Deep-Sea Research II 113 (2015) 246–259

Contents lists available at ScienceDirect

Deep-Sea Research II

journal homepage: www.elsevier.com/locate/dsr2

Modelling the impact of climate change on South Pacific albacore tuna

Patrick Lehodey [a,*], Inna Senina [a], Simon Nicol [b], John Hampton [b]

[a] CLS, Space Oceanography Division, 8-10 rue Hermes, 31520 Ramonville, France
[b] Secretariat of the Pacific Community, Oceanic Fisheries Programme, Noumea, New Caledonia

ARTICLE INFO

Available online 10 November 2014

Keywords:
Climate change
Fisheries
Tuna
Albacore
Ecosystem
Modelling
Management
SEAPODYM
Population dynamics
Maximum Likelihood Estimation

ABSTRACT

The potential impact of climate change under the IPCC AR4–A2 scenario (close to the AR5-RCP8.5 scenario) on south Pacific albacore tuna (*Thunnus alalunga*) is simulated with the Spatial Ecosystem And Population Dynamics Model (SEAPODYM) and environmental forcing variables provided by the Earth Climate model IPSL-CM4. Parameters controlling the habitat and dynamics of the population were optimized by fitting the model, using maximum likelihood, to a complete fishing data set for the historical fishing period since 1950. Albacore undertake clear seasonal migrations between feeding and spawning grounds, as evidenced by seasonal catch and size composition changes. This seasonality was well predicted by the SEAPODYM albacore simulations. The total biomass estimate of south Pacific albacore was predicted to have decreased from ~1.8 million tonnes (Mt) at the beginning of industrial fisheries in 1950 to 1.25 Mt in 2006, in good agreement with an independent estimate from stock assessment analysis. A simulation without fishing indicated an equivalent contribution of environmental variability and fishing to the historical decrease of the stock biomass. The parameterized SEAPODYM model was used to project the dynamics of the population until the end of the 21st century with an average fishing effort based on recent years. Under this fishing and climate change scenario, the population was predicted to decrease and to stabilize after 2035 just below 0.8 Mt, i.e., 55% below the initial biomass of 1960. After 2080 however, the trend was reversed when a new spawning ground emerged in the north Tasman Sea. A test simulation highlighted the sensitivity of the model results to projected dissolved oxygen concentration for which there is large uncertainty in the tropical region. A second test simulation showed that genetic selection favouring albacore with preferences for higher optimal ambient spawning temperature would maintain a reduced level of spawning in current tropical spawning areas, suppress the emergence of an area of spawning in the north Tasman Sea and therefore keep stock abundance at low 2035 levels.

1. Introduction

The tuna fisheries of the Pacific Ocean are now the largest of their type in terms of catch volume (~3.5 M metric tonnes/year) and economic value (>6 USD billion) (FAO, 2013). In the Western and Central Pacific Ocean (WCPO), tuna stocks represent the greatest shared natural resource for Pacific Island Countries (PICs). Tuna fishing is estimated to contribute USD 260 million to their combined gross domestic product and provides over 13,000 jobs to Pacific island people (Gillett, 2009). For some PICs, the licence fees obtained from distant water fishing nations to harvest tuna from their Exclusive Economic Zones (EEZs) represent between 10% and 42% of all government revenue (Gillett, 2009). Although the tuna fisheries are dominated by the truly tropical species, skipjack *Katsuwonus pelamis*, yellowfin *Thunnus albacares*, and bigeye tuna *T. obesus*, in terms of catch and economic return, albacore *Thunnus alalunga* also makes an important contribution, making up around 1/3rd of the annual catch by longline vessels per year (37% in 2012; Williams and Terawasi, 2013).

In the South Pacific Ocean, albacore is a particularly important catch component of longline fleets operating in the Cook Islands, Fiji, New Zealand, Niue, Samoa, Solomon Islands, Tokelau, Tonga, Vanuatu and the French territories of New Caledonia and French Polynesia (Williams and Terawasi, 2013). The assertion of more ownership and management rights over resources by PICs within their EEZs has been suggested as one mechanism to provide additional opportunities for generating income for PICs from tuna (Aqorau, 2007). This includes the provision of joint venture agreements and onshore processing facilities as conditions for granting of licenses to foreign companies as well as sub-regional

* Corresponding author.
E-mail address: plehodey@cls.fr (P. Lehodey).

http://dx.doi.org/10.1016/j.dsr2.2014.10.028
0967-0645/

cooperation to limit catch or fishing effort to ensure stocks remain at economically viable levels for harvest.

An important consideration in the development of these policies is a good understanding of the relationship between tuna distributions and abundances with climate. Albacore are strongly influenced by ocean temperature and variables such as dissolved oxygen, currents and prey concentration (Briand et al., 2011; Brill, 1994; Domokos et al., 2007). Hence, changes in these oceanographic variables at seasonal, inter-annual (El Niño Southern Oscillation: ENSO) and multi-decadal (Pacific Decadal Oscillation: PDO) time scales likely affect albacore tuna distributions and may influence population dynamics processes such as recruitment (e.g., a possible enhanced recruitment for albacore in the South Pacific during the La Niña phase of ENSO; Fournier et al., 1998; Lehodey, 2004; Lu et al., 1998), and fishery performance by altering catchability to fishing gears (Bigelow et al., 2002).

Longer term trends in the oceanography of the Southern Hemisphere have been also detected, which may have influenced the large scale dynamics of albacore tuna in addition to the variability linked to climate oscillations. Over the past 50 years, the average temperature of the upper (0–200 m) tropical and subtropical Pacific Ocean has warmed by up to 2 °C in some regions (e.g., near 10 °S; 160 °W), while below this a broad-scale cooling has occurred in the Southern Hemisphere (Durack and Wijffels, 2010; Ganachaud et al., 2011). Over the same multi-decadal period, there has been an increase in intensity of the South Pacific Subtropical Gyre (Ganachaud et al., 2011; Roemmich et al., 2007) and the East Australian Current, generating substantial warming of the Tasman Sea (Hill et al., 2011; Holbrook et al., 2011). Future oceanographic conditions are projected to change more or less rapidly according to different scenarios of greenhouse gas release (Nakicenovic et al., 2000; Solomon et al., 2007). How these projected changes can affect the distribution of tuna is key information necessary to guide investment and management of tuna fisheries in the Pacific region.

Here we present an evaluation of the potential impacts of climate change on South Pacific albacore, using the projected changes under the SRES-A2 emission scenario defined for the IPCC fourth assessment report (Nakicenovic et al., 2000). This scenario is close to the RCP8.5 "business-as-usual" scenario defined for the last IPCC Assessment Report AR5 (Moss et al., 2010). This scenario forecasts overall temperature increases in the surface layer of the tropical Pacific Ocean of 0.7–0.8 °C by 2035 and 2.5–3.0 °C by 2100 relative to 1980–1999 (Ganachaud et al., 2011). The area of the western equatorial Warm Pool is projected under A2 to increase by ~250% by 2035 and by 800% in 2100. Due to weakening wind regimes at low latitudes and strengthened winds in the subtropical Southern Hemisphere, the South Equatorial Counter-Current (SECC) flowing eastward from the Solomon Islands region to about 160 °W–10 °S, is projected to weaken by ~30–60% in 2100 according to the IPCC scenario used (Ganachaud et al., 2011). ENSO events are projected to continue for the remainder of the twenty-first century at least, although there is little agreement among models about the future frequency or amplitude of El Niño and La Niña episodes (Ganachaud et al., 2011). With climate warming, primary productivity is projected to decrease in the tropical Pacific Ocean (Steinacher et al., 2010), with this effect propagating in the food web through zooplankton (prey of tuna larvae and juveniles) and micronekton (prey of adult tuna). Similar trends in the projections of the main oceanographic variables are predicted under the RCP8.5 scenario (Bopp et al., 2013).

To investigate the possible impacts of these environmental changes on South Pacific albacore, we use the Spatial Ecosystem and Population Dynamics Model (SEAPODYM) modelling framework that describes the spatial dynamics of tuna and tuna-like species under the influence of both fishing and environmental effects. This model has been described in detail in Lehodey et al. (2008; 2010a), Lehodey and Senina (2009) and Senina et al. (2008), and has been used for investigating tuna fishing management scenarios (Sibert et al., (2012)) and climate change impacts on skipjack (Bell et al., 2013; Lehodey et al., 2013a) and bigeye tuna (Lehodey et al., 2010a; 2011).

2. Methods

2.1. Modelling approach

The optimized model applied to albacore in this paper includes estimated parameters (Senina et al., 2008) describing preferred spawning and non-spawning habitat, movements in response to habitat quality, basin-scale seasonal migrations, accessibility of forage for tunas within different vertical layers (Lehodey et al., 2010b), natural mortality and the effectiveness and size selectivity of fishing effort.

Physical and biogeochemical conditions influence tuna population dynamics through changes in spawning conditions, habitat suitability and distributions of food resources that result in changes in fish movement behaviour, reproduction and mortality. The SEAPODYM framework uses environmental variables to functionally characterize the habitat of the population depending on its thermal, biogeochemical and forage preferences (Lehodey et al., 2008; 2010b; Lehodey and Senina 2009; Senina et al., 2008). There are three types of habitat indices in the model: thermal, spawning and feeding. The thermal habitat is defined using a Gaussian function with an optimal (mean) temperature decreasing with age (size) and the standard deviation increasing with weight. Therefore, spawning habitat (egg production) and larvae have the warmest mean optimal temperature value (Lehodey et al., 2008). The spawning habitat combines temperature preference and coincidence of spawning with the presence or absence of predators and food for larvae with favourable conditions for spawning individuals (food and oxygen). The feeding habitat is based on the accessibility of prey groups to tuna (Lehodey et al., 2008). Six functional groups of prey (micronekton) are simulated in three depth layers and characterized by their vertical behaviour, i.e., with or without diel migration between vertical layers (Lehodey et al., 2010b). The three vertical layers have been defined relative to the euphotic depth (Z_{eu}), assuming that light is the key driver of the vertical migration of micronektonic organisms, with increasing vertical depth boundaries of 1.5, 4.5 and 10.5 times the euphotic layer (with a maximum set at 1000 m) based on visual inspection of acoustic transects.

The habitat indices are used to control population dynamics processes (both spatial and temporal) such as movement to the feeding grounds (feeding habitat) or the spawning grounds (thermal habitat shifting from feeding to spawning optimal temperature range), natural mortality and predation. Successful larval recruitment is linked to spawning stock biomass and mortality occurring during passive drifting of individuals with currents over the first month of the life cycle. Habitat quality is used to adjust locally the natural mortality of cohorts. The model also predicts the catch and size frequency of the catch by fleet, based on observed fishing effort. Habitats, movement, mortality, and fisheries parameters of the model are estimated through data assimilation techniques using a Maximum Likelihood Estimation approach (Senina et al., 2008).

The structure of the population is defined by age (monthly cohorts) and life stages (larvae, juvenile, young immature and mature adult fish) for which the model describes different behavioural rules. There is one cohort for the larvae life stage and two cohorts for the juvenile stage, 51 cohorts for young immature and