TATIANA BELTRÃO ALVES DA COSTA

ANÁLISE COMPORTAMENTAL E DISTRIBUIÇÃO DA ATIVIDADE PESQUEIRA NO ARQUIPELÁGO DE FERNANDO DE NORONHA (NORDESTE, BR) BASEADA EM DADOS DE GPS

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Tatiana Beltrão Alves da Costa

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Profa. Dra. Sophie Bertand

Orientadora

Departamento de Pesca e Aquicultura – UFRPE

Profa. Dra. Beatrice Padovani Ferreira

Centro de Tecnologia e Geociências – Departamento de Oceanografia – UFPE

Prof. Dr. Humber Agrelli Andrade

Departamento de Pesca e Aquicultura – UFRPE

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RESUMO

Informações sobre a dinâmica espaço temporal das frotas pesqueiras vem sendo amplamente utilizada para inferir sobre diversos aspectos da ciência pesqueira, como na avaliação de padrões de distribuição de espécies, investigar impactos sobre habitats devido ao esforço pesqueiro, na distribuição das embarcações de pesca, entre outros. Neste trabalho descrevemos a distribuição espacial e a composição de captura de acordo das frotas artesanal e recreativa do Arquipélago de Fernando de Noronha, baseando-se em dados de GPS. Para descrição da distribuição espacial foi aplicado um modelo Oculto de Markov a fim de segmentar as trajetórias em diferentes atividades, denominadas estados comportamentais. Para validar a predição dos modelos foram utilizados dados de observador de bordo que acompanharam 20% das viagens monitoradas via GPS. Valores de acurácia sobre e subestimação da atividade pesqueira estimadas pela modelagem foram calculados através de matrizes de confusão. Além disso, foram aplicados modelos de florestas aleatórias para definir quais variáveis (banco de dados, período de interpolação, número de estados, família de distribuição dos passos e família de distribuição dos ângulos) eram mais importantes na acurácia, sobre e subestimação da pesca de acordo com modelos. De acordo com resultados de distribuição, ambas frotas ocupam áreas similares, tendendo a desempenhar a pesca em pontos tradicionalmente conhecidos pelos pescadores. No entanto, ainda que compartilhando zonas pesqueiras parecidas as composição e estrutura das capturas diferem-se. A frota artesanal concentra sua captura em indivíduos de tamanho médio, principalmente barracudas (*Sphyraena barracuda*) e peixe-rei (*Elagatis bipinnulata*), enquanto que a pesca esportiva captura peixes de tamanhos mais variados, sendo eles principalmente barracudas e tunídeos. Quanto a modelagem das trajetórias pesqueiras, de modo geral os modelos obtiveram bons valores de acurácia entre 58% e 79%. Além disso, sobre estimação e subestimação média da atividade de pesca ficaram em aproximadamente 21% e 6.5%, respectivamente. Segundo resultados das florestas aleatórias, o tipo de banco de dados, número de estados e período de interpolação foram consideras as variáveis mais influentes para variação da acurácia, sobre estimação e subestimação do estado de captura. Foi observado que os modelos tenderam a sobrestimar eventos de pesca em percursos com alta sinuosidade e alta velocidade. Em adição, modelos também subestimaram a pesca em porções da trajetória onde os barcos navegavam em linha reta e em velocidade moderada. Em relação ao número de estados, a adição de um terceiro estado comportamental não significou o incremento de um novo estado comportamental servindo apenas para o refinamento da estimação do estado de pesca. No geral, os resultados adquiridos nesse trabalho podem auxiliar o entendimento da dinâmica espacial das frotas pesqueiras de Fernando de Noronha, salientando importantes zonas de pesca que em sua maioria circundam os limites do Parque Nacional Marinho. As informações aqui apresentadas podem servir para melhor esclarecer as particularidades dos pescadores artesanais e recreativos de Fernando de Noronha e também na previsão de quais impactos alterações nas unidades de conservação poderiam causar na distribuição das embarcações.

Palavras-chave: Frota pesqueira, Modelo Oculto de Markov, Modelagem comportamental, Trajetória pesqueira; Geolocalização.

ABSTRACT

Information on the temporal dynamics of the fishing fleets has been widely used to infer many aspects of fisheries science, such as the evaluation of species distribution patterns, investigate impacts on habitats due to fishing effort, in distribution of fishing vessels, among others. In this work we described the spatial distribution and catch composition of the artisanal and recreational fleets of the Fernando de Noronha Archipelago, based on GPS data. For the description of the spatial distribution, a Hidden Markov model was applied in order to segment the trajectories in different activities, called behavioral states. Onboard observer's data from 21% of the trips monitored via GPS were used to validate the prediction of the models. Values of accuracy over and underestimation of fishing activity estimated by the modeling were calculated through confusion matrixes. In addition, random forest models were applied to define which variables (subset, interpolation period, number of states, step distribution family and angular distribution family) were most important in the accuracy, over and underestimation. According to distribution results, both fleets occupy similar areas, tending to perform fishing at points traditionally known by fishermen. However, although sharing similar fishing zones the composition and structure of catches differ among fishery fleet. The artisanal fleet concentrates its catch on medium-sized individuals, mainly barracudas (Sphyraena barracuda) and rainbow runner (Elagatis bipinnulata), while the recreative catches fish of more varied sizes, mainly barracudas and tunas. Regarding the modeling of the fishing trajectories, the models generally obtained good values of accuracy between 58% and 79%. In addition, the mean overestimation and mean underestimation of fishing activity were approximately 21% and 6%, respectively. According to results from the random forests, the subset, number of states and period of interpolation were considered the most influential variables for accuracy, overestimation and underestimation of catching state. It was observed that the models tended to overestimate fishing events in high sinuosity and high-speed segments. In addition, models also underestimated fishing in portions of the trajectory where boats sailed straight and at moderate speed. In relation to the number of states, the addition of a third behavioral state resulted in better accuracy results, but it did not mean the increment of a new behavioral state serving only to refine the estimation of the fishing state. In general, the results obtained in this work can help to understand the spatial dynamics of the fishing fleets of Fernando de Noronha, highlighting important fishing areas that mostly surround the limits of the Marine National Park. The information presented here may serve to better clarify the particularities of the artisanal and recreational fishermen of the archipelago and also in the forecast the impacts that changes in the conservation units could cause in the distribution of the vessels.

Keywords: Fishing fleet, Hidden Markov Models, Behavioral modeling, Fishing track, Geolocation.

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INTRODUÇÃO

O crescente uso dos ambientes costeiros e marinhos por atividades antrópicas e a elevada exploração dos recursos aquáticos tem aumentado a pressão para o estabelecimento de medidas de manejo que visem ordenar a exploração desses ambientes de forma holística, considerando a conectividade entre os ambientes e organismos ali presentes (ARKEMA et al., 2006; DOUVERE e EHLER, 2009; ALONGI, 2009; JOHNSON et al., 2013). Dentre tais atividades as pescarias têm se destacado por afetar diretamente a composição e estrutura da comunidade marinha, podendo gerar perturbações no funcionamento dos ecossistemas (DAYTON et al., 1995; PAULY et al., 2002; HAZEN et al., 2018). Além disso, o aumento no uso dos espaços marinhos tem causado conflitos de interesses, sendo estes agravados em regiões de fronteira devido à alta competição pela exploração dos recursos naturais, assim como em regiões insulares pela limitação espacial de áreas para uso antrópico, como no caso de Fernando de Noronha (Nordeste, Brasil) (DOUVERE, 2008; LOPES et al., 2017).

O Arquipélago de Noronha é um conjunto de ilhas oceânicas de origem vulcânica, situado em pleno Atlântico equatorial oeste (03°51'S / 32°25'W), cujo entorno possui 70% da sua área integralmente protegida pelo Parque Nacional Marinho (PARNAMAR), criado em 1988 (BRASIL, 1988), onde atividades extrativistas como a pesca são proibidas e o turismo fortemente supervisionado. Os 30% restantes são zonas de exploração sustentável (áreas de proteção ambiental – APA), onde a pesca é permitida (ICMbio, 2016). A implementação de tais unidades de conservação causou diversos conflitos entre pescadores e órgãos ambientais já que zonas pesqueiras tradicionais próximas ao arquipélago ficaram inacessíveis aos pescadores, sendo a pesca permitida apenas além da isóbata de 50 metros de profundidade, sendo este o limite externo do PARNAMAR (IBAMA, 2017).

Planos de manejo devem incorporar os conhecimentos e demandas das comunidades pesqueiras assim como se faz importante conhecer o uso efetivo do espaço que se quer proteger (SANCHIRICO et al., 2010; NUTTERS e PINTO DA SILVA, 2012). Para isso, iniciativas ao redor do mundo vem sendo implementadas a fim de monitorar as posições das embarcações de pesca via satélite (vessel monitoring system - VMS), sendo esta uma ferramenta crucial para o controle e compreensão da dinâmica pesqueira (e.g. DENG et al., 2005; LEE et al., 2010; CRESPO et al., 2018). Informações da caracterização da distribuição espaço-temporal das pescarias podem servir como subsídio para definição de cotas de captura por zonas, períodos de defeso e aplicação de medidas de manejo espacialmente limitantes, como as áreas de proteção marinha (DINMORE et al., 2003; BABCOCK et al., 2005; ALLEN e SINGH, 2016). Informações sobre a contração ou dispersão na distribuição das embarcações pesqueiras podem ser utilizadas para identificar possíveis pressões exercidas sobre os recursos aquáticos (BERTRAND et al., 2007). O bacalhau do atlântico (*Gadus morhua* (Limneus, 1758)) é um exemplo onde métodos tradicionais de avaliação de estoques, como a captura por unidade de esforço (CPUE), foram ineficientes na detecção desse declínio populacional (HILBORN e WAITERS, 1992; HUTCHINGS, 1996;). A análise da distribuição espacial dos barcos pesqueiros ao longo do tempo pode ser usada com informação adicional para evitar interpretações errôneas da CPUE (hiperestabilidade). Mills et al. (2007), constatou a importância do uso da geolocalização das embarcações de pesca como instrumento de manejo pesqueiro e de planejamento espacial marinho.

Pesquisas baseadas em dados de geolocalização vem utilizando e desenvolvendo modelos estatísticos para definir padrões espaço-temporais de pesca, diferenciar métodos e estratégias pesqueiras, definir tipos de trajetórias, identificar relações entre a atividade e a distribuição de espécies e/ou variações abióticas do ambiente aquático (WALTER et al., 2007; CHANG, 2011; RUSSO et al., 2016). Modelos são expressões específicas ou generalistas desenvolvidas para analisar/explicar hipóteses, muitas vezes denotados através de equações matemáticas (HALL, 1988; HILBORN e MANGEL, 1997). Através da modelagem estatística estimam-se parâmetros a partir de dados observados, sendo possível inferir sobre populações ou processos (BURNHAM e ANDERSON, 2004; PAWITAN, 2008). Modelos podem ser descritivos, voltados a sumarizar de forma clara e sucinta os fatos, a fim de guiar o pesquisador até as informações mais relevantes sobre os dados (HAND et al. 2001). Passeios aleatórios, análises fractais, tempo de primeira passagem, entre outros, são exemplos já usados na modelagem da dinâmica espacial de embarcações pesqueiras (SCHICK et al. 2008; BERTRAND et al. 2015; SOUZA et al., 2016). Além disso, modelos podem ser inferenciais quando deduzem sobre determinado fator desconhecido, porém previsível, atribuindo probabilidades estimadas a partir de dados amostrais ou simulados, com o intuito de estimar parâmetros e explicar o fenômeno desconhecido (MARTIN e LIU, 2011).

Dentre as principais etapas na modelagem comportamental dos pescadores baseadas em dados de GPS, está a segmentação das trajetórias em diferentes atividades, como navegando, pescando ou procurando, as quais são denominadas estados comportamentais (JOO, 2013a). Um dos princípios utilizados para descriminar tais estados é a partir da derivação da velocidade entre dois pontos consecutivos de GPS e mudança de direção (ângulo) entre três registros consecutivos de GPS. A combinação de padrões como alta velocidade e baixa variação angular pode ser definido como um estado, enquanto que a baixa velocidade e grande variação de direção pode ser definido como um segundo estado, que posteriormente podem ser analisados e interpretados como viagem e pesca em se tratando de trajetórias pesqueiras por exemplo. Dentre os métodos utilizados para a definição de estados comportamentais os Modelos Ocultos de Markov (do inglês Hidden Markov Models - HMM) vem sendo bastante explorados devido a sua flexibilidade e por estimar arranjos probabilísticos que podem ser intimamente relacionados a estados não observados em uma viagem de pesca (ex.: pescando, navegando, etc.) (PEEL e GOOD, 2011; JOO et al., 2013; CHARLES et al., 2014).

O Modelo Oculto de Markov é um processo estocástico duplo, que considera que determinada sequência discreta e finita de observações é gerada devido a um processo oculto composto por estados conhecidos, porém não observados (LEVINSON, 1983; BLUNSOM, 2004; HANDEL, 2008). Muitos modelos são desenvolvidos para os mais diversos fins, como no reconhecimento de fala, restauração de imagens, sequenciamento de DNA, segmentação de trajetórias, entre outras aplicações (EPHRAIM e MERHAV, 2001). Na ecologia do movimento a aplicação dos HMMs foi utilizada por Joo et al. (2013), Langrock et al. (2012), Paddersen et al. (2011), entre outros. No presente trabalho segmentamos as trajetórias pesqueiras da frota do Arquipélago de Fernando de Noronha (Pernambuco, BR) utilizando o pacote moveHMM (desenvolvedores), elaborado para ambiente R, que implementa Modelos Ocultos de Markov e recursos adicionais para segmentação de estados comportamentais e seleção de modelos, principalmente voltado a dados de movimentação animal. Além disso, visamos inferir sobre a dinâmica espaço temporal da frota pesqueira do Arquipélago de Fernando de Noronha (Pernambuco, BR), denotando as características de cada modalidade e suas distribuições durante eventos de pesca.

OBJETIVO GERAL

Inferir sobre a dinâmica espacial das frotas pesqueiras artesanal e recreativa do Arquipélago de Fernando de Noronha (Pernambuco, BR), baseando-se em dados de geolocalização.

OBJETIVOS ESPECÍFICOS

- Descrever as frotas pesqueiras e a composição da captura das frotas pesqueiras atuantes no Arquipélago de Fernando de Noronha.
- Identificar unidades comportamentais utilizando através de Modelo Oculto de Markov, baseando-se na distância e variação de ângulos entre registros consecutivos de GPS.
- Identificar efeitos de variáveis, como período de interpolação, família de distribuições de probabilidade, entre outras, sobre a performance dos modelos.
- Mapear a distribuição espacial das frotas pesqueiras, identificando principais zonas de pesca e estimando o esforço de uma maneira espacialmente explicita.

REFERÊNCIAS

ALLEN, Andrew M.; SINGH, Navinder J. Linking Movement Ecology with Wildlife Management and Conservation. **Frontiers in Ecology and Evolution**, v. 3, n. January, p.1–13, 2016. Disponível em: <http://journal.frontiersin.org/Article/10.3389/fevo.2015.00155/abstract>.

ALONGI, Daniel M. **The Energetics of Mangrove Forests**. [S.l: s.n.], 2009.

ARKEMA, Katie K; ABRAMSON, Sarah C; DEWSBURY, Bryan M. Marine ecosystem-based management KK Arkema et al. 526. 2006. Disponível em: <www.frontiersinecology.org>.

BABCOCK, Elizabeth A. et al. A perspective on the use of spatialized indicators for ecosystem-based fishery management through spatial zoning. **ICES Journal of Marine Science**, v. 62, n. 3, p. 469–476, 2005.

BERTRAND, Sophie; DÍAZ, Erich; LENGAIGNE, Matthieu. Patterns in the spatial distribution of Peruvian anchovy (Engraulis ringens) revealed by spatially explicit fishing data. **Progress in Oceanography**, v. 79, n. 2–4, p. 379–389, 2008. Disponível em: <http://dx.doi.org/10.1016/j.pocean.2008.10.009>.

BERTRAND, Sophie; JOO, Rocío; FABLET, Ronan. Generalized Pareto for pattern-oriented random walk modelling of organisms' movements. **PLoS ONE**, v. 10, n. 7, p. 1–16, 2015.

BLUNSOM, P. Hidden Markov Models. **Methods in Molecular Biology**, v. 802, p. 337–344, 2004.

BRASIL. Decreto n. 96.693, de 14 de set. de 1988. Parque Nacional Marinho de Fernando de Noronha, Brasília,DF, set 1988.

BURNHAM, Kenneth P.; ANDERSON, David R. **Multimodel inference: Understanding AIC and BIC in model selection**. **Sociological Methods and Research**. [S.l: s.n.]. , 2004

CHANG, Shui Kai. Application of a vessel monitoring system to advance sustainable fisheries management-Benefits received in Taiwan. **Marine Policy**, v. 35, n. 2, p. 116–121, 2011. Disponível em: <http://dx.doi.org/10.1016/j.marpol.2010.08.009>.

CHARLES, Colin; GILLIS, Darren; WADE, Elmer. Using hidden Markov models to infer vessel activities in the snow crab (*Chionoecetes opilio*) fixed gear fishery and their application to catch standardization. **Canadian Journal of Fisheries and Aquatic Sciences**, 2014.

CRESPO, Guillermo Ortuño et al. The environmental niche of the global high seas pelagic longline fleet. **Science Advances**, v. 4, n. 8, p. 1–14, 2018.

DAYTON, Paul K. et al. Environmental effects of marine fishing. **5th International Symposium on Life-Cycle Engineering, IALCCE 2016**, v. 5, n. February 1994, p. 1257–1264, 1995. Disponível em: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85018635538&partnerID=40&md5=84589420132e7a3ea934be32dea62f60>.

DE SOUZA, Erico N. et al. Improving fishing pattern detection from satellite AIS using data mining and machine learning. **PLoS ONE**, v. 11, n. 7, p. 1–20, 2016.

DENG, Roy et al. Can vessel monitoring system data also be used to study trawling intensity and population depletion? The example of Australia's northern prawn fishery. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 62, n. 3, p. 611–622, 2005. Disponível em: <http://www.nrcresearchpress.com/doi/abs/10.1139/f04-219>.

DINMORE, T. A. et al. Impact of large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. **ICES Journal of Marine Science**, v. 3139, n. 03, p. 1298–1317, 2003.

DOUVERE, Fanny. The importance of marine spatial planning in advancing ecosystem-based sea use management. **Marine Policy**, v. 32, n. 5, p. 762–771, 2008.

DOUVERE, Fanny; EHLER, Charles N. New perspectives on sea use management: Initial findings from European experience with marine spatial planning. **Journal of Environmental Management**, v. 90, n. 1, p. 77–88, 2009. Disponível em: <http://dx.doi.org/10.1016/j.jenvman.2008.07.004>.

EPHRAIM, Yariv; MERHAV, Neri. Hidden markov processes - Information Theory, IEEE Transactions on. v. 48, n. 6, p. 1–52, 2001.

FROESE, Rainer et al. What catch data can tell us about the status of global fisheries. **Marine Biology**, v. 159, n. 6, p. 1283–1292, 2012.

HALL, Charles A.S. An assessment of several of the historically most influential theoretical models used in ecology and of the data provided in their support. **Ecological Modelling**, 1988.

HANDEL, R. V. Hidden Markov Models. **IEEE Transactions on Consumer Electronics**, v. 42, n. 3, p. 583–591, 2008.

HAZEN, Elliott L. et al. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. **Science Advances**, v. 4, n. 5, p. 1–8, 2018.

HILBORN, R; MANGEL, M. **The ecological detective: confronting models with data**. [S.l: s.n.], 1997.

HILBORN, R; WAITERS, C J. Book reviews Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. **Reviews in Fish Biology and Fisheries**, v. 2, p. 177–186, 1992.

HUTCHINGS, J A. Spatial and temporal variation in the density of northern cod and a review of hypotheses for the stock's collapse. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 53, n. 5, p. 943–962, 1996.

JOHNSON, Andrew F. et al. Linking temperate demersal fish species to habitat: Scales, patterns and future directions. **Fish and Fisheries**, v. 14, n. 3, p. 256–280, 2013.

JOO, Rocio et al. Hidden Markov Models: The Best Models for Forager Movements? **PLoS ONE**, v. 8, n. 8, 2013.

JOO, Rocío. A behavioral ecology of fishermen: hidden stories from trajectory data in the Northern Humboldt Current System. 2013.

LANGROCK, Roland et al. Flexible and practical modeling of animal telemetry data: hidden Markov models and extensions. **Ecology**, v. 93, n. 11, p. 1–22, 2012. Disponível em: <http://www.esajournals.org/doi/abs/10.1890/11-2241.1>.

LEE, Janette; SOUTH, Andy B.; JENNINGS, Simon. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. **ICES Journal of Marine Science**, v. 67, n. 6, p. 1260–1271, 2010.

LEVINSON, S.E. An introduction to the application of the theory of probabilistic functions of a Markov chain. **The Bell System Technical Journal**, v. 62, n. 4, p. 1035–1074, 1983.

LOPES, P F M et al. Tourism as a driver of con fl icts and changes in fi sheries value chains in Marine Protected Areas. **Journal of Environmental Management**, v. 200, p. 123–134, 2017. Disponível em: <http://dx.doi.org/10.1016/j.jenvman.2017.05.080>.

MARTIN, R; LIU, C. Inferential models. **Submitted manuscript**, v. 108, n. 501, p. 301–313, 2011. Disponível em: <http://www.tandfonline.com/doi/abs/10.1080/01621459.2012.747960%0Apapers3://publication/doi/10.1080/01621459.2012.747960>.

MILLS, C M et al. Estimating high resolution trawl fishing effort from satelite-based vessel monitoring system data. **ICES Journal of Marine Science**, v. 64, p. 248–255, 2007. Disponível em: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.491.7100&rep=rep1&type=pdf%0Ahttps://oup.silverchair-cdn.com/oup/backfile/Content_public/Journal/icesjms/64/2/10.1093/icesjms/fsl026/2/fsl026.pdf?Expires=1491103717&Signature=I9vdrffkSDvUT3VfyQ0ljQX>.

NUTTERS, Heidi M.; PINTO DA SILVA, Patricia. Fishery stakeholder engagement and marine spatial planning: Lessons from the Rhode Island Ocean SAMP and the Massachusetts Ocean Management Plan. **Ocean and Coastal Management**, v. 67, p. 9–18, 2012. Disponível em: <http://dx.doi.org/10.1016/j.ocecoaman.2012.05.020>.

PAULY, Daniel et al. Towards Sustainability in Fishery.Pdf>. v. 418, n. August, p. 689–695, 2002.

PAWITAN, Yudi. In All Likelihood. **Oxford University Press**, 2008.

PEDERSEN, M. W. et al. Estimating animal behavior and residency from movement data. **Oikos**, v. 120, n. 9, p. 1281–1290, 2011.

PEEL, David; GOOD, Norman M. A hidden Markov model approach for determining vessel activity from vessel monitoring system data. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 68, n. 7, p. 1252–1264, 2011. Disponível em: <http://www.nrcresearchpress.com/doi/abs/10.1139/f2011-055>.

RUSSO, T. et al. Assessing the fishing footprint using data integrated from different tracking devices: Issues and opportunities. **Ecological Indicators**, 2016.

SANCHIRICO, James N et al. Comprehensive Planning, Dominant-Use Zones, And User Rights: A New Era In Ocean Governance. **Bulletin Of Marine Science**, v. 86, n. 2, p. 1–14, 2010.

SCHICK, Robert S. et al. Understanding movement data and movement processes: Current and emerging directions. **Ecology Letters**, v. 11, n. 12, p. 1338–1350, 2008.

WALTER, John F.; HOENIG, John M.; GEDAMKE, Todd. Correcting for effective area fished in fishery-dependent depletion estimates of abundance and capture efficiency. **ICES Journal of Marine Science**, v. 64, n. 9, p. 1760–1771, 2007.

YOUNG, Jeffery L. et al. Integrating physiology and life history to improve fisheries management and conservation. **Fish and Fisheries**, v. 7, n. 4, p. 262–283, 2006.

Description and movement modeling of the fishery off Fernando de Noronha Archipelago

INTRODUCTION

Changes in fishery dynamic is one of the most unpredictable factors affecting management plans, and the lack of information about the distribution of fishing fleets during the implementation of management and conservation actions can lead to inefficient results (WILEN et al., 2002; FULTON et al., 2011). Since the acquisition of stock information through scientific surveys is limited due to high costs, data from fishery fleets are the major source of knowledge about fisheries resources (CAMPBELL, 2015; COSTELLO et al. 2016; PAULY and ZELLER, 2016). In the last decades, data on fishing vessels movements have been also used to estimate the impacts on fish resources (e.g. RIJNSDORP et al., 1998; POSEN et al., 2014), the effects of management actions (e.g. DINMORE et al., 2003; MURAWSKI et al., 2005; WALKER; BEZ, 2010; JOO et al., 2015;), to estimate a spatially explicit fishing effort (e.g. RIJNSDORP et al., 2001; MILLS et al., 2007), to infer the spatial distribution of fisheries resources (e.g. BERTRAND et al., 2004; BERTRAND et al., 2008). The emerging need for an ecosystem-based management (EBM) tools have bring to spotlight the importance of including high spatial-temporal resolution data in ecosystems management; in particular, the dynamic of fishermen spatial behavior, which influences the dynamics of natural aquatic resources, has grown concerns (FAO, 2003; BRANCH et al. 2006)

Data on fishermen spatial behavior increased in the last decades since new and more sophisticated tracking devices have become available for scientific purposes, causing the increase in diversity, quality and size of datasets (PATTERSON et al., 2008; VERMARD et al. 2010). To process these datasets and model fishermen behaviours, there has been a need for developing or refining existing statistical approaches, then. many different methods have been explored (CAGNACCI et al. 2010; HEBBLEWHITE and HAYDON, 2010). A major point in the description of fishermen dynamic is the definition of behavioral modes or states, which consists in the segmentation of a fishing trip into different activities; fishing, sailing, setting the gear, etc. (JOO, 2013). Nowadays, there are two tendencies in the movement ecology investigation, first the use of complex statistical models which is a problem for the integration of ecologists in the field and second the use of simplistic models that could lead to erroneous conclusions (PATTERSON et al., 2017).

Using simple thresholds on speed has been the most widely used approach (LEE et al. 2010), yet this may produce large rates of error in the estimation of fishing events (e.g. 180% of overestimation, see Bertrand et al. 2008). Alternatively, statistically more grounded approaches, and possibly supervised (cases where a validation sample is available), were then used to identify those states, such as artificial neural networks by Bertrand et al. (2008) and Joo et al. (2011). More recently, other machine/statistical learning features have appeared as an option to deal with scenarios where the fishing state duration is smaller than the polling period of the VMS record, however those supervised methods are suitable only for large datasets (DE SOUZA et al. 2016; O'FARRELL et al. 2017). The Hidden Markov Models (HMM) have attracted attention as tool for animal behavior modelling, probably, due to its flexibility (MICHELOT et al. 2016). In the present study, we used HMM that belongs to a special group of state-switching models commonly used to decompose trajectories into different underlying states. It considers a finite number of states (hidden underlying process) such as, fishing traveling or searching, and the movement metrics correspond to the explicit observed variable of the model (tuning angle and speed) (LANGROCK et al. 2012; MCKELLAR et al. 2015). Moreover, it considers that the present state (t) depends only on the previous (t-1), ignoring all process preceding t-1, as stated in the Markovian chain properties (RABINER, 1989; ROSENBLATT, 2012; SUEN, 2014) (Further detailed on methods). Worldwide studies have implemented the HMM in order to identify the behavioral modes along fishing trip tracks, such as Joo et al. (2013), Gloaglen et al. 2013 and Vermard et al. (2010).

In Brazil, there are few publications on dynamics of fishing behavior based on data from the national vessel monitoring program (PREPS), such as Zagaglia et al., (2009) and Lemos et al., (2016). However, those authors used the speed criteria to determine the behavioral modes of fishing boats. Those studies were applied in a southern purse seine fishing fleet that targets mullet (*Mugil liza),* as well as in a trawler fleet from Amazon, which targets catfish (*Brachyplatystoma vaillantii*), both interested on the management of the target specie. In the present study we aimed to describe the fishing activity in Fernando de Noronha because of the socio-economic importance of fishing activity and the presence of regulatory measures long stablished in the archipelago. Then, we utilized fishery geolocation data registered through GPS devices to infer about fishery fleet spatial dynamic. We segmented fishing GPS tracks using Hidden Markov Models to define fishing activities and validated the results by comparing them with activities recorded by on board observers. In addition, we analyzed information about fishery catch composition to describe and compare the artisanal and recreative fleet from the island.

METHODS

Study Area and Local Fishery

The study was conducted in the Fernando de Noronha Archipelago, an important group of tropical Atlantic islands that give biological support to their surrounding oligotrophic environment (Tchamabi et al., 2016). The archipelago is composed by 20 islands of volcanic origin emerged from the Mid-Atlantic Ridge located 345 km off the Brazilian Northeast coast (03° 51' S; 32° 26' W) (Maida and Ferreira, 1997). Since 1988, Fernando de Noronha has been protected by two management tools (Fig.1), first a National Marine Park (PARNAMAR), which is a no-take marine reserve where extractive activities are not allowed and recreational are heavily monitored. Second an Environmental Protected Area, which is a partially protected area, where fishing and other activities are permitted, but with regulatory restrictions (ICMbio, 2016).

Two fishing fleets operate in the archipelago waters, one artisanal and one recreative, both targeting multiple species, but working with different fishing strategies. The artisanal fishing boats are equipped with a very basic set of tools. These fishermen use two fishing methods, one trolling handlines by the side of the boats while they are slightly drifting towards the archipelago, locally known as "pargueira"; the other trolling the lines by the stern of the boats, is known as "corrico". Normally, they set two or three handlines with sardines (*Harengula clupeola*) or bigeye scad (*Selar crumenophtalmus*) as live bait and their boats have few or none automated system as GPS or echo sounder, what is a limitation for the range of their fishing area (TRAVASSOS and CARVALHO, 2002). On the other hand, the recreative crews also use corrico as fishing strategy, but operating four or five reels and rods with artificial baits, such as @rapalas. In addition, those boats can account with GPS and echo sounders to increase their fishing power.

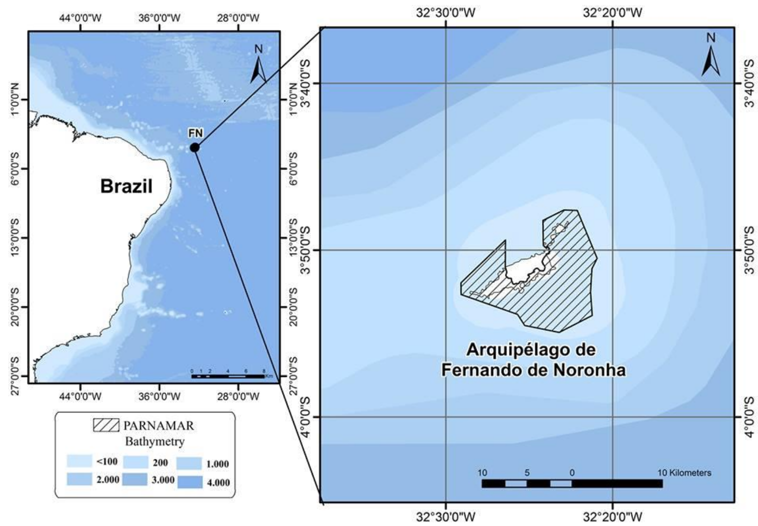


Figure 1. Fernando de Noronha location map. Hatched area represents the area of national marine park. A courtesy of Leandro Nolé.

Data Sample and Analysis

We obtained geolocation data from artisanal and recreative fishing fleets from Fernando de Noronha in three campaigns. The samplings were performed in September/October of 2015, September/October of 2016 and April/May of 2017. Miniaturized GPSs were set to record positioning data each second and they were deployed on the boats in the morning at the beginning of fishing trips and removed by their end in the afternoon. However, in few occasions the GPSs were recovered only the following day. Prior to statistical analysis, a pre-processing was performed to clean and prepared the tracking data. During the three years of the project, eight boats, four for each fishery type, were monitored registering 35 fishing days, what generated 70 fishing routes, among which 14 monitored also by onboard observers (Table 1). It was necessary to remove positioning data within or nearby to harbor area, on land positions and duplicated points.

Table 1. Number of days monitored, fishing trips and trips with onboard observer by fishery type and fishing strategy.

Fishing type	**Artisanal**		**Recreational**	**General**
Fishing strategy	**Pargueira**	**Corrico**	**Corrico**	
Days of monitoring	15	9	11	35
#Fishing trips	38	19	13	70
#Trips observed	2	6	6	14

Besides the geolocation data of boats, 20% of the fishing trips had an onboard observer to register the activities carried out during fishing trips. Since there were discrepancies during on board observer's registers, where some information about gear release and recovery is missing, in this study we limited the validation of the catching state, which is the literal period when the fishers are capturing the fishes. In addition, the catch composition and size of individuals were registered to characterize each type of fishery, recreative and artisanal.

A trajectory recorded by GPS is in fact a sequence of segments called steps, defined by the distance between two consecutive GPS positions. From one step we can derive a length (homogeneous to speed as the recording is regular in time) and from two consecutive steps, we can derive turning angles, which are the variation of direction between two consecutive steps. Calculating these values all along the track, we obtain two distributions, which can be used for the segmentation of a fishing track. In this study we used Hidden Markov Models (HMM) to identify different activities along a fishing trip. The HMM are time series models composed by, observed variables (Y) and a hidden sequence of states (S). In practical words, we use HMM to predict the probability of being in the states fishing (S=f) given a combination of observed variables, in our case, speed (Y = sp) and turning angle (Y = ta). This state-space model follows the properties of a first order Markov chain which assume that the future state (S_{t+1}) is only dependent on the current state (S_t), not considering how the process achieved that ongoing state (Grigoletti, 2015) (Fig. 2).

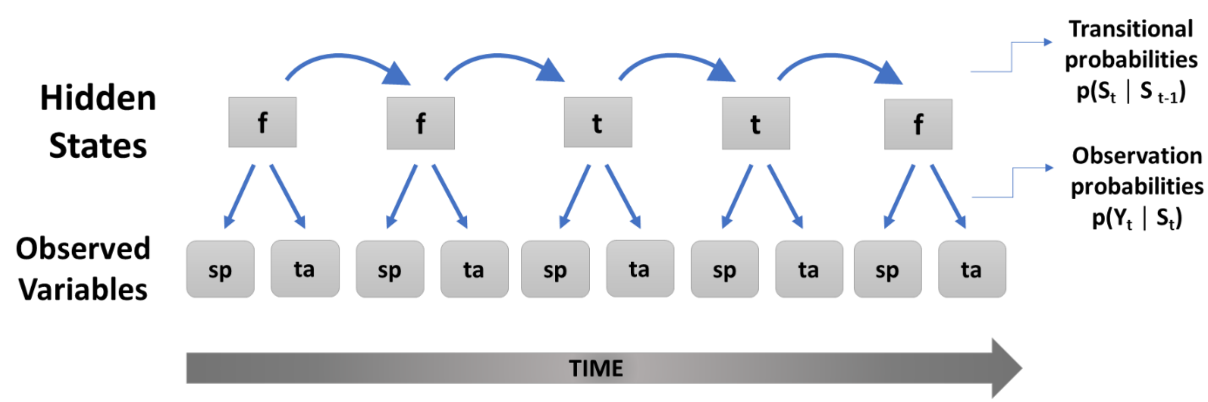


Figure 2. Hidden Markov model state transition scheme. Each current state (St) depends only on the previous state (St-1).

Some probabilities must be specified to define the HMM (Equations i, ii and iii), (i) a matrix of transitional probabilities, which consists in the probabilities of switching or not from one state (S_t) for another considering the previous state (S_{t-1}), (ii) a matrix of observation probabilities, which are the probabilities of been in one state (S_t) considering what was observed (O_t) in terms of speed and turning angle and (iii) a vector of initial probabilities, which are the general probabilities of been in one state or other (See Rabiner, (1989) and Bengio (1999) for detailed information on HMM).

(i) $\mathrm{P}(\mathrm{S_t} \mid \mathrm{S_{t-1}})$

(ii) $\mathrm{P}(S_t \mid O_t)$

(iii) $\mathrm{P}(S_{t=0})$

In the present work, the observed variables were the step length and turning angles distributions, as it is common in ecological studies about animal spatial behavior. We used a package developed for the R environment called moveHMM (MICHELOT et al., 2016). This package was developed for researchers interested in animal movement analysis facilitating the application and offering a variety of HMMs composed by different model's parameters. In this package there are four probability distributions available for step length information (Weibull, Gamma, Exponential and Log-normal), but only Weibull and Gamma were used in this study, since they remaining family distributions were not adequate. The exponential distribution was not representing the shape of our dataset and the log-normal family was problematic dealing with zero inflated dataset. In addition, there are two family distribution for modeling turning angle distribution, Wrapped Cauchy and Von-Misses, both used in this study.

Other parameter that some author determine before the modeling procedure is the number of states in which the trajectory should be segmented. The number of states depends on the number of behaviors that is expected to be found or analyzed. In our project, we are interested in the identification of catching and non-catching states and we compared trajectories segmented into two and three states to identify any improvement on model performance. The number of states chosen has influence over the determination of initial parameters required during modeling procedure of moveHMM package. The initial parameters are important to find the maximum likelihood estimate used in the trajectory segmentation (MICHELOT et al., 2016). To define the initial parameters, we used K-means algorithms that consists in classifying the step length into two or three clusters (depend on the number of states considered) by defining centroid values while keeping them as lower as possible.

The fishery of Fernando de Noronha is characterized by the use of different gears and fishing strategies. There are two categories of fishers (recreational and artisanal) that work with three métiers (pargueira, artisanal corrico and recreative corrico). To understand how the HMM algorithm performs with mixed-gear dataset, we created 5 databases (subsets), classified as: (i) general: (ii) pargueira (iii) corrico, (iv) artisanal and (v) recreative. The general subset includes all trajectories recorded. The pargueira subset has only trajectories that performed pargueira métier. The corrico subset includes the artisanal corrico and recreative corrico. The artisanal is formed by trajectories of pargueira métier and artisanal corrico. The recreative subset is formed only by recreative corrico. We denominated those datasets as subset during modeling because we cannot consider them as métiers, since they have different métiers included on them. Furthermore, each subset was resampled with different interpolation periods: 10 seconds, 30 seconds, 60 seconds and 120 seconds. Because the temporal resolution of GPS can be a source of error; while a too low GPS frequency could underestimate the real distance covered (and the corresponding speed), the high frequency (like our case), lead to summing the GPS slight location error and could overestimate the real distance traveled (PALMER, 2007). In addition, high resolutions could increase the autocorrelation between states, violating the 1st order correlation hypothesis used in the Markov chain.

Summarizing, in this study we combined different model's parameters been, two family distributions for step length and two for turning angle, four temporal resolutions, five subset types and the trajectories were segmented in two ways, resulting in 160 models

Model Performance Evaluation

As mentioned before the modeling process carried in this work is going to evaluate the fishing activity of vessels from the archipelago of Fernando de Noronha. Due to data registering problems, for validating the behavioral modeling we considered that fishing activity is the moment when the fishermen are catching fishes literally.

The Akaike Information Criterion (AIC), which is an estimator of the relative Kullback-Leibler distance, that represents how much information was lost when using a given model to approximate the reality (Akaike, 1974), was applied to evaluate the fitness of the models.

Additionally, confusion matrixes (commonly used in machine learning processes) were also used to assess model's effectiveness. It consists in summarizing the results of a classification model into a simple 2x2 matrix, composed by columns of predicted values (resulted from modeling) crossed over with rows of real observations (activities registered by onboard observers) (Table 2). The results of True Positive and True Negative are used to calculate the accuracy of models. From False Positive results is calculated the overestimation and the False Negative to obtain underestimation (Equations iv, v and vi). A Kruskall-Wallis test was performed to identify significative differences for accuracy, under and overestimations by model parameters.

Table 2. Confusion matrix representation. Results from crossing over real observations with predicted model outcomes.

Predicted / Real	**NO**	**YES**
NO	True Negative TN	False Positive FP
YES	False Negative FN	True Positive TP

$$\boldsymbol{Accuracy = \frac{TP + TN}{Total} * 100} \qquad \text{(iv)}$$

$$\boldsymbol{Underestimation = \frac{FN}{Total} * 100} \qquad \text{(v)}$$

$$\boldsymbol{Overestimation = \frac{FP}{Total} * 100} \qquad \text{(vi)}$$

To estimate the relative importance of variables that fed the models on the accuracy, under and overestimation of fishing activity definition we run a random forest (RF) algorithm. Random forests are combinations of decision trees that are constructed through a bootstrapping procedure of the original dataset (BREIMAN, 2001). The randomization during the selection of attributes for each three of the forest increases the differences between them, consequently lower their autocorrelation and the classification error rate of the forest decreases (BREIMAN, 2004; OSHIRO, 2013). This method allows ranking the importance models parameters by computing the variation of error while one variable is kept out and the other are kept in, then it can identify which explicative variables have higher impact on the response variable (LIAW and WIENER, 2002).

RESULTS

Fishery Behavioral Modeling

Geolocation data of the boats were used to infer fishermen behavior, based on speed and turning angle variation derived from GPS records. Trajectories were organized into five subsets (1) artisanal, (2) recreative, (3) corrico, (4) pargueira and (5) general. Each subset was resampled through linear interpolation in four temporal resolutions (10s, 30s, 60s and 120s), which resulted in 20 datasets that were used for modeling the trajectory segmentation. Speed strongly varied between subsets as well as between temporal resolutions. The turning angle histograms tended to keep values close to zero for all scenarios, but their zero's concentration varied according to subset or interpolation period.

Since there were only two pargueira trajectories accompanied by onboard observers we decide to exclude this dataset for further analysis to prevent misinterpretation of model performances. Overall, considering the mean accuracy (MA) of catching state estimation, the recreative subset presented higher results (74%) and there was found significant differences for the values of mean accuracy between subset type (Kruskal-Wallis chi-squared = 36.218, df = 3, p-value = 6.734e-08). There were no significant differences between values of mean accuracy regarding family distribution of turning angle and Wrapped Cauchy presented higher results of MA (72%). The Weibull distribution had better result of MA (73%) been significantly different from result of Gamma distribution (Kruskal-Wallis chi-squared = 5.2654, df = 1, p-value = 0.02175). Concerning interpolation period, the 10 seconds time interval had the greatest values (74%) and the 120 seconds the weakest results of mean accuracy (69%). Significant differences were found among mean accuracy results of interpolation period (Kruskal-Wallis chi-squared = 36.848, df = 3, p-value = 4.954e-08). Finally, the models that segmented the trajectories into two states had 72% of mean accuracy while the trajectories segmented into 3 states had 71% of MA. Results of mean accuracy are synthetized in figure 3.

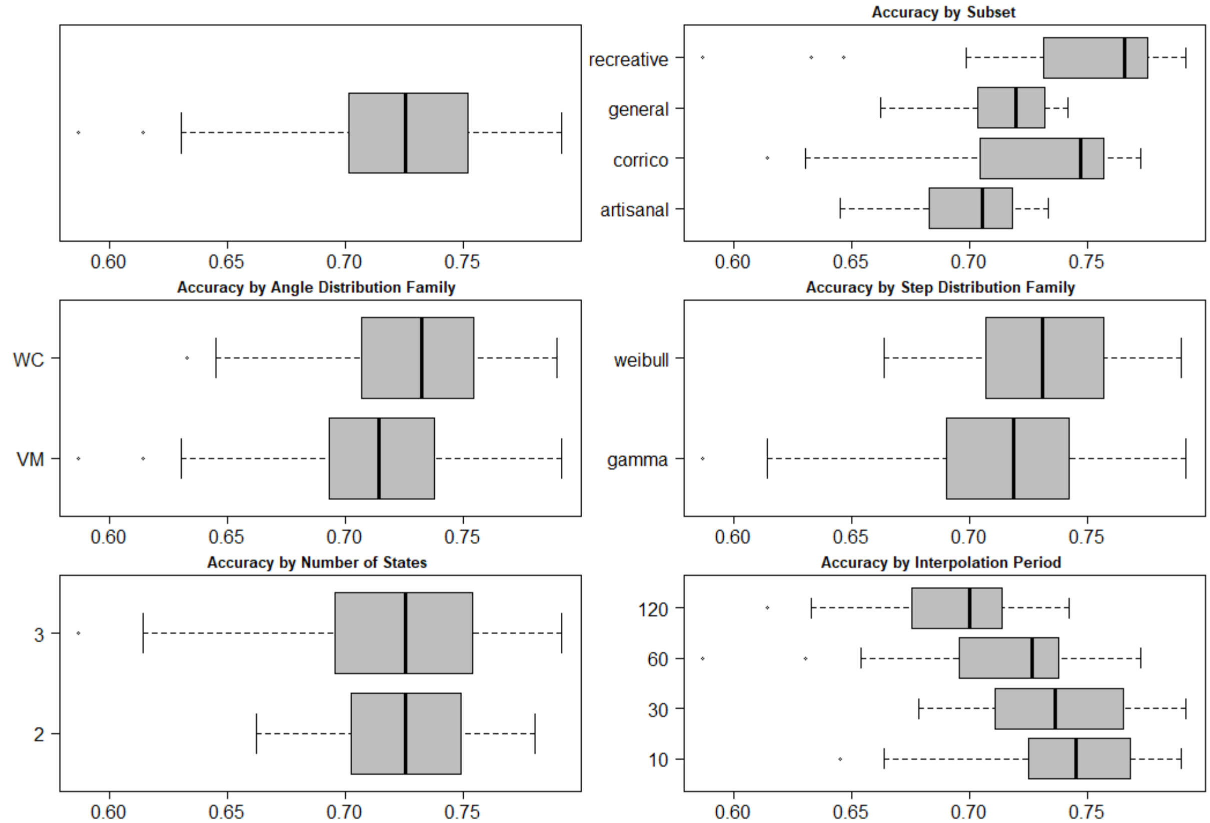


Figure 3. Boxplots of general accuracy and mean accuracy for each independent variable (y axis), excluding pargueira subset. WC stands for Wrapped Cauchy and VM for Von Misses.

For complementing accuracy results, under and over estimation of catching states were calculated to infer about model's quality. Underestimation varied from 0.7% to 23%, with mean underestimation (MU) of 6.5%. In respect to overestimation results ranged from 1.3% to 38.5%, with an average of 21.2%. Since results of MU, MO and accuracy are complementary, the variables with higher results of mean overestimation of catching states presented the lowest values of mean underestimation. The highest values of mean overestimation were found for the artisanal subset (27%). There was found significant difference of MO among the subset types (Kruskal-Wallis chi-squared = 47.611, df = 3, p-value = 2.576e-10). The Von Mises distribution had 22% of mean overestimation, been significantly different from Wrapped Cauchy value (Kruskal-Wallis chi-squared = 5.3422, df = 1, p-value = 0.02081). The Gamma distribution was slightly worse than Weibull distribution presenting 22% and 19% of mean overestimation, respectively. Regarding the number of states in which the trajectories were segmented the two and three states models had equal results of MO, both with 21%. Finally, the poorest temporal resolution which is 120 seconds had the worse result of MO (26%) and there was found significant differences among the interpolation periods in respect to MO values (Kruskal-Wallis chi-squared = 36.151, df = 3, p-value = 6.956e-08). The overall results of under and overestimation of catching states can be seen in figure 4.

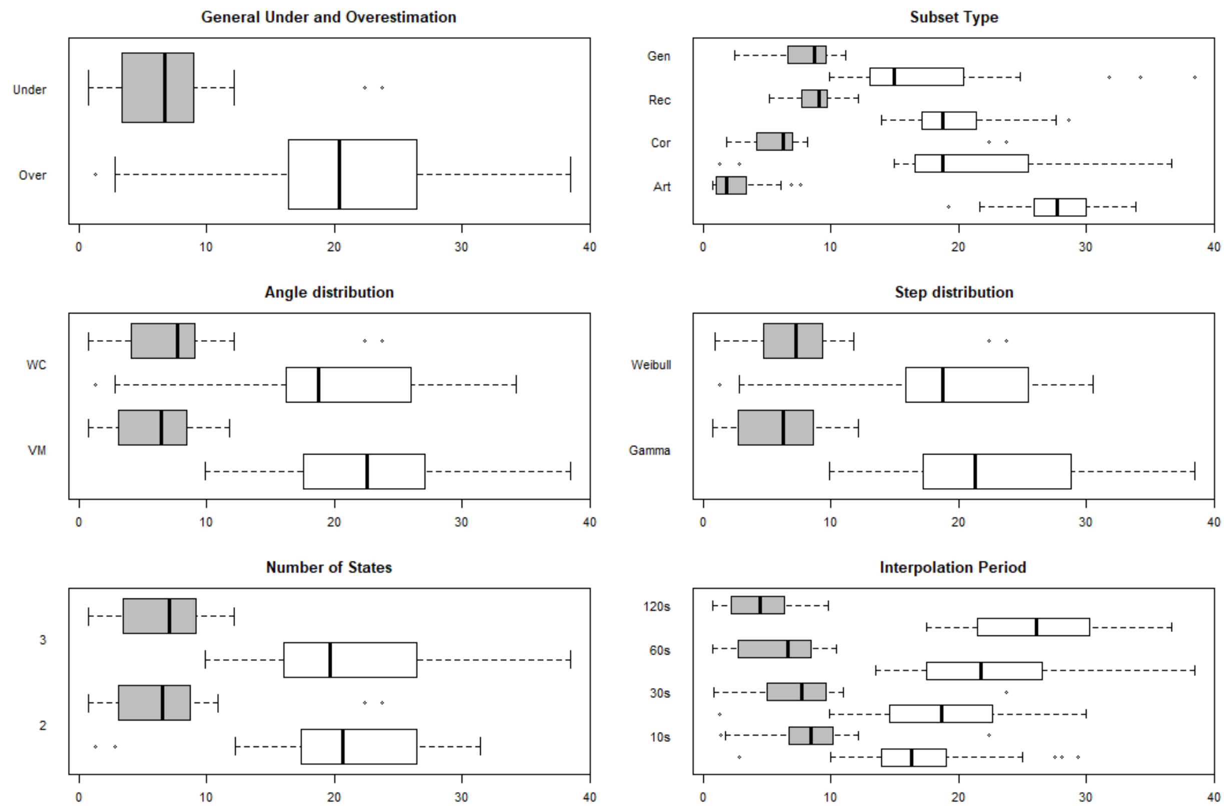


Figure 4. Boxplots for under and overestimation by variables of fishing activity. Grey boxes: overestimation; white boxes: underestimation.

Analysis of AIC (Fig. 5) were not conclusive about what model parameter would present the best fit in general. However, it was observed that the models with best fit were mostly composed by Gamma distribution, except by models with interpolation period of 30 seconds (Fig. 5, panel B). The models with 60 seconds of time interval had better fit when modeled with Von Mises distribution (Fig. 5, panel C). Regarding number of states, the 10 seconds and 60 seconds models had better results when segmented into two states (Fig. 5, panels A and C).

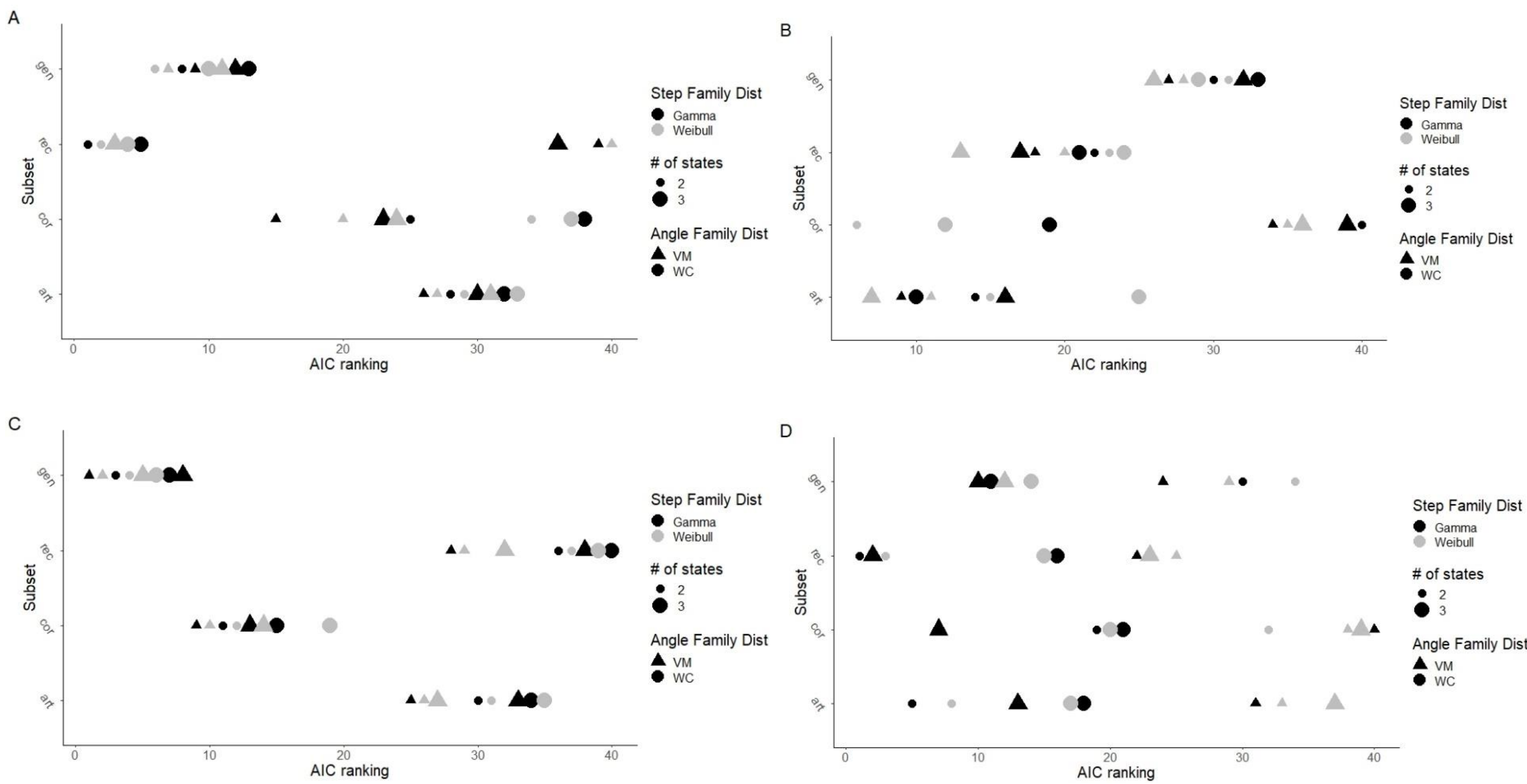


Figure 5. Model performance according to the Akaike Information Criterion (AIC) by interpolation period and subset type. Models closest to 0 are considered with higher quality. Panels present different interpolation periods (A) 10 seconds, (B) 30 seconds, (C) 60 seconds and (D) 120 seconds

To define the importance of model's parameters for accuracy, underestimation and overestimation of catching state results random forest algorithms were run (Fig. 6). For accuracy, the most important parameter was the number of states followed by the subset type and interpolation period. For under and overestimation of catching state, the most important variables were the subset type, number of states and interpolation period, consecutively. In general, the families of step length and turning angle distributions had small or no importance over results of accuracy, under and overestimation.

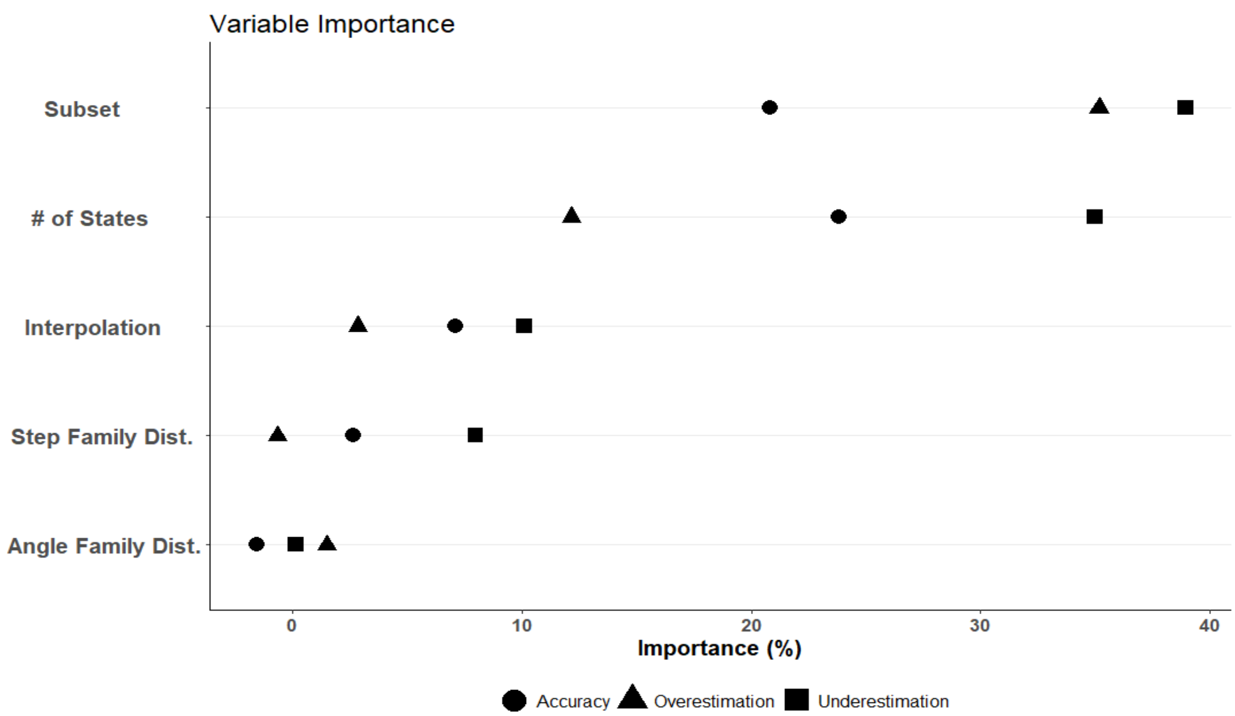


Figure 6.Variable importance for accuracy, over and underestimation of fishing state

In absolute values, the results of accuracy ranged from 59% to 79%. The best and worst model in terms of accuracy, differs their structure just by the interpolation period used, which is 30 second period for the best models and a 60 seconds time interval for the worst. All models present a high autocorrelation, which increases when finer temporal resolution is assumed, however it does not reflect negatively on the results of model estimation capability. Table 3 shows the five best and the five worst models in terms of accuracy. Figure 7 presents the comparison between real catch distributions and model catch distribution estimation as well as model fitting and autocorrelation plots of general best and worst models.

Table 3. Best and worse models in terms of accuracy by database (subset) and their corresponding combination of model's parameters.

	Subset	Distribution for Step Length	Distribution for Turning Angle	Number of States	Interpolation Period	Accuracy	Underestimation	Overestimation
Best Models	Recreative	Gamma	Von Mises	3 States	30 Seconds	79%	10.9	9.8
	Corrico	Weibull	Von Mises	3 States	60 Seconds	77%	7.8	14.9
	General	Weibull	Wrapped Cauchy	2 States	10 Seconds	74%	9.4	16.4
	Artisanal	Weibull	Wrapped Cauchy	2 States	10 Seconds	73%	1.7	24.9
Worst Models	Recreative	Gamma	Von Mises	3 States	30 Seconds	58%	2.7	38.4
	Corrico	Gamma	Von Mises	3 States	120 Seconds	61%	1.8	38.6
	General	Gamma	Von Mises	2 States	120 Seconds	66%	5.21	28.5
	Artisanal	Gamma	Wrapped Cauchy	3 States	10 Seconds	64%	6.1	29.3

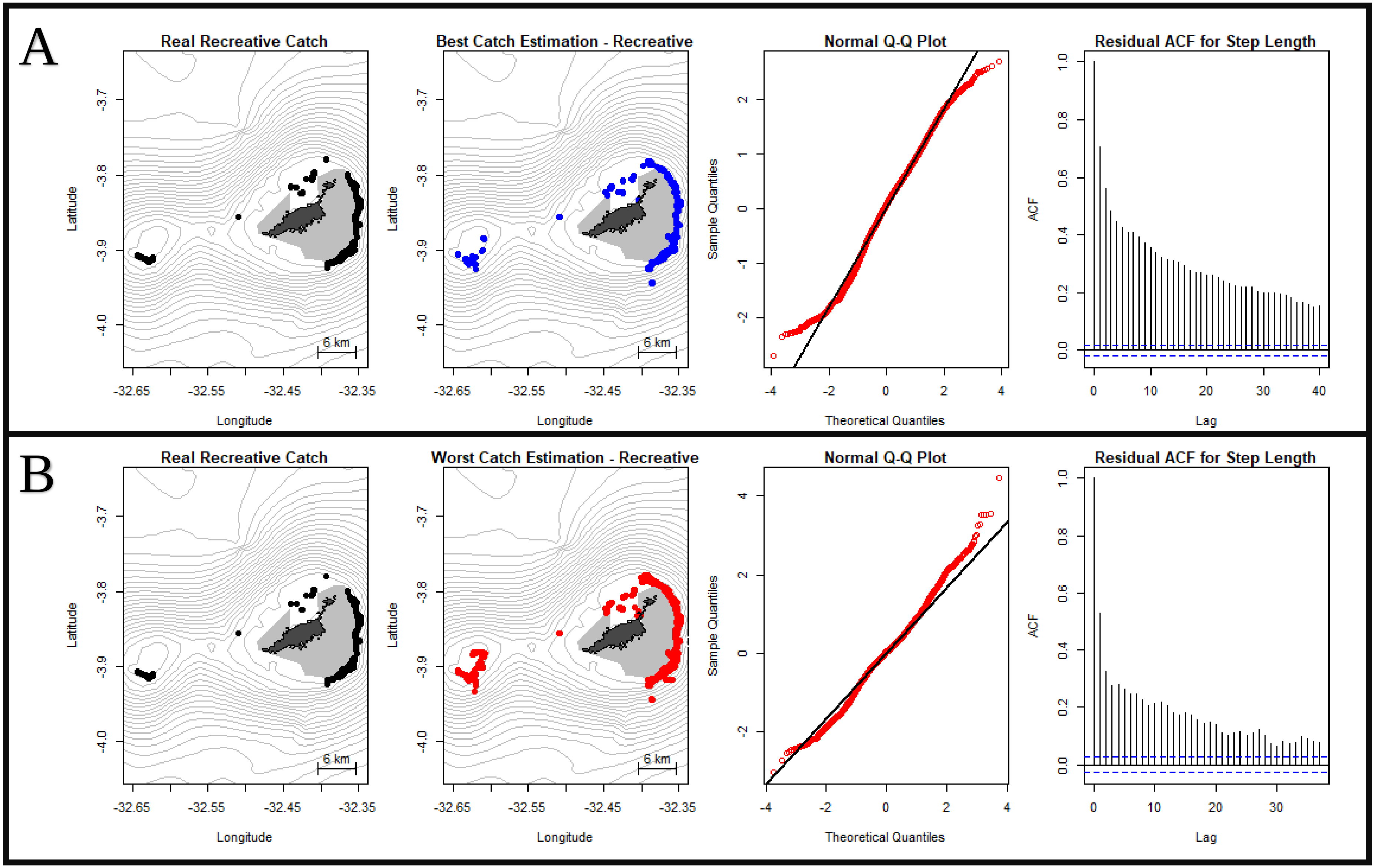


Figure 7. Real recreative crew catch zone, best (upper rectangle A) and worse (lower rectangle B) model catch zone estimation, godness of fit plots and residual autocorrelation of step lengths.

Fishing Activity Characterization

Analyzing the distribution of both fleets there are no major differences among the spatial distribution of fishing vessels. Based on results of the modeling process, the time and distance spent in each state (catching and non-catching) were calculated for both fleets using estimations from the best models. The artisanal fleet navigated about 56 km per trip and spent an average of nine hours per fishing trip, of which five were in catching operation. On the other hand, the recreative crew traveled about 73 km per fishing trip and spent seven hours per fishing trip, however they spend only two hours catching the resources. The fishers tend to concentrate their catch zones around locally well-known fishing areas, such as the “Drina”, “Casinha Branca” and “Pico com Frade” in the east side of the AFN, also called “outside sea”, along the boundaries of PARNAMAR, which is over the 50 meters depth isobath (Fig. 8).

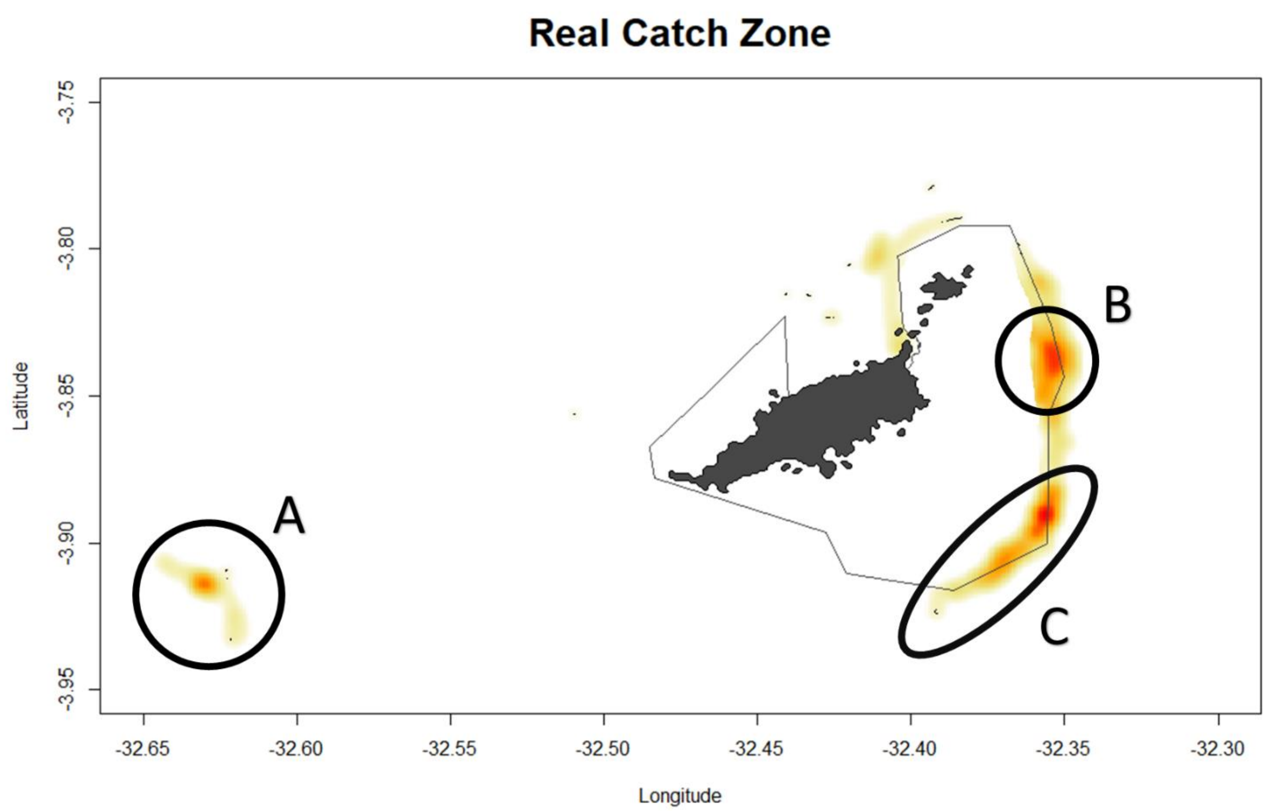


Figure 8. Traditional fishing grounds explored by fishermen of Fernando de Noronha. (A) "Drina", (B) "Casinha Branca" and (C) "Pico com Frade".

Besides the similar fishing spatial distribution (Fig. 9), the catch composition of the two fleets distinguish themselves in terms of total productivity, species and fish size. During the tree years, 316 fish were captured and informally identified, 199 by the artisanal fishery (~25 ind./trip) and 117 by the recreative (~15 ind./trip). Numbers of individuals that were hooked, but lost, were also registered, being 75 lost fish by the artisanal and 12 by the recreative. The catch composition of the fleets is given in table 4. The artisanal fleet captured more species than recreative, however it was concentrated mainly on Barracuda (*Sphyraena barracuda*) and Rainbow runner (*Elagatis bipinnulata*) responsible for almost 88% (N = 117 and N = 58, respectively) of all identified individuals. In contrast, the recreative crew had 50% of production composed by Barracuda and the remaining taxa were found in similar quantities. A considerable difference between the catch composition of the fleets is the high presence of wahoo (*Acanthocybium solandri*) and tunas in the recreative catch, absent in the artisanal ones, as well as the number of rainbow runners in artisanal in comparison with recreative. Taxa and number of individuals caught by artisanal and recreative fleet of Fernando de Noronha during three years of monitoring.

Table 4. Taxa and number of individuals caught by artisanal and recreative fleet of Fernando de Noronha during three years of monitoring.

Taxa	**Artisanal**		**Recreative**	
	#	**%**	**#**	**%**
Barracuda	117	59	59	50
Rainbow runner	58	29	15	13
Tunas	3	1.5	21	17
Wahoo	1	0.5	11	10
Lutjanidae	10	5	0	0
Carangidae	6	3	11	10
Balistidae	4	2	0	0
Total	**199**	**100**	**117**	**100**

Results of CPUE using the modeling results presented a more realistic scenario than when calculated through traditional method, using the time of departure and arrival to port. In the following example (Fig. 10), improvement of CPUE does not seen to be significant, however if used in fisheries where the time of effort allocation is considerably smaller than the total time of a fishing trip, the improvement would be more relevant.

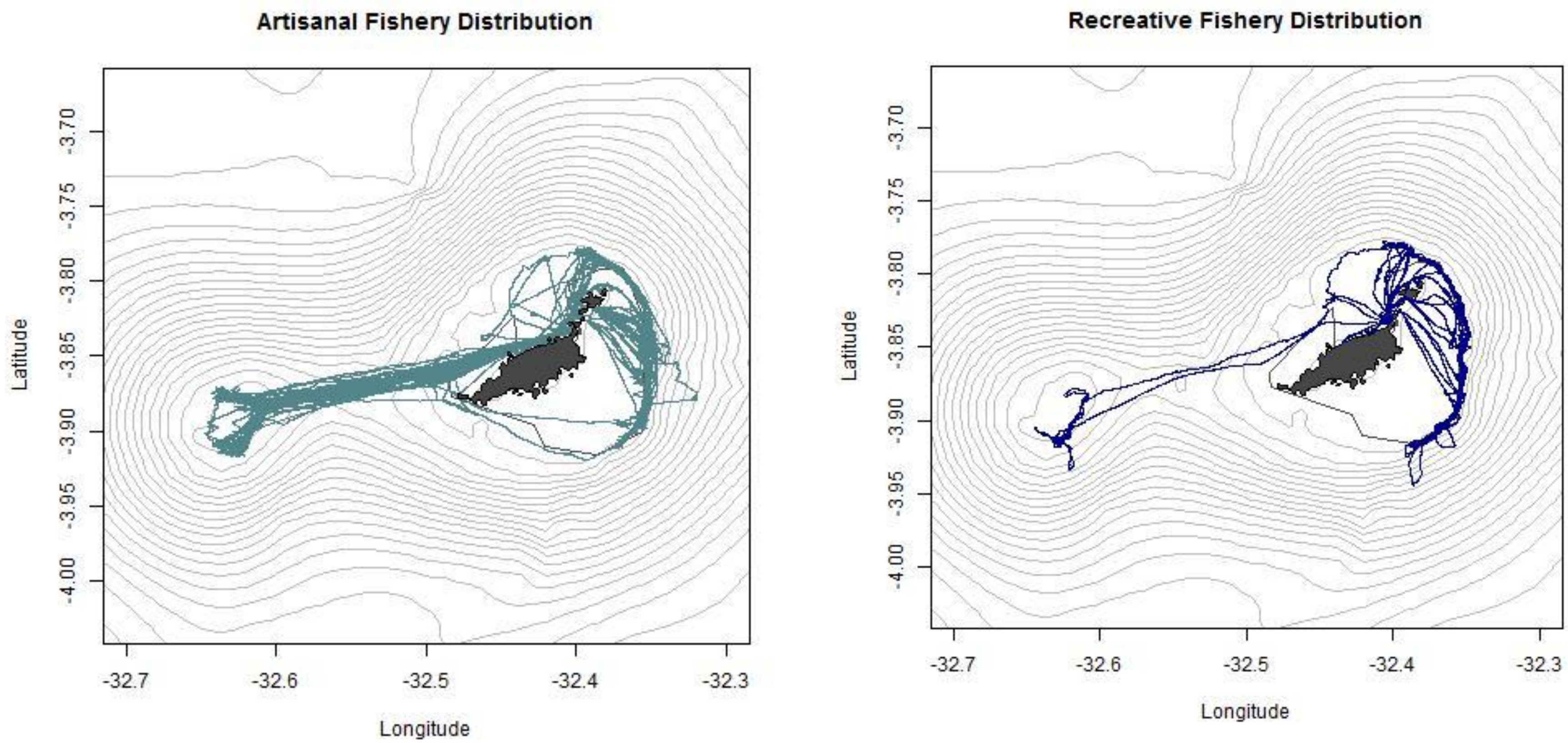
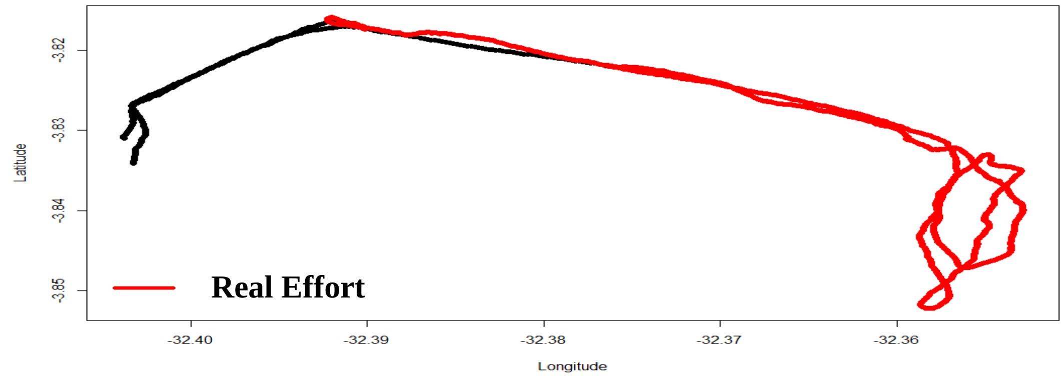


Figure 9. Fishing vessel's trajectories recorded during the three years project in Fernando de Noronha Archipelago.

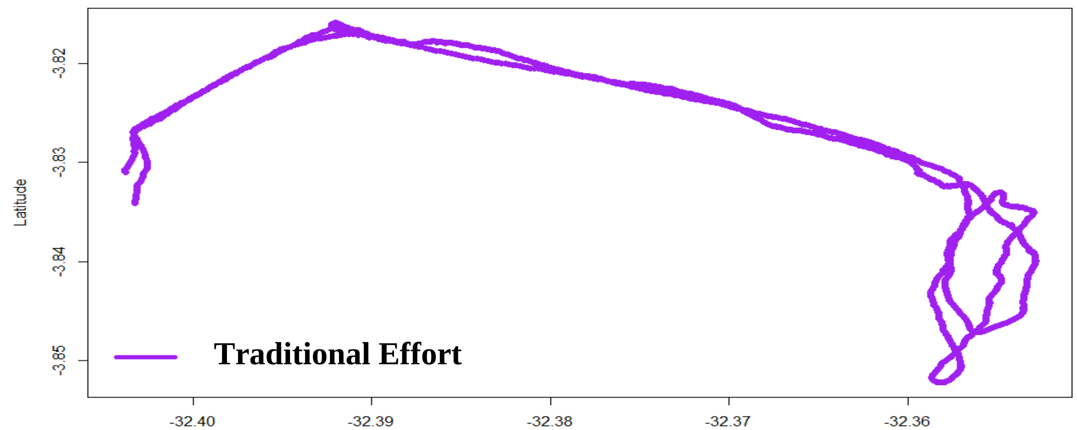
1. Real CPUE
    a. Start Time = 6:43h
    b. Final Time = 10:15h
        i. Total Effort Time = 3.32h

CPUE = 1.8



2. Traditional CPUE
    a. Departure Time = 06:13h
    b. Arrival Time = 10:15h
        i. Total Effort Time = 4:02h

CPUE = 1.5



3. Model Estimated CPUE
    a. Estimated Effort Time = 3:48h

CPUE = 1.6

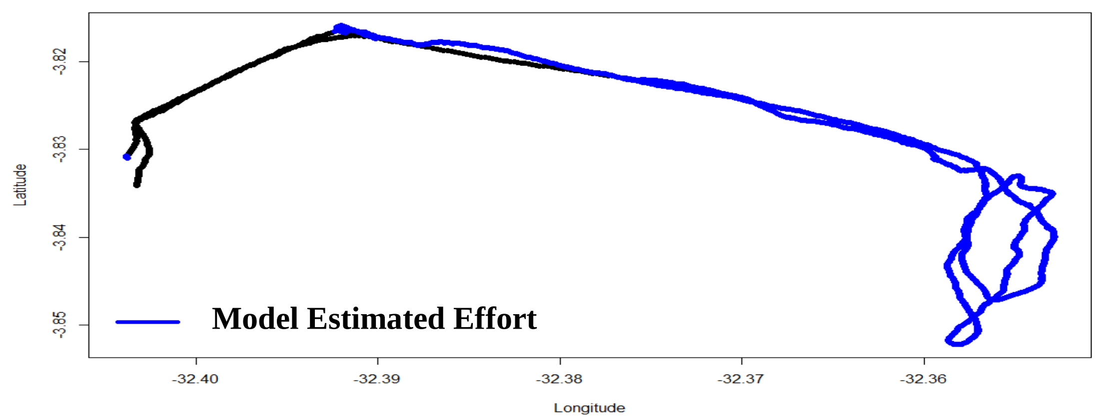


Figure 10. Comparison between real CPUE results (1), CPUE based on traditionally calculated effort time (2) and effort time estimated by HMM modeling (3)

A map of general catch zone estimation considering the 70 trajectories modeled can be seen in figure 11. The model estimation of catch zones is appropriate since they are concentrated in areas where fishers actually operates. However, attention must be taken to the indication of fishing activity been carried into the PARNAMAR limits as well as the tendency of the models to overestimate the catch state.

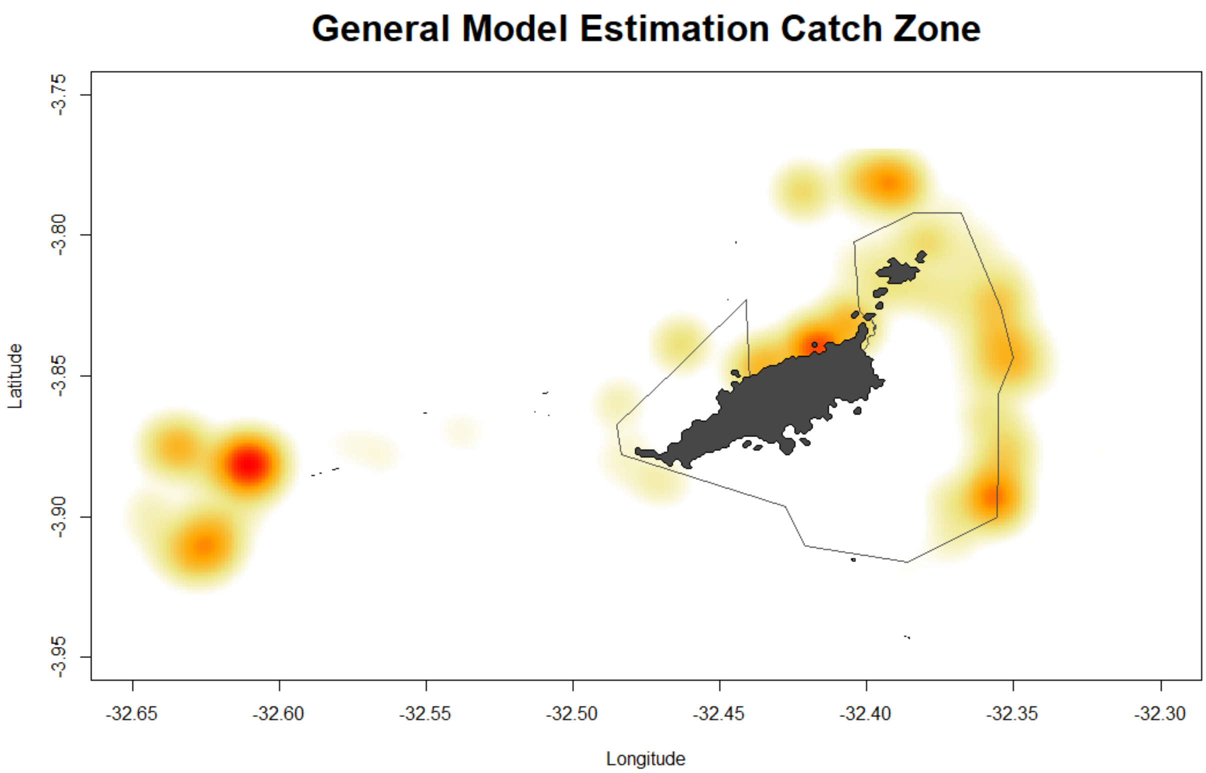


Figure 11. General catch zone estimation based on the 70 trajectories monitored through GPS devices. PARNAMAR limits denoted by polygon.

DISCUSSION

In this study we explicitly presented the spatial displacement of fishermen from Fernando de Noronha archipelago denoting the persistence of using locally traditional fishing grounds (Fig. X). Moreover, considering that ~76% (N=97) of the models considered (N=128) presented accuracy higher than 70%, we affirm that HMM are appropriate to model the behavioral activity of fishermen of Fernando de Noronha.

Fishery Behavioral Modeling

The HMM has been successfully used for modeling animal behavior for decades (CODLING and DUMBRELL, 2012; EDELHOLFF et al., 2016; PATTERSON et al., 2017). For fishermen behavioral modeling, Vermard et al (2010), identified various behavioral modes through HMM algorithms as well as quantified the effort allocation of pelagic trawlers. Peel and Good (2011), reinforced the efficiency of this method when implementing HMMs to model individual fishermen trajectories. In our project, we successfully modeled the behavior of fishermen from Fernando de Noronha Archipelago and described the fishery dynamics based on the results.

First, in this project there were some methodological inconveniences about onboard observers and interpolation processes. First, different onboard observers carried out the registering of information on logbooks and it may have caused a non-standardization of data reported, mainly in concern to time of gear deployment and recovery. Since we lack information of effort allocation, we limited our analysis to the moment of effective capture of fish (information registered for all trips observed), which is an explanation for the tendency for overestimating the fishing states. A second issue is related to interpolation of fishing trajectories, which could not be used in the original temporal resolution of GPS (1 second) due to computational limitations. The moveHMM package took about 2 hours to model each path segmentation with interpolation period of 1s. We tested 40 models for each interpolation period and saved them as Rprojects, but the 1 second project had more than 2 gigabytes and could not be load to R environment due to computer low capacity. In addition, high temporal resolutions implicate in high autocorrelation, which is an obstacle in the HMM application, then we excluded this resolution from analysis.

Based on random forests results, over the five model parameters analyzed the type of database used for modeling fishermen behavior was the most important for model's performance. Turning angles and step length are the movement metrics used to estimate the behavioral states and during the modeling process the dataset organization can influence how the metrics are interpreted. Looking at the movement metrics we can infer about animal behavior and relate the findings with environmental features, climatic variations, ontological phases and others. For example, Eckert et al (2008) associated the different behavioral modes of loggerhead turtle (Caretta caretta) to their body size and oceanographic variables to describe how this specie behave according to different morphological characteristics or environmental circumstances. Regarding fishermen behavior, Joo et al (2015) based on 14 metrics, such as trip duration, trip distance, maximum distance from coast, among others, classified Peruvian fishermen into four major groups. In our case, the recreative crew operates with higher speed than artisanal fishermen, which result in a step length distribution concentrated to the right, while the contrary is valid to the artisanal with lower concentration of large steps. This difference can be used to characterize the two fishery types. Moreover, when considering only the artisanal fishery, the step length distributions of pargueira and corrico strategies were different, which is a signal of distinct movement dynamic into this fishery type. Our results showed that when selecting the trajectories from a single fishing strategy we can have higher values of accuracy than using a generalist database. However, since all database used presented great values of mean accuracy the decision what is the most adequate to use depends on the research question. For a whole overview of fishing ground distribution, the general database would be satisfying. The partitioning of dataset into single métier subsets would be suggested in case when the study aim is to identify differences between space use according to fishery fleet or if a high value of precision is demanded, for example to identify inadequate use of marine area, to identify hotspots of fish aggregation or to monitor displacement of fishing zones over the time.

The second most important model parameter was the number of states in which the trajectories were segmented. According to mean accuracy values, the trajectories segmented into two states had better results. In most of scenarios, the addition of a third state did not increase the number of behavioral modes, it just added or subtracted some points in segments that were similarly estimated as catching by the two state models. However, a few models segmented the trajectories into three different well-defined states. Unfortunately, we cannot interpret each state because we do not have detailed information about every activity carried out during the fish trips, which limited our inference just for catching state as previously cited. The AIC results did not elucidate which number of states would produce the best fit, differently from what was described by other authors. Studies have shown that number of states selection through AIC tend to suggest the models with higher number of states as best fitting because as new states are added to the modeling process, clusters with less overlapping would be created, however it leads to an unrealistic translation for biological meanings (De RUITER et al., 2016; LI and BOLKER, 2017)

The third most important model parameter was the temporal resolution in which the trajectories were resampled. It is extensively discussed on literature due to its impact over model performance. Some concerns about interpolation period are related to the loss of information when low frequency is assumed and on the other hand the increase in autocorrelation in higher resolutions (RYAN et al. 2004; FIEBERG et al., 2010; PATTERSON et al., 2010; CAGNACCI et al., 2010). In this study the 120 seconds interpolation period presented the lowest value of mean accuracy, confirming that information can be lost as we decrease the temporal resolution. Reinforcing it, our findings showed that models with interpolation time of 10, finest temporal resolution had greater values of mean. Autocorrelation is an intrinsic property of movement ecology data and the removal of this factor may have impacts over biological interpretation of movement (De SOLLA et al., 1999; BOYCE et al.., 2010; GUARARIE et al., 2010). In our study, the high residual autocorrelation for step length distribution did not have negative impacts for the segmentation of trajectories, as denoted by the best results for the 10 seconds temporal resolution.

One of the first stages on the behavioral modeling through Hidden Markov Model is to define which family of distribution better represents the dataset studied. The Gamma and Weibull distributions were used in the modeling process and both had similar performance denoted through coincident values of mean accuracy. For each model one of those families (Gamma or Weibull) were assumed to represent all states present in the step length distribution of a trajectory. The most appropriate method would be to find the better fit distribution to each state, since this generalization can cause confuse interpretations of data distribution where the tails are not well modeled, and an overlap of state distributions can occur. In relation to turning angle distributions, we found significant differences between the accuracy of models for Von Misses and wrapped Cauchy families. These distributions have been vastly used for turning angle modeling of animal movement and they are assumed to be equivalent since they have similar shape (BOVET and BENHAMOU, 1988; CODLING et al., 2004; MORALES et al., 2004). In our case, the wrapped Cauchy better expressed our data distribution. The wrapped Cauchy is characterized by higher concentration of data over the mean parameter (commonly assumed to be 0), when compared to Von Misses (CODLING and HILL, 2005; BARTUMEUS et al., 2008). This pattern suggests a low diffusive behavior, which is in accordance with the behavioral distribution found for the fishermen of Fernando de Noronha, who tended to travel directly to and from fishing grounds at the beginning and finish of fishing activity.

Fishing Activity Characterization

Geolocation data from artisanal and recreative fleets of Fernando de Noronha were registered via GPS devices to be used for describing fishing activity in the archipelago. Our results demonstrate that even applying diverse fishing techniques and strategies the fishers from both fleets permuted and shared common fishing grounds around the islands (Fig. x). However, however the catch composition of the fleets in Fernando de Noronha have substantial differences independently from the similarity of fisheries spatial distribution. Considering the potential problems of using fishery data, it is essential to understand the dynamic of each fishery to avoid misjudgments about ecosystem conditions. Marchal et al. (2008) discussed how catch profiles can be used to characterize métiers of a mixed-fisheries and they have found that both concepts are interlinked, and they can be used as descriptors of each other at some scale. In AFN the type of baits and the fish strategy adopted (métier) are more likely to be affecting the catch composition. Baits have been demonstrated as a factor influencing catch composition and size structure of fish captured (BROADHURST AND HAZIN, 2001; ARLINGHAUS et al., 2008; ALÓS et al., 2009). In addition, each métier is operated in different depth ranges and variation on fish community through depth gradient is well known, since it is closely related to temperature, oxygen, prey availability and other parameters (TOLIMIERI and LEVIN, 2006; ZINTZEN et al., 2017).

Beyond the exploration of traditionally known fishing zones, the fishing is performed on the border of National Marine Park (PARNAMAR) limits, which demonstrate the close relationship of this management measure with the fishery activity. Marine protected areas (MPAs) are increasingly been proposed as an appropriate measure to deal with the growing spatial occupation by different anthropogenic activities. For fisheries, when adequately planned can improve the profit as well as the supply of ecosystem services (SANCHIRICO et al., 2006; GAYLORD et al., 2005). Considering the small-scale fisheries, it is important to consider the social impacts of MPA implementations, since the fisher may modify their traditional behavior due to policy requirements (MASCIA et al., 2010). As presented by Lunn and Dearden (2006) in a case study conducted in Thailand, almost 52% of small-scale fishers interviewed by them were not aware of the prohibition of fishing activity with a national park limit. This lack of communication among stakeholders, policy makers and community are a huge problem leading to inefficient management plans. On the other hand, Gleason et al (2010) showed how successful an

MPA implementation can be when a planning process is clearly defined, involving the whole community using robust scientific data in accord with local legislation.

In addition to the importance to understand the fishermen distribution and their relationship with the surrounding areas, fishery behavioral modeling is the calculation of a spatially explicit CPUE. In addition, information on the contraction or dispersion in the distribution of fishing vessels can be used to identify possible pressures exerted on the aquatic resources (BERTRAND et al., 2007). With vessel distribution and effort allocation data a spatially explicit CPUE can be calculated and problems with CPUE hyperstability can be avoided. Lessa et al. (1998) is one of the few studies focused on CPUE of Fernando de Noronha fishery, and it was achieved a 73kg/trip in 1989, which was considered a high value when compared with results of CPUE from the Northeast of Brazil for the same period. A decrease in CPUE was noticed by these authors and it was explained by the reduction of effort. Nonetheless, misinterpretation of CPUEs can lead to tremendous outcomes, as it occurred in the Atlantic cod (Gadus morhua (Limneus, 1758)) fishery, when traditional methods of stock assessment, such as catch per unit effort (CPUE), were inefficient in detecting this population decline (HILBORN and WAITERS, 1992; HUTCHINGS , 1996).

Overall, data over fishery distribution has become more accessible in the last decades, however it is true for industrial and large-scale fisheries. Talking for artisanal and small-scale fisheries there are not much information about their displacement even they are responsible for employing more than 90% of the fishers around the world and produce about 50% of the capture in developing countries (FAO, 2016). This study has reinforced the use of behavioral modeling based on GPS devices as an effective method to describe the spatial distribution as well as to estimate the catching activity of small- scale fisheries that operates on the Archipelago of Fernando de Noronha. Considering the growing concerns to apply management actions based on ecosystem, and the high competition for marine spatial use, understand and include the displacement of fishermen in management plans has become necessary to guarantee a complete and successful implementation of sustainable policy of marine exploration.

CONSIDERAÇÕES FINAIS

É notável a crescente necessidade da coleta de informações que integrem conhecimentos acerca do ecossistema em geral e em alta resolução espaço temporal para garantir o desenvolvimento e implementação de medidas de manejo eficazes. No atlântico tropical, o Arquipélago de Fernando de Noronha desempenha um importante papel ecológico para região oceânica e por isso muitos são os esforços para garantir a sustentabilidade no uso dos recursos naturais locais. Este trabalho gerou resultados inéditos quanto a distribuição espacial da atividade pesqueira em alta resolução e também sobre a alocação do esforço pesqueiro das frotas recreativa e artesanal atuantes no entorno das ilhas. Também foi evidenciada a eficácia da modelagem comportamental das frotas pesqueiras através de Modelos Ocultos de Markov, o que possibilita a inferência sobre a dinâmica das embarcações não acompanhadas, porém rastreadas via GPS. Com tais informações podem ser calculados índices de abundância precisos e de forma espacialmente explícita. Além disso, dados de composição das capturas podem servir para melhor entender as particularidades cada frota pesqueira de Fernando de Noronha. Em geral, as informações presentes nesse trabalho podem servir como subsídio para futuras discussões sobre o manejo dos recursos naturais capturados pela pesca. Em adição, estes dados podem auxiliar o entendimento da relação entre pescadores e as medidas protetivas implementadas no arquipélago e as possíveis respostas que os mesmos teriam com alterações nessas unidades de conservação.

REFERENCES

AKAIKE H. (1974) A New Look at the Statistical Model Identification. In: Parzen E., Tanabe K., Kitagawa G. (eds) Selected Papers of Hirotugu Akaike. **Springer Series in Statistics (Perspectives in Statistics)**. Springer, New York, NY

ALLEN, ANDREW M.; SINGH, NAVINDER J. Linking Movement Ecology with Wildlife Management and Conservation. **Frontiers in Ecology and Evolution**, v. 3, n. January, p. 1–13, 2016. Available in: <http://journal.frontiersin.org/Article/10.3389/fevo.2015.00155/abstract>.

ALOS, J., ARLINGHAUS, R., PALMER, M., MARCH, D., ALVAREZ, I. The influence of type of natural bait on fish catches and hooking location in a mixed-species marine recreational fishery, with implications for management. **Fisheries Research**. 97, 270–277. 2009

ARLINGHAUS, R., KEFLOTH, T., KOBLER, A., COOKE, S.J. Size Selectivity, Injury, Handling Time, and Determinants of Initial Hooking Mortality in Recreational Angling for Northern Pike: The Influence of Type and Size of Bait. **North American Journal of Fisheries Management**, v. 28, n. 1, p. 123–134, 2008.

BARTUMEUS F, CATALAN J, VISWANATHAN GM, RAPOSO EP, DA LUZ MGE. The influence of turning angles on the success of non-oriented animal searches. **Journal of Theoretical Biology**, v. 252, n. 1, p. 43–55, 2008.

BENGIO, Y. Markovian Models for Sequential Data 1 Introduction. **Neural Computing Surveys**, v. 2, p. 129--162, 1999.

BERTRAND, S., DEWITTE, B., TAM, J., DIA´Z, E., AND BERTRAND, A. Impacts of Kelvin wave forcing in the Peru Humboldt Current system: Scenarios of spatial reorganizations from physics to fishers. **Progress in Oceanography**, v. 79, n. 2–4, p. 278–289, 2008. Available in: <http://dx.doi.org/10.1016/j.pocean.2008.10.017>.

BERTRAND S, BURGOS JM, GERLOTTO F, ATIQUIPA J. Lévy trajectories of Peruvian purse-seiners as an indicator of the spatial distribution of anchovy (Engraulis ringens). **ICES Journal of Marine Science**, v. 62, n. 3, p. 477–482, 2005.

BERTRAND, S; DÍAZ, E; LENGAIGNE, M. Patterns in the spatial distribution of Peruvian anchovy (Engraulis ringens) revealed by spatially explicit fishing data. **Progress in**

Oceanography, v. 79, n. 2–4, p. 379–389, 2008. Available in: <http://dx.doi.org/10.1016/j.pocean.2008.10.009>.

BERTRAND, S; DÍAZ, E; ÑIQUEN, M. Interactions between fish and fisher's spatial distribution and behaviour: An empirical study of the anchovy (Engraulis ringens) fishery of Peru. **ICES Journal of Marine Science**, v. 61, n. 7, p. 1127–1136, 2004.

BERTRAND, S; JOO, R; FABLET, R. Generalized Pareto for pattern-oriented random walk modelling of organisms' movements. **PLoS ONE**, v. 10, n. 7, p. 1–16, 2015.

WALKER, E., GAERTNER, D., GASPAR, P. & BEZ, N. Fishing activity of tuna purse seiners estimated from vessel monitoring system (VMS) data and validated by observers' data. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 68, n. 11, p. 1998–2010, 2010. Available in: <http://www.nrcresearchpress.com/doi/abs/10.1139/f2011-114>.

BOVET, P; BENHAMOU, S. Spatial analysis of animals' movements using a correlated random walk model. **Journal of Theoretical Biology**, v. 131, n. 4, p. 419–433, 1988.

BOYCE, M. S., PITT, J., NORTHRUP, J. M., MOREHOUSE, A. T., KNOPFF, K. H., CRISTESCU, B. & STENHOUSE, G. B. Temporal autocorrelation functions for movement rates from global positioning system radiotelemetry data. **Philosophical Transactions of the Royal Society B: Biological Sciences**, v. 365, n. 1550, p. 2213–2219, 2010.

BRANCH, T.A., HILBORN, R., HAYNIE, A.C., FAY, G., FLYNN, L., GRIFFITHS, J., MARSHALL, K.N., RANDALL, J.K., SCHEUERELL, J.M., WARD, E.J., YOUNG, M. Fleet dynamics and fishermen behavior: lessons for fisheries managers. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 63, n. 7, p. 1647–1668, 2006. Available in: <http://www.nrcresearchpress.com/doi/abs/10.1139/f06-072>.

BREIMAN, Leo. Consistency for a simple model of random forests. **Statistics**, 2004.

BREIMAN, Leo. Random forests. p. 1–33, 2001.

BROADHURST, MATT K.; HAZIN, FABIO H.V. Influences of type and orientation of bait on catches of swordfish (Xiphias gladius) and other species in an artisanal sub-surface longline fishery off northeastern Brazil. **Fisheries Research**, v. 53, n. 2, p. 169–179, 2001.

BUHL-MORTENSEN L, VANREUSEL A, GOODAY AJ, LEVIN LA, PRIEDE IG. Biological structures as a source of habitat heterogeneity and biodiversity on the deep ocean margins. **Marine Ecology**, v. 31, n. 1, p. 21–50, 2010.

CAGNACCI, F., BOITANI, L., POWELL, R.A. & BOYCE, M.S. Animal ecology meets GPS-based radiotelemetry: A perfect storm of opportunities and challenges. **Philosophical Transactions of the Royal Society B: Biological Sciences**, v. 365, n. 1550, p. 2157–2162, 2010.

CAMPBELL, Robert A. Constructing stock abundance indices from catch and effort data : Some nuts and bolts. **Fisheries Research**, v. 161, p. 109–130, 2015. Available in: <http://dx.doi.org/10.1016/j.fishres.2014.07.004>.

CODLING, E. A.; HILL, N. A. Sampling rate effects on measurements of correlated and biased random walks. **Journal of Theoretical Biology**, v. 233, n. 4, p. 573–588, 2005.

CODLING, EDWARD A.; PLANK, MICHAEL J.; BENHAMOU, SIMON. Random walk models in biology. **Journal of the Royal Society Interface**, v. 5, n. 25, p. 813–834, 2008.

CODLING, EDWARD A; DUMBRELL, ALEX J. CODLING, DUMBRELL **Interface Focus** Mathematical and theoretical ecology linking models with ecological processes. n. February, p. 144–149, 2012.

CHRISTOPHER COSTELLO, DANIEL OVANDO, TYLER CLAVELLE, C. KENT STRAUSS, RAY HILBORN, MICHAEL C. MELNYCHUK, TREVOR A. BRANCH, STEVEN D. GAINES, CODY S. SZUWALSKI, RENIEL B. CABRAL, DOUGLAS N. RADER, AND AMANDA LELAND. Global fishery prospects under contrasting management regimes. Proceedings of the National Academy of Sciences, 113 (18) 5125-5129. 2016

COSTELLO, C., RASSWEILER, A., SIEGEL, D., DE LEOD, G., MICHELIE, F. & ROSENBERG, A. The value of spatial information in MPA network design. Proceedings of the National Academy of Sciences of the United States of America 107, 18294–18299, 2010.

S. R. DE SOLLA, R. BONDURIANSKI, R. J. BROOKS. Eliminating autocorrelation reduces biological relevance of home range estimates. **Journal of Animal Ecology**, v. 68, n. 2, p. 221–234, 2001.

] E. N. DE SOUZA, K. BOERDER, S. MATWIN, AND B. WORM. Improving fishing pattern detection from satellite AIS using data mining and machine learning. **PLoS ONE**, v. 11, n. 7, p. 1–20, 2016.

DERUITER, S., LANGROCK, R., SKIRBUTAS, T., GOLDBOGEN, J., CALAMBOKIDIS, J., FRIEDLAENDER, A. & SOUTHALL, B. A multivariate mixed hidden Markov model to analyze blue whale diving behaviour during controlled sound exposures. p. 1–26, 2016. Available in: <http://arxiv.org/abs/1602.06570>.

DINMORE, T.A., DUPLISEA, D.E., RACKHAM, B.D., MAXWELL, D.L. AND JENNINGS, S. Impact of large-scale area closure on patterns of fishing disturbance and the consequences for benthic communities. **ICES Journal of Marine Science**, v. 3139, n. 03, p. 1298–1317, 2003.

ECKERT SA, MOORE JE, DUNN DC, VAN BUITEN RS, ECKERT KL. .Modeling loggerhead turtle movement in the Mediterranean: importance of body size and oceanography. **Ecol Appl** 18: 290–308. 2008

EDELHOFF, HENDRIK; SIGNER, JOHANNES; BALKENHOL, NIKO. Path segmentation for beginners: an overview of current methods for detecting changes in animal movement patterns. **Movement Ecology**, v. 4, n. 1, p. 21, 2016. Available in: <http://movementecologyjournal.biomedcentral.com/articles/10.1186/s40462-016-0086-5>.

FIEBERG, J., MATTHIOPOULOS, J., HEBBLEWHITE, M., BOYCE, M. S. & FRAIR, J. L Correlation and studies of habitat selection: Problem, red herring or opportunity? **Philosophical Transactions of the Royal Society B: Biological Sciences**, v. 365, n. 1550, p. 2233–2244, 2010.

FULTON, E. A., SMITH, A. D. M., SMITH, D. C. & VAN PUTTEN, I. E Human behaviour: The key source of uncertainty in fisheries management. **Fish and Fisheries**, v. 12, n. 1, p. 2–17, 2011.

GLOAGUEN P, MAHÉVAS S, RIVOT E, WOILLEZ M, GUITTON J, VERMARD Y, ET AL An autoregressive model to describe fishing vessel movement and activity. **Environmetrics**, v. 26, n. 1, p. 17–28, 2015.

GURARIE, ELIEZER; ANDREWS, RUSSEL D.; LAIDRE, KRISTIN L. A novel method for identifying behavioural changes in animal movement data. **Ecology Letters**, v. 12, n. 5, p. 395–408, 2009.

HEBBLEWHITE, MARK; HAYDON, DANIEL T. Distinguishing technology from biology: A critical review of the use of GPS telemetry data in ecology. **Philosophical Transactions of the Royal Society B: Biological Sciences**, v. 365, n. 1550, p. 2303–2312, 2010.

HOLYOAK M, CASAGRANDI R, NATHAN R, REVILLA E, SPIEGEL O Trends and missing parts in the study of movement ecology. **Proceedings of the National Academy of Sciences**, v. 105, n. 49, p. 19060–19065, 2008. Available in: <http://www.pnas.org/cgi/doi/10.1073/pnas.0800483105>.

HUNTINGTON, HENRY, P. Using Traditional Ecological Knowledge in Science : Methods and Applications. **Ecological applications**, v. 10, n. 5, p. 1270–1274, 2000. Available in: <http://www.esajournals.org/doi/abs/10.1890/1051-0761(2000)010[1270:UTEKIS]2.0.CO;2.>.

ILARRI, M. I.; SOUZA, A. T.; ROSA, R. S. Community structure of reef fishes in shallow waters of the Fernando de Noronha archipelago: Effects of different levels of environmental protection. **Marine and Freshwater Research**, v. 68, n. 7, p. 1303–1316, 2017.

JOO, R., SALCEDO, O., GUTIERREZ, M., FABLET, R., BERTRAND, S., Defining fishing spatial strategies from VMS data: Insights from the world's largest monospecific fishery. **Fisheries Research**, v. 164, p. 223–230, 2015. Available in: <http://dx.doi.org/10.1016/j.fishres.2014.12.004>.

JOO, R.; BERTRAND, S.; TAM, J.; FABLET, R. Hidden Markov Models: The Best Models for Forager Movements? **PLoS ONE**, v. 8, n. 8, 2013.

JOO, R., BERTRAND, S., CHAIGNEAU, A., NIQUEN, M Optimization of an artificial neural network for identifying fishing set positions from VMS data: An example from the Peruvian anchovy purse seine fishery. **Ecological Modelling**, v. 222, n. 4, p. 1048–1059, 2011.

LANGROCK, R., R. KING, J. MATTHIOPOULOS, L. THOMAS, D. FORTIN, AND J. M. MORALES Flexible and practical modeling of animal telemetry data: hidden Markov models and extensions. **Ecology**, v. 93, n. 11, p. 1–22, 2012. Available in: <http://www.esajournals.org/doi/abs/10.1890/11-2241.1>.

LEE, JANETTE; SOUTH, ANDY B.; JENNINGS, SIMON. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. **ICES Journal of Marine Science**, v. 67, n. 6, p. 1260–1271, 2010.

LEMOS, VALÉRIA M.; ÁVILA TROCA, DÉBORA F.; CASTELLO, JORGE PABLO; PAES VIEIRA, JOÃO. Tracking the southern Brazilian schools of Mugil liza during reproductive migration using VMS of purse seiners. **Latin American Journal of Aquatic Research**, vol. 44, núm. 2, mayo, 2016, pp. 238-246, 2016.

LI, MICHAEL; BOLKER, BENJAMIN M. Incorporating periodic variability in hidden Markov models for animal movement. **Movement Ecology**, v. 5, n. 1, p. 1–12, 2017. Available in: <http://dx.doi.org/10.1186/s40462-016-0093-6>.

LIAW, ANDT; WIENER, MATTHEW. Classification and Regression by randomForest. **R news**, v. 2, n. December, p. 18–22, 2002.

MAIDA, MA; FERREIRA, BEATRICE PADOVANI. Coral Reefs of Brazil : Overview and Field Guide. **8th Int Coral Reef Sym**, n. January 1997, p. 263–273, 1997.

MARCHAL, Paul. A comparative analysis of métiers and catch profiles for some French demersal and pelagic fleets. **ICES Journal of Marine Science**, v. 65, n. 4, p. 674–686, 2008.

ST MARTIN, K., MCCAY, B.J., MURRAY, G., JOHNSON, T. & OLES, B Communities, knowledge and fisheries of the future. **International Journal of Global Environmental Issues**, v. 7, n. 2/3, p. 221, 2007.

GLEASON M, MCCREARY S, MILLER-HENSON M, UGORETZ J, FOX E, MERRIFIELD M, MCCLINTOCK W, SERPA P, HOFFMAN K. Science-based and stakeholder-driven marine protected area network planning: a successful case study from north central California. **Ocean and Coastal Management** 53: 52–68. 2010.

MCKELLAR, A., LANGROCK, R., WALTERS, J. & KESLER, D Using mixed hidden Markov models to examine behavioral states in a cooperatively breeding bird. **Behavioral Ecology**, v. 26, n. 1, p. 148–157, 2015.

MICHELOT, Author Theo et al. Package ‘ moveHMM ’ R topics documented : 2017.

MICHELOT, THÉO; LANGROCK, ROLAND; PATTERSON, TOBY A. moveHMM: an R package for the statistical modelling of animal movement data using hidden Markov models.

Methods in Ecology and Evolution, v. 7, n. 11, p. 1308–1315, 2016.

MILLS, C M et al. Estimating high resolution trawl fishing effort from satelite-based vessel monitoring system data. **ICES Journal of Marine Science**, v. 64, p. 248–255, 2007. Available in: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.491.7100&rep=rep1&type=pdf%0A https://oup.silverchair-cdn.com/oup/backfile/Content_public/Journal/icesjms/64/2/10.1093/icesjms/fsl026/2/fsl026.pdf?Expires=1491103717&Signature=I9vdrffkSDvUT3VfyQ0ljQX>.

MORALES JM, HAYDON DT, FRAIR J, HOLSNER KE, FRYXELL JM. Extracting More out of Relocation Data : Building Movement Models as Mixtures of Random Walks. **Ecological Society of America America**, v. 85, n. 9, p. 2436–2445, 2004.

MURAWSKI, S.A., WIGLEY, S.E., FOGARTY, M.J., RAGO, P.J., AND MOUNTAIN, D.G. Effort distribution and catch patterns adjacent to temperate MPAs. **ICES Journal of Marine Science**, v. 62, n. 6, p. 1150–1167, 2005.

NATHAN, R. An emerging movement ecology paradigm. **Proceedings of the National Academy of Sciences**, v. 105, n. 49, p. 19050–19051, 2008.

O'FARRELL, S.O., SANCHIRICO, J.N., CHOLLETT, I., COCKRELL, M., MURAWSKI, S.A., WATSON, J.T., HAYNIE, A.C., STRELCHECK, A., PERRUSO, L., Improving detection of short-duration fishing behaviour in vessel tracks by feature engineering of training data. **ICES Journal of Marine Science**, v. 74, n. 5, p. 1428–1436, 2017.

OSHIRO, THAIS; PEREZ, PEDRO; BARANAUSKAS, JOSÉ. How Many Trees in a Random Forest?\rMachine Learning and Data Mining in Pattern Recognition. v. 7376, p. 154–168, 2012. Available in: <http://dx.doi.org/10.1007/978-3-642-31537-4_13>.

PABLO SOUZA GRIGOLETTI. Cadeias de Markov. n. April 2014, 2015.

PALMER, MICHAEL C. Calculation of distance traveled by fishing vessels using GPS positional data: A theoretical evaluation of the sources of error. **Fisheries Research**, v. 89, n. 1, p. 57–64, 2008.

PATTERSON, T.A., THOMAS, L., WILCOX, C., OVASKAINEN, O. & MATTHIOPOULOS, J. State-space models of individual animal movement. **Trends in Ecology and Evolution**, v. 23,

n. 2, p. 87–94, 2008.

PATTERSON, T.A., PARTON, A., LANGROCK, R., BLACKWELL, P.G., THOMAS, L., AND KING, R. Statistical modelling of individual animal movement : an overview of key methods and a discussion of practical challenges. **AStA Advances in Statistical Analysis**, v. 101, n. 4, p. 399–438, 2017.

PATTERSON, T. A.; McCONNELL, B. J.; FEDAK, M.A.; BRAVINGTON, M. V.; HINDELL, M.A. Using GPS data to evaluate the accuracy of state — space methods for correction of Argos satellite telemetry error GPS data to evaluate the accuracy of state ? space methods error satellite for correction of Argos telemetry. v. 91, n. 1, p. 273–285, 2010.

PAULY, DANIEL. Theory and · Management of Tropical Multispecies Stocks A Review , with Emphasis on. **Management**, n. 1, 1979.

PAULY, DANIEL; ZELLER, DIRK. declining. **Nature Communications**, v. 7, p. 1–9, 2016. Available in: <http://dx.doi.org/10.1038/ncomms10244>.

PEEL, DAVID; GOOD, NORMAN M.; QUINN II, TERRANCE. A hidden Markov model approach for determining vessel activity from vessel monitoring system data. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 68, n. 7, p. 1252–1264, 2011. Available in: <http://www.nrcresearchpress.com/doi/abs/10.1139/f2011-055>.

POHLE, J., LANGROCK, R., VAN BEEST, F. M., AND SCHMIDT, N. M.Selecting the Number of States in Hidden Markov Models: Pragmatic Solutions Illustrated Using Animal Movement. **Journal of Agricultural, Biological, and Environmental Statistics**, v. 22, n. 3, p. 270–293, 2017.

POSEN, P.E., LEE, J., LARGE, P., KENNY, A. Using vessel monitoring system (VMS) data to assess the impact of marine protection boundaries on blue ling fishing northwest of the British Isles. **Aquatic Living Resources**, v. 27, n. 1, p. 17–26, 2014. Available in: <http://www.alr-journal.org/10.1051/alr/2014001>.

POWELL, E. N., BONNER, A. J., MULLER, B., AND BOCHENEK, E. A. Vessel time allocation in the US Illex illecebrosus fishery. **Fisheries Research**, v. 61, n. 1–3, p. 35–55, 2003.

RABINER, Lawrence R. A Tutorial on Hidden Markov Models and Selected Applications in

Speech Recognition. **Proceedings of the IEEE**. [S.l: s.n.]. , 1989

RIJNSDORP, A.D., GROOT, P. AND VAN BEEK, F.A. Micro-scale distribution of beam trawl effort in the southern North Sea between 1993 and 1996 in relation to the trawling frequency of the sea bed and the impact on benthic organisms. **ICES Journal of Marine Science**, v. 55, n. 3, p. 403–419, 1998.

RIJNSDORP, A D; PIET, G J; POOS, J J. Effort allocation of the Dutch beam trawl fleet in response to a temporarily closed area in the North Sea. **Ices CM 2001/N:01**, p. 1–17, 2001.

RYAN, P. G., PETERSEN, S. L., PETERS, G. & GRE´MILLET, D. GPS tracking a marine predator: The effects of precision, resolution and sampling rate on foraging tracks of African Penguins. **Marine Biology**, v. 145, n. 2, p. 215–223, 2004.

SALAS, SILVIA; SUMAILA, USSIF RASHID; PITCHER, TONY. Short-term decisions of small-scale fishers selecting alternative target species: a choice model. **Canadian Journal of Fisheries and Aquatic Sciences**, v. 61, n. 3, p. 374–383, 2004.

SCHOFIELD, G., BISHOP, C. M., MACLEAN, G., BROWN, P., BAKER, M., KATSELIDIS, K. A., DIMOPOULOS, P., PANTIS, J. D. & HAYS, G. C. Novel GPS tracking of sea turtles as a tool for conservation management. **Journal of Experimental Marine Biology and Ecology**, v. 347, n. 1–2, p. 58–68, 2007.

SOTO, CRISTINA GRACIELA. Socio-cultural barriers to applying fishers' knowledge in fisheries management: an evaluation of literature cases. **Spring**, p. 357, 2006. Available in: <http://research.rem.sfu.ca/theses/SotoCristina_2006>.

STEVENSON, T C; TISSOT, B N. Fisher Behaviour Influences Catch Productivity and Selectivity in West Hawaii'S Aquarium Fishery. **of Using Marine**v. 68, p. 813–822, 2013. Available in: <http://research.wsulibs.wsu.edu/xmlui/bitstream/handle/2376/4713/Stevenson_wsu_0251E_10646.pdf?sequence=1#page=11>.

TCHAMABI, Christine C et al. Ichthyoplankton transport around the Brazilian Fernando de Noronha archipelago and Rocas Atoll : Are there any connectivity patterns ? g Very High Resolution. v. 47, n. 04, p. 812–818, 2018.

TOLIMIERI, NICK; LEVIN, PHILLIP S. Assemblage Structure of Eastern Pacific Groundfishes on the U.S. Continental Slope in Relation to Physical and Environmental Variables. **Transactions of the American Fisheries Society**, v. 135, n. 2, p. 317–332, 2006.

TORRES-IRINEO, E., GAERTNER, D., CHASSOT, E., AND DREYFUS-LEON, M Changes in fishing power and fishing strategies driven by new technologies: The case of tropical tuna purse seiners in the eastern Atlantic Ocean. **Fisheries Research**, v. 155, p. 10–19, 2014. Available in: <http://dx.doi.org/10.1016/j.fishres.2014.02.017>.

TURCHIN, PETER. **Quantitative Analysis of Movement**. **Measuring and Modeling Population Redistribution in Animals and Plants**. [S.l: s.n.]. , 1998

VERMARD, YOUEN. Archimer Identifying fishing trip behaviour and estimating fishing effort from VMS. **Ecological Modelling**, v. 221, n. 15, p. 1757–1769, 2010.

WILEN, J. E., M. D. SMITH, D. LOCKWOOD, AND L. W. BOTSFORD Avoiding Surprises: Incorporating Fishermen Behaviour into Management Models. **Bulletin of Marine Science**, v. 70, n. 2, p. 553–575, 2002.

WIYONO ES, YAMADA S, TANAKA E, ARIMOTO T, KITAKADO T Dynamics of fishing gear allocation by fishers in small-scale coastal fisheries of Pelabuhanratu Bay, Indonesia. **Fisheries Management and Ecology**, v. 13, n. 3, p. 185–195, 2006.

ZAGAGLIA, CLAUDIA R., SANTOS, RODRIGO C., BRICHTA, MAURICIO., BARBOSA, MAICON G. 'Dinâmica Espaço-temporal da Frota Pesqueira na Captura da Piramutaba com Rede de Arrasto no Estuário Amazônico com Base nos Dados do Programa Nacional de Rastreamento de Embarcações Pesqueiras por Satélite - PREPS. **Simposio Brasileiro de Sensoriamento Remoto**. p. 4535-4542. 2009

ZINTZEN, V., ROBERTS, C.D., ANDERSON, M.J., HARVEY, E.S., STEWART, A.L. Effects of latitude and depth on the beta diversity of New Zealand fish communities. **Scientific Reports**, v. 7, n. 1, p. 1–10, 2017. Available in: <http://dx.doi.org/10.1038/s41598-017-08427-7>.