-interest areas
	Establish temporally explicit bans and catch limits of high-interest areas so they will coincide with periods of high market demand
	Coupled with species dynamics the model can help determine the location of MPAs in areas of low economic and high ecologic relevance
	Integrate fishers' knowledge in management frameworks

categorization of fishing zones in qualities can help fishers optimize their foraging strategy by selecting high-quality areas. This would reduce harvesting time and costs and increase their economic yield, since high-quality barnacles receive higher market prices (Figure 4). Additionally, the increased selectivity in harvest can help reduce bycatch (Worm *et al.*, 2009). Other coastal invertebrate fisheries, particularly gooseneck barnacle, can also receive these benefits by incorporating our simple landscape-metrics model to classify their fishing sites by quality (Table 3).

One could argue that the economic benefits obtained through the incorporation of landscape metrics will lead to localized harvesting, in our case of the high-quality barnacles, which promotes the overexploitation of the resource and might induce a stock collapse (Hunt *et al.*, 2011). This scenario is unlikely in the Asturian gooseneck barnacle co-management system where the species' ecological processes, particularly larval dispersal scales, and local policies prevent its overexploitation. Cantabrian populations of gooseneck barnacles display larval dispersal scales of 10–50 km (Rivera *et al.*, 2013). Thus, high-quality zones receive a constant input of larvae from neighbouring, less exploited low-quality areas, exhibiting source-sink dynamics (Pulliam, 1988). Low-quality areas are naturally protected from overexploitation due to their low economic value (Figure 4). Therefore, by incorporating landscape metrics to classify fishing zone quality managers can gain insight on areas that can be population sinks or sources. This knowledge can be integrated into management policies by creating a network of no-take marine protected areas (MPA) along the Asturian coastline in low-quality zones (Table 3). This would ensure the persistence of the resource, repopulate high-quality areas and is likely to receive public support considering their main source of income, high-quality areas, remains open.

Besides the implementation of MPAs, other spatially explicit management policies, such as small-scale, spatial, and temporal bans that match the scale of topographic effects (Table 3), can help prevent the overexploitation of the resource and allow the population to recover (Horwood *et al.*, 1998). This strategy is already being employed in the Asturian gooseneck barnacle co-management system, where temporal bans are placed on high-quality fishing zones (Rivera *et al.*, 2014). Moreover, when these closures match market cycles, they can ensure the resource will receive the highest prices possible (Rivera *et al.*, 2014).

For spatially explicit management measures to be effective, they must be carried out at the same ecological or topographical scale that is exerting an effect on the species (Sanchirico and Wilen, 2005). In Asturias, the *plans* are managed at a 10 s of km scale and management of fishing zones through bans is done at a 100 s meter scale (Figure 1), these match those reflected by our model (Figure 2). Therefore, the spatially explicit bans they are currently employing are accurate and can be an essential part to the sustainable catches present in the system (Rivera *et al.*, 2015). Spatially explicit management measures can be included in other sessile invertebrate fisheries through the use of simple map-derived landscape metrics. Nevertheless, we must keep in mind that these small-scale measures are easier to incorporate in co-management systems, where fishers aid in the enforcement of regulations (Rivera *et al.*, 2014). Incorporating these measures in open access fisheries would incur in high enforcement costs. However, these costs might be offset by the financial benefits of increased abundance (Davis *et al.*, 2015).

Finally, our topographic model would not have been possible without the incorporation of fishers' knowledge (Rivera *et al.*, 2014). Our models balanced accuracy, the average accuracy obtained for each class, was higher for low and high than for intermediate quality zones (Table 2). High and low qualities might be easier to differentiate by the fishers but intermediate quality areas are likely a *black box* for areas whose quality cannot be easily defined. Therefore, our model is likely reflecting this variability. Still, the model is effective from a management perspective where harvest and revenue are focused on high-quality areas (Figure 4), which were correctly identified in our model 72% of the times. This highlights the importance of incorporating fishers' and scientific knowledge in an integrated resource management (Mackinson, 2001). The gooseneck barnacle fishery in Asturias incorporates landscape, biological, and socio-economic factors within its management frameworks. This integrated approach aids in the ecological and economic sustainability of the fishery (Rivera *et al.*, 2015).

Conclusions

Through the simple, map-based landscape metrics model presented in this study gooseneck barnacle fisheries can obtain a general approximation of the distribution of high-quality zones which will be much more efficient temporally and economically than a painstaking and costly *in situ* identification of the individual zones.

Nonetheless, these classifications should also be accompanied by management policies to protect areas from overexploitation. Regulations could include the establishment of MPAs and/or spatial and temporal closures (Rivera *et al.*, 2014). Landscape metrics have proved to be a useful tool in determining the scales and drivers of gooseneck barnacle quality. These findings could have a direct application in the spatial management of the resource. Incorporating landscape concepts in sedentary invertebrate fisheries management frameworks is a promising research field, which should continue to be explored in future research.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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