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Identifying fish diversity hot-spots in data-poor situations

Vinícius Prado Fonseca [a], Maria Grazia Pennino [b, c, *], Marcelo Francisco de Nóbrega [d], Jorge Eduardo Lins Oliveira [d], Liana de Figueiredo Mendes [a]

[a] Laboratório do Oceano – LOC, Ecology Department, Federal University of Rio Grande do Norte, Natal, Brazil
[b] Fisheries Ecology, Management and Economics Unit – FEME, Ecology Department, Federal University of Rio Grande do Norte, Natal, Brazil
[c] Instituto Español de Oceanografía, Centro Oceanográfico de Murcia, C/ Varadero 1, San Pedro del Pinatar, 30740, Murcia, Spain
[d] Laboratório de Biologia Pesqueira e Mergulho Científico – LABIPE, Department of Oceanography and Limnology, Federal University of Rio Grande do Norte, Natal, Brazil

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ABSTRACT

One of the more challenging tasks in Marine Spatial Planning (MSP) is identifying critical areas for management and conservation of fish stocks. However, this objective is difficult to achieve in data-poor situations with different sources of uncertainty. In the present study we propose a combination of hierarchical Bayesian spatial models and remotely sensed estimates of environmental variables to be used as flexible and reliable statistical tools to identify and map fish species richness and abundance hot-spots. Results show higher species aggregates in areas with higher sea floor rugosity and habitat complexity, and identify clear richness hot-spots. Our findings identify sensitive habitats through essential and easy-to-use interpretation tools, such as predictive maps, which can contribute to improving management and operability of the studied data-poor situations.

1. Introduction

In recent years there has been increasing demand in marine ecology for more effective Marine Spatial Planning (MSP) to aid conservation and restore sustainable exploitation of marine fisheries (Lubchenco et al., 2003). In fact, about 76% of global fish stocks are already fully exploited or over-fished, and each year billions of unwanted fish and other animals – such as dolphins, marine turtles, seabirds, sharks, and corals - needlessly die from inefficient, illegal, and destructive fishing practices (WWF Global). However, identifying effective areas for efficient management and conservation is a challenging task as habitat requirements and preferences of most species are still poorly understood (Cook and Auster, 2005).

Recently, multiple efforts have been made to identify conservation areas that embrace biodiversity and critical habitats as much as possible and, therefore, protect the ecosystem against unpredicted impacts and potential miscalculations (Sumaila, 2000; Hiscock, 2008; Stelzenmüller et al., 2013; Mouillot et al., 2014). To that end, rather than allocate these conservation areas on a species-specific basis, one could protect areas with more habitat complexity and variability which, in return, tend to shelter more biodiversity (Dalleu et al., 2010). Indeed, habitat variability in terms of different geo-environments, such as seagrass beds and mangroves, can be very important in the marine landscape with respect to particular vulnerable habitats such as coral reefs, because they can influence connectivity and accessibility from the reef (both for fishes that use these habitats for shelter or feeding, and their predators and preys) (Dorenbosch et al., 2007). Reef habitats represent some of the most biologically diverse shallow water marine ecosystems, and numerous species from various taxa largely depend on the reef habitat environments given that their niches are restricted to these habitats (Roberts et al., 2002). Therefore, by preserving reef complex areas and their surroundings, we can increase the chances of protecting various different habitats and conserve additional species that are not necessarily directly related to the reef system (Dalleu et al., 2010). Additionally, reefs are severely threatened by human activities (Carpenter et al., 2008). Threats such as overfishing, pollution, resource extraction, climate change, loss of habitat and invasive species have severe impacts on distribution, abundance and overall health of organisms (Dunn and Halpin, 2009; Mora et al., 2011).

* Corresponding author. Fisheries Ecology, Management and Economics Unit – FEME, Ecology Department, Federal University of Rio Grande do Norte, Natal, Brazil.
E-mail address: graziapennino@yahoo.it (M.G. Pennino).

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In order to protect these areas, quantitative spatially explicit information on reef fish and their surrounding community distributions along with solid knowledge of the relationships with their environment are required (Bellwood et al., 2004; Pennino et al., 2013; Paradinas et al., 2015; Roos et al., 2015). In this context, habitat and species mapping are essential tools as they provide a clear picture of marine resource distribution, which facilitates their conservation management (Guisan et al., 2000). Indeed, habitat suitability models are widely used in both terrestrial and marine systems to quantify species realized niches, species-environment relationships and to predict species occurrence and/or density at un-surveyed locations (Muñoz et al., 2013). Applying these models allows us to characterize species' geographical patterns, identify spatial ontogenetic shifts of commercially exploited fish species (Lauria et al., 2015b), and to test the effect of climate change on species distribution.

However, in systems where data availability is limited, such as in developing countries like Brazil, conventional analytical spatial models that demand large datasets may not be applicable (Rufener et al., 2017). Therefore, flexible and reliable statistical tools that perform well with limited information are paramount (Bentley, 2014). In these cases with limited data, Bayesian methods could prove to be reliable in obtaining reasonable model estimates using available data, while transferring uncertainty from one analysis to another (Pennino et al., 2013). Indeed, unlike classical inference which defines probability in terms of long-run relative event frequencies, under the Bayesian prism probability is grounded on an individual's degree of belief of an event. Moreover, whereas frequentist inference model parameters are treated as fixed variables, in Bayesian inference they are considered to be random (Ellison, 2004). Furthermore, the biggest advantage of Bayesian statistics is that they are able to integrate all types of uncertainties using probability as the exclusive metric. By combining uncertainty into the data (expressed by likelihood) with extra-data information (expressed by prior distributions), posterior probability distributions for all unknown quantities of interest (i.e., parameters) are built using Bayes' theorem (Banerjee et al., 2014). Intuitively quantifying uncertainty is fundamentally important for decision makers and, to achieve more realistic scenarios, complex ecological models can be built straightforwardly by specifying successive modeling levels (also known under Hierarchical models). Additionally, when dealing with data-poor situations like the one presented in this study, hierarchical Bayesian models can provide satisfactory results when posterior distributions provide relevant model stabilizing factors, either from further data related to the evaluated issue (Rufener et al., 2017), or if data-poor species borrow strength from data-rich species (Jiao et al., 2011).

Within this context, we combined hierarchical Bayesian spatial models in a data-poor situation with remotely sensed estimates of environmental variables to develop spatial predictive models for fish species richness and abundance in a reef system on the coast of Brazil's Northeast region (Santos et al., 2007). Since 2001, there has been a Conservation Unit in the area called "Environmental Protection Area of Coral Reefs" (Área de Proteção Ambiental dos Recifes de Corais- APARC), which has been facing intense pressure from such anthropogenic stressors as overfishing and tourism expansion (do Nascimento Araújo and Farias do Amaral, 2016). Fishing and tourism are the local population's main economic activities, yet they are difficult to manage given the lack of information.

This study's approach could provide essential tools, such as predictive maps, for identifying sensitive areas under data-poor conditions, and thus help implement marine spatial planning and conservation of these reef complexes.

2. Material and methods

2.1. Study area

The study area is located in the south Atlantic Ocean and comprises the northern coastal shelf of Rio Grande do Norte between 36° 58′ 12″ - 35° 22′ 48″ W and 5° 9′ 25.2″ - 4° 48′ 46.8″ S (Fig. 1). This continental shelf ranges from 40 to 50 km with a maximum depth of 60 m (Vital et al., 2005). Situated between the municipalities of Tibau and Touros, the area extends for about 244 km. The climate is tropical dry or semi-arid with the dry season from May to December and rainy season between January and April. Mean monthly rainfall ranges from 601 to 854 mm but can reach 2.238 mm annually (Nimer, 1989; Vital et al., 2005; Tabosa, 2006). The main economic activities in the area are marine and terrestrial oil exploration, salt extraction, and shrimp farming (Vital et al., 2005).

2.2. Data sampling

Between March 2013 and June 2014, roughly three experimental fishing trips were conducted monthly by fishing vessels of the artisanal fleets which operate along the study area. Bottom gillnets were used to collect 42 samples in depths ranging from 4.6 to 36 m. The nets were made of nylon monofilament with 40–60 mm between mesh knots, and a length of 509–3644 m and a height of

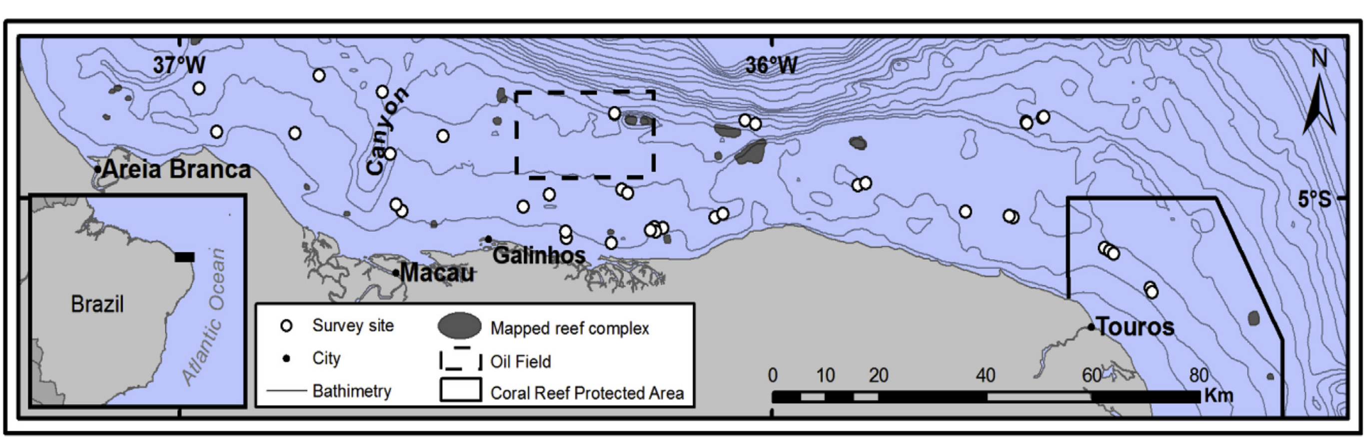

Fig. 1. Study area location in Brazil's Northeast region (Atlantic Ocean). White dots represent the survey sites sampled in 2013 and 2014.