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Global habitat preferences of commercially valuable tuna

Haritz Arrizabalaga [a,*], Florence Dufour [b], Laurence Kell [c], Gorka Merino [a], Leire Ibaibarriaga [d], Guillem Chust [d], Xabier Irigoien [e], Josu Santiago [d], Hilario Murua [a], Igaratza Fraile [a], Marina Chifflet [a], Nerea Goikoetxea [d], Yolanda Sagarminaga [a], Olivier Aumont [f], Laurent Bopp [g], Miguel Herrera [h], Jean Marc Fromentin [i], Sylvain Bonhomeau [i]

[a] AZTI—Tecnalia, Marine Research Division, Herrera Kaia Portualdea z/g, 20110 Pasaia, Basque Country, Spain
[b] NALDEO, 55 rue de la villette. F-69425 Lyon Cedex 03, France
[c] ICCAT Secretariat, Corazón de María 8, 28002 Madrid, Spain
[d] AZTI—Tecnalia, Marine Research Unit, Txatxarramendi Ugartea z/g, 48395 Sukarrieta, Basque Country, Spain
[e] Red Sea Research Center, King Abdullah University of Science and Technology, Thuwal 23955-6900, Saudi Arabia
[f] Laboratoire d'Océanographie et du Climat: Expérimentations et Approches Numériques (LOCEAN), Centre IRD de Bretagne, F-29280 Plouzané, France
[g] Laboratoire des Sciences du Climat et de l'Environnement, UMR CEA-CNRS, CEA Saclay, F-91191 Gif-sur-Yvette, France
[h] IOTC Secretariat, PO Box 1011, Victoria, Seychelles
[i] Ifremer, UMR 212 EME, boulevard Jean Monnet, BP 171, Sete Cedex 34203, France

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ABSTRACT

In spite of its pivotal role in future implementations of the Ecosystem Approach to Fisheries Management, current knowledge about tuna habitat preferences remains fragmented and heterogeneous, because it relies mainly on regional or local studies that have used a variety of approaches making them difficult to combine. Therefore in this study we analyse data from six tuna species in the Pacific, Atlantic and Indian Oceans in order to provide a global, comparative perspective of habitat preferences. These data are longline catch per unit effort from 1958 to 2007 for albacore, Atlantic bluefin, southern bluefin, bigeye, yellowfin and skipjack tunas. Both quotient analysis and Generalised Additive Models were used to determine habitat preference with respect to eight biotic and abiotic variables. Results confirmed that, compared to temperate tunas, tropical tunas prefer warm, anoxic, stratified waters. Atlantic and southern bluefin tuna prefer higher concentrations of chlorophyll than the rest. The two species also tolerate most extreme sea surface height anomalies and highest mixed layer depths. In general, Atlantic bluefin tuna tolerates the widest range of environmental conditions. An assessment of the most important variables determining fish habitat is also provided.

1. Introduction

Tunas are oceanic top predators that play an important role in marine ecosystems, account for nearly 20% of the value of marine capture fisheries and contribute to meeting worldwide protein requirements (FAO, 2011). The most economically important tuna species are the temperate tunas albacore (*Thunnus alalunga*), Atlantic bluefin tuna (*Thunnus thynnus*) and southern bluefin tuna (*Thunnus maccoyii*) and the tropical tunas yellowfin tuna (*Thunnus albacares*), bigeye tuna (*Thunnus obesus*) and skipjack tuna (*Katsuwonus pelamis*). Tunas migrate long distances during their life cycle, and are widely distributed over the Atlantic, Indian and Pacific Oceans. There is a single population for southern bluefin tuna inhabiting the southern ocean, and typically one or two populations of tropical and temperate tunas per ocean basin, except for albacore that has 3 populations in the Atlantic (Albaina et al., 2013). Tuna stocks are managed by 5 Tuna Regional Fishery Management Organizations (TRFMOs) with the primary objective of maintaining the productivity of each stock at its maximum, although in recent years there have been efforts towards the implementation of the Ecosystem Approach to Fisheries Management (EAFM).

Biotic and abiotic environmental variables affect tuna distribution and abundance (Lehodey et al., 1997; Ravier and Fromentin, 2004; Sund et al., 1981). Characterising tuna habitat is thus essential to understand tuna spatio-temporal distribution and

* Corresponding author. Tel.: +34 667 174 477; fax: +34 94 657 25 55.
E-mail address: harri@azti.es (H. Arrizabalaga).

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variability. This helps in interpretation of commercial fishery data, such as time series of catch per unit effort (CPUE) used in stock assessments to develop management advice (e.g. on Total Allowable Catches). Improved knowledge about tuna habitat and spatial distribution also allows spatial and temporal management measures to be considered, e.g. for by-catch mitigation while maintaining the profitability of fisheries (Hobday and Hartmann, 2006; Hobday et al., 2011; Teo and Block, 2010).

Local habitat studies allow local problems, i.e. for specific fleets and individual TRFMOs, to be addressed. In contrast, global habitat studies covering the worldwide distribution of all tunas are required to address global management issues and facilitate the integration of EAFM in a consistent way across TRFMOs. For instance, in the short term, global habitat studies are required to determine optimum placements for large oceanic marine protected areas (Kaplan et al., 2013; Pala, 2013) based on hotspots of biodiversity and/or abundance (Worm et al., 2005). In the longer term, anthropogenic climate change effects will need to be addressed, as part of the EAFM by TRFMOs and other governance bodies (Maury et al., 2013). The provision of science to support TRFMOs decisions is critical (Hobday et al., 2013) and collaborative efforts are required between research disciplines and management agencies to better monitor and understand the impacts of short-term variability and longer-term climate change on oceanic fisheries (Salinger et al., 2013). Habitat models can be used to predict future impacts of anthropogenic climate change on tuna distribution and abundance (Hobday, 2010; Lehodey et al., 2013), allowing to develop alternative management strategies and adapt to future socio economic scenarios (Bell et al., 2013).

In spite of its pivotal role in future implementations of the EAFM within TRFMOs, current knowledge about tuna habitat preferences remains fragmented and heterogeneous. The latest generation of electronic tags has provided important new insights (Bestley et al., 2009; Galuardi and Lutcavage, 2012; Schaefer and Fuller, 2010; Schaefer et al., 2007). Although some large deployment efforts have characterised habitat preference and movement patterns at relevant scales for management (e.g. Block et al., 2005; Block et al., 2011; Hartog et al., 2011; Hazen et al., 2013; Hobday and Hartmann, 2006), most tagging studies are local with short deployment periods (e.g. Cosgrove et al., 2014), and provide information about habitat characteristics only around deployment areas (Hobday and Evans, 2013).

Additional efforts to study tuna habitat preferences have been undertaken using fishery data, commonly assuming that CPUE is proportional to fish abundance. Data on the position and time of fishing events allow relationships between the presence and/or abundance of tunas with environmental conditions to inform habitat preferences using a range of modelling approaches. For example empirical distributions of relative abundance binned across environmental variables can inform habitat preferences (Cheung et al., 2013; Sagarminaga and Arrizabalaga, 2010; Zainuddin et al., 2006). Fromentin et al. (2014) characterised the environmental niche of Atlantic bluefin tuna using a non-parametric probabilistic environmental niche model (NPPEN, Beaugrand et al., 2011), and Reygondeau et al. (2012) used a hierarchical clustering method to identify different tuna and billfish communities and describe their environmental conditions. Several other authors used Generalised Linear Models (GLM, Briand et al., 2011, Lan et al., 2013) and Generalised Additive Models (GAMs, Lan et al., 2013; Maury et al., 2001; Mugo et al., 2010; Sagarminaga and Arrizabalaga, 2010) to describe habitat preferences of tunas. Finally, coupled biophysical models such as SEAPODYM (Lehodey et al., 2008) or APECOSM (Maury, 2010) are being used to describe the spatial dynamics of tunas and can incorporate different habitat indices (e.g. spawning habitat and feeding habitat) as well as submodels for the distribution of tuna forage (Bertignac et al., 1998, Lehodey et al., 1998). Guisan and Zimmermann (2000) suggest that there is no best model. Instead, the choice of the model depends on the objective of the study as well as the nature of the available data.

A range of environmental variables influence tuna spatial distribution. Temperature and oxygen affect important biological processes and thus determine the spatial distribution of tunas (Barkley et al., 1978; Boyce et al., 2008; Brill, 1994; Stramma et al., 2012). Salinity can influence large scale spatial distribution (e.g. Fromentin et al., 2014; Maury et al., 2001; Reygondeau et al., 2012). The mixed layer depth can limit the vertical distribution of tuna and tuna like species (Bernal et al., 2009; Prince et al., 2010), while the sea surface height anomaly (SSH) provides information on the open-ocean physical habitat of pelagic species. For example, positive and negative anomalies are associated with eddies and gyres, describing convergent and divergent areas where tuna prey may aggregate. Frontal systems around these gyres can also potentially aggregate tunas (Arrizabalaga et al., 2008; Olson et al., 1994; Podestá et al., 1993; Royer et al., 2004; Sagarminaga and Arrizabalaga, 2014). In addition to the physical environment, the distribution of prey is also one of the main drivers of the spatial distribution and behaviour of tunas (Bertignac et al., 1998; Schick and Lutcavage, 2009, Bernal et al. 2009). Chen et al., 2005 have shown that higher primary production attracts tunas, but data on tuna prey distribution and abundance is scarce and is mostly available from models (Lehodey et al., 1998).

Habitat studies using fishery or survey data are often spatially limited and focused on single species (e.g. Chen et al., 2005; Sagarminaga and Arrizabalaga, 2010). Therefore, each study provides a particular view of the habitat preference of a given species or stock, commonly based on one variable (mostly sea surface temperature) or a limited set of environmental variables. In this context, comparison between different habitat preferences is difficult due to differences in the datasets, methods, and studied areas, and this affects our ability to determine which environmental variables are the most important drivers of tuna distribution. In fact, there are few studies where the habitat preferences of a group of species are analysed using similar datasets and methods at broad spatial scales (but see Reygondeau et al., 2012). Therefore, the aim of this study is, based on a common dataset and consistent methodology, to provide a global comparative perspective of habitat preferences for six commercially important tuna species and to identify the most important variables driving tuna spatial distribution.

2. Material and methods

2.1. Fishery data

The main commercial species of tuna, namely Atlantic bluefin, southern bluefin, albacore, bigeye, yellowfin and skipjack are considered. These large predators of the pelagic ecosystem are highly migratory and their distribution covers most of the tropical and temperate areas around the globe. They are mainly caught by industrial pelagic fisheries. Among the fishing methods, pelagic longlines show the largest spatio-temporal coverage, since they have operated for several decades across all oceans, targeting all main commercial tuna species except skipjack. Longlines resemble long baited transects and catch a wide range of species in a consistent way over a vast spatial scale and longline catch data have been previously used to analyse changes in abundance (Myers and Worm, 2003), diversity (Worm et al., 2005), range contraction (Worm and Tittensor, 2011) and biogeography (Reygondeau et al., 2012).

Tuna longline catch and effort data for the Atlantic, Indian and Pacific Oceans were obtained from the five TRFMOs, i.e.