Impact of climate change on tropical tuna species and tuna fisheries in Pacific Island waters and high seas areas

Final Report (CI-3) for SAN 6003922

Modelling the effects of climate change on tuna abundance in areas beyond national jurisdiction

Prepared by Inna Senina, Patrick Lehodey (CLS), Neville Smith, John Hampton (SPC), Chris Reid (FFA), Johann Bell (CI) and partners

07 September 2018

Abstract

A third of the world tuna catch, made up essentially of skipjack, yellowfin and bigeye tuna and South Pacific albacore (hereafter 'albacore'), comes from the Exclusive Economic Zones (EEZs) of the 22 Pacific Island countries and territories (PICTs) in the Western and Central Pacific Ocean (WCPO). We investigated how climate change could affect the distribution and abundance of these tuna species at the Pacific basin scale and within the EEZs of PICTs. This study relied on the application of the Spatial Ecosystem and Population Dynamics Model (SEAPODYM) to each tuna species, first with a model parameterization phase over the historical period (1980-2010) using a reanalysis of ocean conditions, and then with projections of an ensemble of simulations to explore key sources of uncertainty. Five different atmospheric forcing datasets from earth system models projected under the ("business as usual") International Panel on Climate Change (IPCC) Representative Concentration Pathway (RCP) 8.5 emissions scenario were used to drive a coupled physical-biogeochemical model (NEMO-PISCES) first, and then SEAPODYM, over the 21st Century. Additional scenarios were included to explore uncertainty associated with future primary production and dissolved oxygen concentration, as well as possible adaptation through phenotypic plasticity of these tuna species to warmer spawning grounds. The impact of ocean acidification was also included for yellowfin tuna based on results from laboratory experiments. The historical simulations reflect key features of the ecology and behaviour of the four tuna species and match the total historical catch in terms of both weight and size frequency distributions. The projections confirm previous results, showing an eastern shift in the biomass of skipjack and yellowfin tuna over time, with a large and increasing uncertainty for the second half of the century, especially for skipjack tuna. The impact is weaker for bigeye tuna and albacore due to revised parameter estimates, which predict a wider and warmer range of favourable spawning habitat. For albacore, a strong sensitivity to sub-surface oxygen conditions resulted in a very large envelope of projections. Historical fishing pressure was estimated to have reduced the adult stocks of all four tuna species by 30-55 % by the end of 2010, depending on species and region. The effects of fishing on biomass strongly outweighed the decreases attributed to climate change. Thus, fishing pressure is expected to be the dominant driver of tuna population status until at least mid-century. The projected changes in abundance and redistribution of tuna species associated with climate change could have significant implications for the economic development of PICTs, and the management of tuna resources, at basin scale. In particular, larger proportions of the catch of each species is increasingly expected to be made in international waters, making the monitoring and control of the fisheries more difficult.

Part I - Introduction [1]

The rich tuna resources of the Western and Central Pacific Ocean (WCPO) supply 60% of the world's tuna. About half of this (1.5 Mt; Williams et al. 2017) is extracted from the waters of the 22 Pacific Island countries and territories (PICTs) that span much of this large oceanic region. Four species of tuna dominate the catch: skipjack, yellowfin and bigeye tuna and albacore. Management of these resources by the regional fisheries management organizations [2] (RFMOs) depends partly on:

1) understanding the proportions of each of the tuna stocks within the exclusive economic zones (EEZs) of PICTs, Indonesia and the Philippines, and in high seas areas; and

2) estimating catch levels that will optimize the economic and social benefits of tuna fishing for coastal states and distant water fishing nations, while keeping exploitation of tuna resources within safe sustainable limits.

Therefore, much of WCPO tuna management is aimed at assessing the effect of fishing effort on the spawning biomass of each tuna species to establish target and limit reference points for total catches, and harvest control rules. However, because climatic variability influences the distribution and abundance of tropical tuna species (Lehodey et al. 1997) and because climate change is also expected to affect the locations where the best catches are made, reliable projections for the expected changes in tuna catches within the EEZs of PICTs and in high seas areas are now a priority for RFMOs. The sensitivity of tuna stocks to climatic variability also has direct implications for the business planning efforts of all stakeholders in the tuna industry.

Climate change is modifying the physical environment of Pacific tropical tunas. Average sea surface temperature (SST) in the Western Pacific Warm Pool has increased by ~0.7 °C since 1900 (Bindoff et al. 2007; Cravatte et al. 2009) and is expected to continue rising by 1.2–1.6 °C by 2050 relative to 1980-1999, and 2.2–2.7 °C by 2100, under a high emissions scenario (Ganachaud et al. 2011). Increasing temperature also intensifies vertical stratification of the water column, leading to reduced mixing, less nutrient inputs from the deeper layer, and less transfer of oxygen from the atmosphere in and below the thermocline. Changes in ocean circulation are also projected to impact the mixing and upwelling process on which oceanic primary productivity and the food web for tuna depend. Most biogeochemical models coupled to Earth Climate models to project future changes in primary production under International

---

[1] Note that this report is in two parts, part one on modelling the impacts of climate change on tuna stocks and part two on economic and management implications of the part one modelling.

[2] The Western and Central Pacific Fisheries Commission (WCPFC), the Pacific Islands Forum Fisheries Agency (FFA), the Parties to the Nauru Agreement (PNA), and the Inter-American Tropical Tuna Commission in the Eastern Pacific Ocean.

Panel on Climate Change (IPCC) scenarios have predicted a decrease in primary production in tropical and subtropical regions, driven by stratification (Steinacher et al. 2010). However, there is high uncertainty for this projection in tropical and subtropical regions. For example, recent simulations, including some at higher resolutions simulating mesoscale activity, suggest that no change or an increase in primary productivity may occur, caused by an intensification of the microbial loop (Laufkötter et al. 2015; Matear et al. 2015). Finally, because the ocean is absorbing a large proportion of the additional atmospheric CO_2 derived from anthropogenic activity, the seawater carbonate chemical equilibrium is shifting towards lower pH, i.e., more acidic waters and lower calcium carbonate saturation states (e.g., Caldeira and Wickett 2003; Feely et al. 2004; Barnett et al. 2005). These changes will impact the many calcifying species, e.g., shell-forming marine organisms, but also probably the physiology and respiration of fishes, especially the more vulnerable early life stages (Pörtner et al. 2014).

The potential impact of these long-term environmental changes on the distributions and abundances of fish, and fisheries production, have been explored using 1) retrospective analyses (Perry et al. 2005; Brander 2010; Nye et al. 2009), 2) projections with statistical models based on past correlations with key predictors, typically temperature and primary production (Hazen et al. 2012); 3) and more complex models that integrate interactions and non-linear effects (Cheung et al. 2008, 2010; Anderson et al. 2013; Dueri et al. 2014; Lehodey et al. 2013, 2015b). These studies point to a general poleward movement of tropical species, a decrease of fisheries productivity in the low latitudes and possibly an increase at mid and high latitudes. All such studies are affected by various sources of uncertainty related to both the bio-physical variables predicted by climate models, and to the specific model developed for the species or group of species studied. The total uncertainty needs to be quantified to provide a level of confidence in the results. The sources of uncertainty also need to be determined to identify where further research, modelling and observation efforts should be focused.

The partitioning of uncertainty in climate modelling (Hawkins and Sutton 2009), and in modelling of marine living resources (Payne et al. 2016; Cheung et al. 2016), has identified structural uncertainty associated with the model design, uncertainty due to initialization, uncertainty generated by the internal variability of the model, parametric uncertainty associated with model parameter values, and uncertainty linked to the scenarios used for projections. Systematic exploration of these different sources of uncertainty leads to a very large ensemble of simulations. Computational limits impose trade-offs during the exploration of these uncertainties. Selection of the most critical sources of uncertainty therefore needs to be based on expert judgement. In general, uncertainty linked to scenarios is considered to increase with time, and initialization uncertainty is thought to dominate at short time-scales and may be ignored

at the centennial time-scale used for climate change projections. A well-bounded model with parametrization achieved using abundant observations in a robust statistical framework (e.g., maximum likelihood and Bayesian methods) are considered to need less sensitivity analyses than a model with parameter estimates fixed from limited datasets or those which are not directly observable.

This is certainly the case for SEAPODYM (Lehodey et al. 2008), which includes a quantitative method to estimate population dynamics, habitats, movements and fisheries parameters with a maximum likelihood estimation (MLE) approach (Senina et al. 2008). SEAPODYM simulates the change in abundance over time and space of a target fish species by age-class from larvae to the oldest adults, and can distinguish between the effects of fishing impact and natural variability (environment and climate). Fish biology and behavior are simulated based on relationships with environmental variables. For instance, the model uses: 1) the distribution of several groups of micronekton (Lehodey et al. 2010a, 2015b) to drive the movement of tuna feeding on them; 2) oceanic currents to redistribute tuna larvae; 3) water temperature and dissolved oxygen concentration to control the habitat preferences of tuna (changing with age); and 4) change in gradient of day light and other variables to trigger spawning migrations. Based on first biological principles and functional relationships to the environmental variables, SEAPODYM uses a small number of parameters (< 25) to estimate the dynamics of target species, and an additional 3-4 parameters to define the selectivity form and catchability of each fishery added in the simulation. Data used to estimate the parameters typically include catch, fishing effort, length frequencies of target species, and release-recapture tagging data (Senina et al. 2018 *submitted*). The full, spatially-explicit representation of SEAPODYM, using an Eulerian advection-diffusion-reaction framework, allows the use of data in the MLE at the resolution of the grid used to solve the model numerically, e.g., a one or two degree square. Therefore, a massive number of observations (several hundred thousand) can be included in one model optimization.

SEAPODYM has been used extensively to study the population dynamics of tropical tunas and the impact of fisheries and environmental variability, including climate change (Lehodey et al. 2010b, 2013; 2015; Sibert el al. 2012; Bell et al. 2013; Dragon et al. 2015). However, previous studies on the impact of climate change on tuna were based on a single Earth System Model projection following the IPCC "business as usual" scenario. In addition, previous studies highlighted a problem of coherence between historical and projected environmental forcings. The fish model component of SEAPODYM needs to be parameterized using a realistic historical reanalysis (i.e., one based on a consistent set of atmospheric observations) to drive the coupled physical-biogeochemical model. Such parameterization allows

matching of the observed variability of the large fishing dataset, e.g., changes in fishing grounds due to an El Niño event.

Projection of such parameterization with future environmental conditions predicted from an IPCC-type model can produce spurious results due to errors and biases in these predictions (Lehodey et al. 2013). A tentative method for correcting the most obvious bias (water temperature) has been proposed but it is still necessary to run MLE over the historical period with the climate model environmental forcing to eventually re-estimate the parameters. This approach is not completely satisfactory, however, because other biases that are more difficult to detect (e.g., in the ocean circulation) are likely to occur. To date, it has not been practical to propose an ensemble of simulations to explore the various sources of uncertainty.

We propose a new approach in this study. First, a single best estimate of SEAPODYM parameters is achieved based on historical available data and a realistic reanalysis of ocean conditions. Then, the historical period is prolonged by an ensemble of projections over the 21st Century using atmospheric forcing variables from 5 different Earth System models predicted under the IPCC RCP8.5 scenario ("business as usual") to drive a coupled physical-biogeochemical model (NEMO-PISCES) first, and then SEAPODYM. However, prior to this, a correction is applied to the atmospheric variables of the projections to avoid abrupt changes when switching from an historical to a projected time series. With this approach, the impact of climate change on skipjack, yellowfin, bigeye tuna and albacore are analyzed with a simulation ensemble focusing on the most critical sources of uncertainty.

Part I - Material and method

A. SEAPODYM tuna model optimization

The history of the tuna populations under the combined effects of fishing pressure and natural climate variability, e.g., El Niño Southern Oscillation (ENSO), is predicted by the SEAPODYM model as a result of the optimization phase to estimate the model parameters. The model simulates tuna age-structured population dynamics with different rules changing according to the life stage (Lehodey et al. 2008; www.seapodym.eu). For example, as larvae and juveniles, tuna drift with currents but later have autonomous movement, i.e., in addition to the velocities of currents their movement has a component linked to fish size and habitat quality. The model also considers fishing (Figure 1 & *Supp. Mat.*, Figure A1) by accounting for fishing mortality, total catch and size frequencies of the catch. Because the model domain covers the whole Pacific Basin, historical fishing datasets were prepared from the combination

of data provided by the Pacific Community (SPC) for the Western Central Pacific Ocean (WCPO) and by the Inter-American Tropical Tuna Commission (IATTC) for the Eastern Pacific Ocean (EPO).

The fully-explicit modelling of spatial dynamics relies on advection-diffusion-reaction equations, i.e., the density of fish and catch are computed in each cell of a computational grid defined over the model domain. The spatial resolution used for both the optimization and projection was 2° x 2° and the resolution for time and age dimensions was one month. The MLE approach developed for SEAPODYM (Senina et al. 2008) takes advantage of this spatially explicit representation by using the numerous catch/effort data, and length frequency catch data, available at these resolutions. The recent addition of release-recapture tagging data to the likelihood function also allowed movement and habitat parameters to be better estimated (Senina et al. 2018 *submitted*). A series of other changes have also been added to the previous version of SEAPODYM (Lehodey et al. 2008). These changes include spawning habitat defined with prey and predator functions separately instead of using the prey-predator ratio, and an additional parameter associated with each functional group of prey (micronekton) that provides more flexibility in the representation of vertical behavior and access to tuna forage.

Fishing mortality is computed either from fishing effort and estimation of catchability and selectivity of the fishery, or directly from observed catches when fishing effort is not available or too uncertain. Finally, *a priori* information to constrain the average stock size estimate is added to the likelihood function with the objective of identifying the minimum stock size, given the spatial distribution predicted by the model that supports all local catch levels. However, to compensate sources of spatial mismatch between highest observed and predicted catch, a local discrepancy of less than 20% is allowed (Senina et al. 2016). Such local errors are inevitable given the coarse spatial resolution of the model, which does not allow prediction of highly heterogeneous fish-density distributions.

Each fishery is defined with a selectivity function and a catchability coefficient that is allowed to vary linearly over time. The catchability parameters are estimated, whereas linear trend parameters are calibrated during the model optimization phase using fishing effort to predict the catch. If the catch removal method is preferred for some fisheries, their catchability coefficients are estimated *a posteriori* (as long as the fishing effort data exist) in order to allow the fishing effort scenarios during the projection period. The fit between observations and predictions is used to validate the optimal solutions of the models. We verify that the total catch is well predicted, as it is a primary objective to include all fishing mortality. The fit by fishery is also validated to ensure that there are no regional biases. The fit between

observed and predicted catch is also analysed spatially, as well as the fit between observed and predicted size frequency distributions and, when available, tagging data.

The necessary input variables to run SEAPODYM are 3D (0~1000m depth) water temperature and currents, dissolved oxygen concentrations, total vertically-integrated primary production and euphotic depths. They are provided by the NEMO-PISCES coupled model. The additional fields of pH used to investigate the future ocean acidification effects are also standard outputs of the PISCES model (Aumont et al. 2015). The ocean physical model NEMO is driven by the ERA40-INTERIM (1979- 2010) atmospheric reanalysis (atmospheric temperature, zonal and meridional wind speeds, radiative heat fluxes, relative humidity, and precipitation) which has been corrected using satellite data (Dee et al. 2011). All forcing variables are interpolated on the same regular grid and resolution prior to use in SEAPODYM simulations. The physical-biogeochemical forcing is used to simulate the zooplankton and micronekton functional groups (Lehodey et al. 2010a, 2015), before running the tuna dynamics and fisheries parameter estimation.

Once the optimal parameterization is achieved for a given species and validated by statistical fits to the data, one more simulation is produced without fisheries data. In this analysis without fishing mortality, the stocks rapidly increase and reach an equilibrium state in a time that is defined by the life span and the stock–recruitment relationship estimated for the species. We assume that at the end of the 30-year reanalysis all four stocks are at their virgin (unfished) state and influenced by environmental variability only. The structure of the populations in December 2010, the last time step of the reanalysis is saved to serve as the initial conditions for the projections starting in 2011. The simulation ensembles are produced without fishing, to highlight the impact of climate change on it own, and with fishing effort scenarios (see below) to project the combined impact of fishing and climate change.

B. Uncertainties explored in the simulation ensemble

Given the long time-scale of these climate change projections and the robust quantitative method used to estimate SEAPODYM parameters, the largest sources of uncertainty concern their accumulation in generating the forcing variables, the model structure and the (IPCC) scenarios. Due to limited resources for computation, the modelling effort is focussed on the first two sources of uncertainty and only one IPCC scenario (RCP8.5 ~ "business as usual") is used.

Uncertainty from atmospheric forcings is integrated into the ensemble simulation by selecting outputs from five Earth System models of the CMIP5 inter-comparison project (Taylor et al. 2011) to drive the coupled physical-biogeochemical model NEMO-PISCES (Table 1). These models have been selected

because they mimic ENSO cycles in their simulations (Bellenger et al. 2014). However, a procedure of correction has been applied to each forcing. The low frequency trends from the climate model variables were extracted and smoothed with a 31-year wide Hanning filter before being added to three successive replications of the 30-year reanalysis variables. The results are 90-year forcing sets that span the period 2010-2100 and mix the past observed variability with long term trends due to climate change. Finally, a control simulation (three successive repetitions of the reanalysis) with the coupled physical-biogeochemical model is produced to verify that there is no long-term trend generated internally without climate change forcing.

Population dynamics of tropical tunas have been shown to be sensitive to the projected decrease in primary production in the western equatorial Pacific, and to decrease in dissolved oxygen concentration in the eastern equatorial Pacific (Lehodey et al. 2013, 2015). Long-term trends projected with coarse-resolution, coupled physical-biogeochemical models are uncertain for these two variables. Warming-induced increases in phytoplankton growth, intensification of the microbial loop or stronger mixing not well represented in climate models using coarse resolution can counter-balance classical expected nutrient limitation due to increased stratification at low latitude (Laufkötter et al. 2015; Matear et al. 2015). Although decreasing trends in dissolved oxygen concentration have been detected from historical datasets (Schmidtko et al. 2017), their origin (observation errors, natural variability or climate change) is not yet clear. Higher resolution in Earth System Models is needed to obtain a better representation of observed changes (Duteil et al. 2014; Long et al. 2016). To account for this uncertainty, one additional member in the simulation ensemble includes a gradual increase in primary production in warm waters of the tropics, defined by SST > 27°C, reaching 10% more than in 2010 at the end of the 21st Century. Another member of the ensemble is also using climatological distribution of dissolved oxygen concentration instead of model projection.

Previous studies have shown that the major drivers of tuna population dynamics under climate change simulations are linked to the evolution of spawning grounds and larval recruitment. The match between environmental conditions and the optimal spawning temperature is a primary factor to consider. Therefore, we investigate the phenotypic plasticity within the population to better adjust to changing ocean temperatures with another simulation, where the estimated optimal spawning temperature increases linearly by two degrees at the end of the 21st Century, i.e., roughly following the temperature increase in the tropics under the RCP8.5 scenario used in this study.

9

The final potential effect investigated is ocean acidification. Based on laboratory experiments (Frommel et al. 2016), it was possible to include a functional relationship to describe additional larval mortality due to decreasing pH for yellowfin tuna. The uncertainty associated with the laboratory experiments is integrated through three different parameterizations - low, medium and high impact (see *Supp. Mat.*, Figure D1).

Table 1: Uncertainty explored in the simulation ensembles produced for this study.

Uncertainty in atmospheric forcing		Structural uncertainty in biogeochemical model	Structural uncertainty in SEAPODYM	Uncertainty in fishing projections
Code	*CMIP5 model*			
IPSL	IPSL-CM5A-MR (Institut Pierre Simon Laplace, France)	- *Primary production:* Increase of PP by 10% (PP10) in tropical waters (defined by SST >27°C) - *Dissolved Oxyge*n: No change (O2clim) = Use of climatological fields	- *Genetic adaptation:* Regular increase in optimal spawning temperature to reach + 2°C at the end of the Century - *Ocean acidification*: Additional mortality on larvae based on laboratory experiments with low medium and high sensitivity to pH (available only for yellowfin).	- Average fishing effort distributions of the last 10 years (1.0f) - Average fishing effort distributions of the last 10 years increased by 50% (1.5f)
MIROC	MIROC-ESM (Model for Interdisciplinary Research on Climate, Japan)			
NorESM	NorESM1-ME (Norwegian Climate Centre, Norway)			
MPI	MPI-ESM-MR (Max Planck Institute for Meteorology, Germany)			
GFDL	GFDL-ESM2G (Geophysical Fluid Dynamics Laboratory, USA)			

Taken together, these different simulations produce an ensemble of 35 members for yellowfin and 20 for the three other species (Table 1). Impact of climate change on tuna is analysed by extracting the mean and standard errors of biomass of tuna for the adults and recruits from the simulation ensembles for different areas (EEZs of PICs, high seas pockets and international waters) shown in Figure 1.

The projection of fishing impact is the other major uncertainty. Two fishing scenarios are combined with the simulation ensembles presented above. The first one considers the projection of the average fishing effort distributions of the last available decade 2001-2010 (referred to as F = 1.0) and the second scenario is the average fishing effort distributions of the last available decade 2001-2010 increased by 50% (referred to as F = 1.5). Biomass and catch projections are computed for the same areas used to analyse the climate impact alone on EEZs and High Seas.
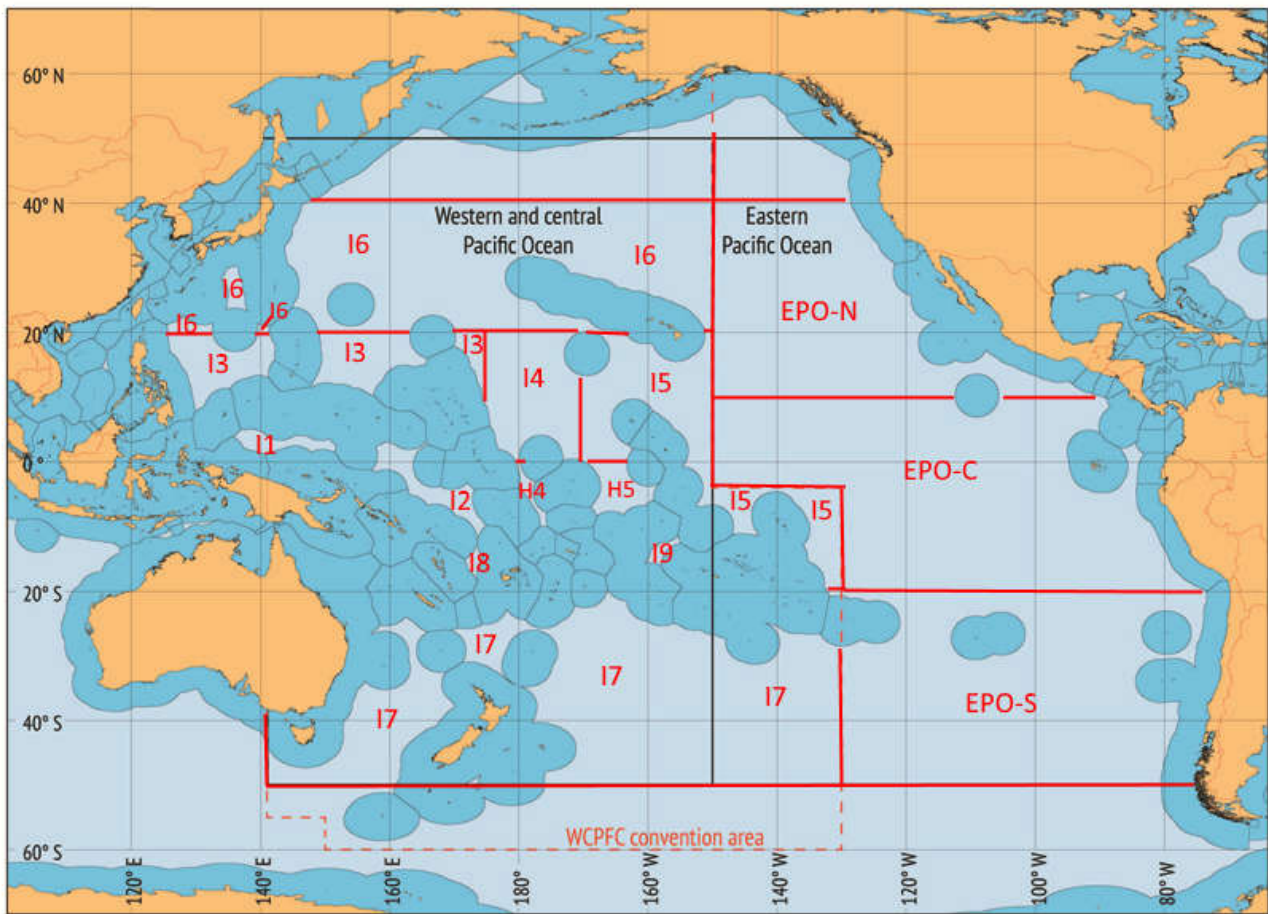
Figure 1: Map of Pacific Island Countries EEZs and definition of International Water (IW) areas, which are used to compute biomass and catch percentage changes due to CC scenarios.

I1: Doughnut hole between PNG and FSM

I2: Doughnut hole between FSM, Solomon Islands, Kiribati, Marshall Is., Nauru and Tuvalu

I3: International waters east of the Philippines to Guam above FSM, around Marshalls, up to 20°N and west of 175°E

I4: International waters Marshall IS. And Kiribati from the Equator up to 20°N and east of 175°E to 170°W

I5: International waters around Line group from the Equator up to 20°N, east of 170°W to 150°W and south of the equator to 20°S from 155°W

I6: The remainder of international waters not covered above in the Northern hemisphere of the WPC-CA up to 40°N

I7: The remainder of international waters not covered above in the Southern hemisphere of the WPC-CA down 50°S

I8: International waters bordered by Fiji, Solomon Is and Vanuatu

I9: International waters between the Cook IS. and French Polynesia

H4: International waters between Tuvalu, Phoenix and Tokelau, from the equator down to 10°S and east of 175°E to 170°W

H5: International waters between Phoenix and Line Groups, from the equator down to 10°S, east of 170°W to 155°W

Part I - Results

A. Historical reference simulations (1980-2010)

Tuna biology and model optimization

The model optimizations provide realistic estimates of the dynamics and distributions of the four species of tuna described by historical fisheries and catch distributions (Figure 2) and general knowledge on these species (e.g., Sharp and Dizon 1978; Sund et al. 1981; Graham and Dickson 2004). Skipjack, yellowfin and bigeye tuna and albacore inhabit a wide range of ecosystems in the epi- and meso-pelagic oceanic layers of the tropical/subtropical Pacific Ocean. Skipjack and yellowfin tuna spend their entire lives in tropical waters, or tropical waters transported by currents into latitudes that are more temperate (e.g., Kuroshio and East Australian Currents). They grow quickly, reach small to medium maximum size, have early age at first maturity and short to medium life spans. In contrast, bigeye tuna and albacore have life-history characteristics that are intermediate between tropical and temperate tunas (e.g. bluefin). They are distributed both in tropical waters and temperate waters, and characterized by intermediate maximum size, and slower rates of growth, greater ages at first maturity and longer life spans (>10 years) than skipjack and yellowfin tuna.

Recent studies on the growth of bigeye tuna (Aires-da-Silva et al. 2015; Farley et al. 2017) suggest that mean length-at-age is larger in the EPO than in the WCPO. This new information has been used to revise the growth function for stock assessments provided for the WCPFC (McKechnie et al. 2017), which now have a lower asymptotic length value (around 150 –160cm, instead of 184 cm used in the 2014 reference case model). Both past and new growth parameters have been tested with SEAPODYM. The overall fit to data is slightly improved with the new parameters, due to a more diffusive population density. When comparing the fit to catch data from the fishery, there is no real differences between the two simulation outputs. However, the structures of the populations are significantly different. In the "new growth" simulation, lower natural mortality coefficients are estimated in old age-classes, allowing a substantial increase in the mean age and biomass of older individuals to compensate for the change associated with lower size (weight) predicted by the growth function. There are also substantial changes in the spawning habitat and subsequent recruitment. The different structures allow a similar fit to catch data but result in a degraded fit to spatially-disaggregated size frequency data of longline fisheries. Therefore, the reference bigeye simulation for the present study retains the growth parameters of the 2014 assessment (Harley et al. 2014).

Sampling at sea indicates that all tuna species spawn in warm waters (mainly with SST > 26 °C) in broad areas of the equatorial and tropical oceans (e.g., Wild and Hampton 1994). Laboratory experiments have identified the optimal range of temperatures for yellowfin tuna larvae as 26° to 31°C (Wexler et al. 2011). The model estimates optimal spawning sea surface temperature (SST) ranges in agreement with these observations, with optimal values between 26.5 and 28.9 °C and standard errors ranging from 1.5 to 3.1°C (*Supp. Mat.*, Table B2). Combined with larval prey and predator mechanisms introduced in the definition of spawning habitat, local density-dependence, and the stock-recruitment mechanism for larvae, the result is an overlapping but gradually changing average distribution of larval density (Figure 3). For skipjack tuna, the core area of this distribution is the Western Pacific Warm Pool. The pattern for yellowfin tuna is similar but slightly more extended to the central-eastern Pacific, whereas bigeye tuna has a more central distribution and albacore has a sub-equatorial distribution (10°S-25°S). These general patterns agree with observations based on larval sampling, catch of juveniles and occurrence of sexually mature adults. The dynamics of these distributions are influenced by ENSO, leading to inter-annual variability in recruitment and stock biomass (Lehodey et al. 2001, 2003, 2017; Senina et al. 2008, 2018 *submitted*).

Skipjack and yellowfin tuna are opportunistic spawners, whereas there is noticeable seasonality in the spawning of albacore, which spend most of their lives feeding in subtropical/warm-temperate waters and migrate to latitudes of 10°S and 25°S to spawn (Ramon and Bailey, 1996). Juvenile albacore (age 1 year, ~45 cm FL) are subsequently caught in surface fisheries in New Zealand's coastal waters. The seasonal switch between feeding and spawning migrations is used in the model for albacore and the associated parameters are estimated effectively with the MLE. This is not the case for the three others (*Suppl. Mat.*, Table B2).

All four species of tuna are voracious opportunistic predators feeding on micronekton organisms. The feeding habitat of immature and adult tuna is defined by their accessibility to the six functional groups of epi- and mesopelagic micronekton included in the model. The accessibility of micronektonic prey depends on the tolerance of tuna to low oxygenated waters, and the temperature preference of tuna species, which change with age. Therefore, accessibility coefficients by tuna species and age for each micronekton group are defined based on relationships with temperature and oxygen. Parameter estimates are provided in *Supp. Mat.* (Table B2). Skipjack tuna, with the narrowest estimated thermal habitat (26°-28.5°C) and the lowest tolerance to low oxygenated waters (threshold value 3.76 mL L^{-1}), is mainly limited to epipelagic forage, i.e., either resident epipelagic or highly migrant mesopelagic micronekton species present in the surface layer at night.
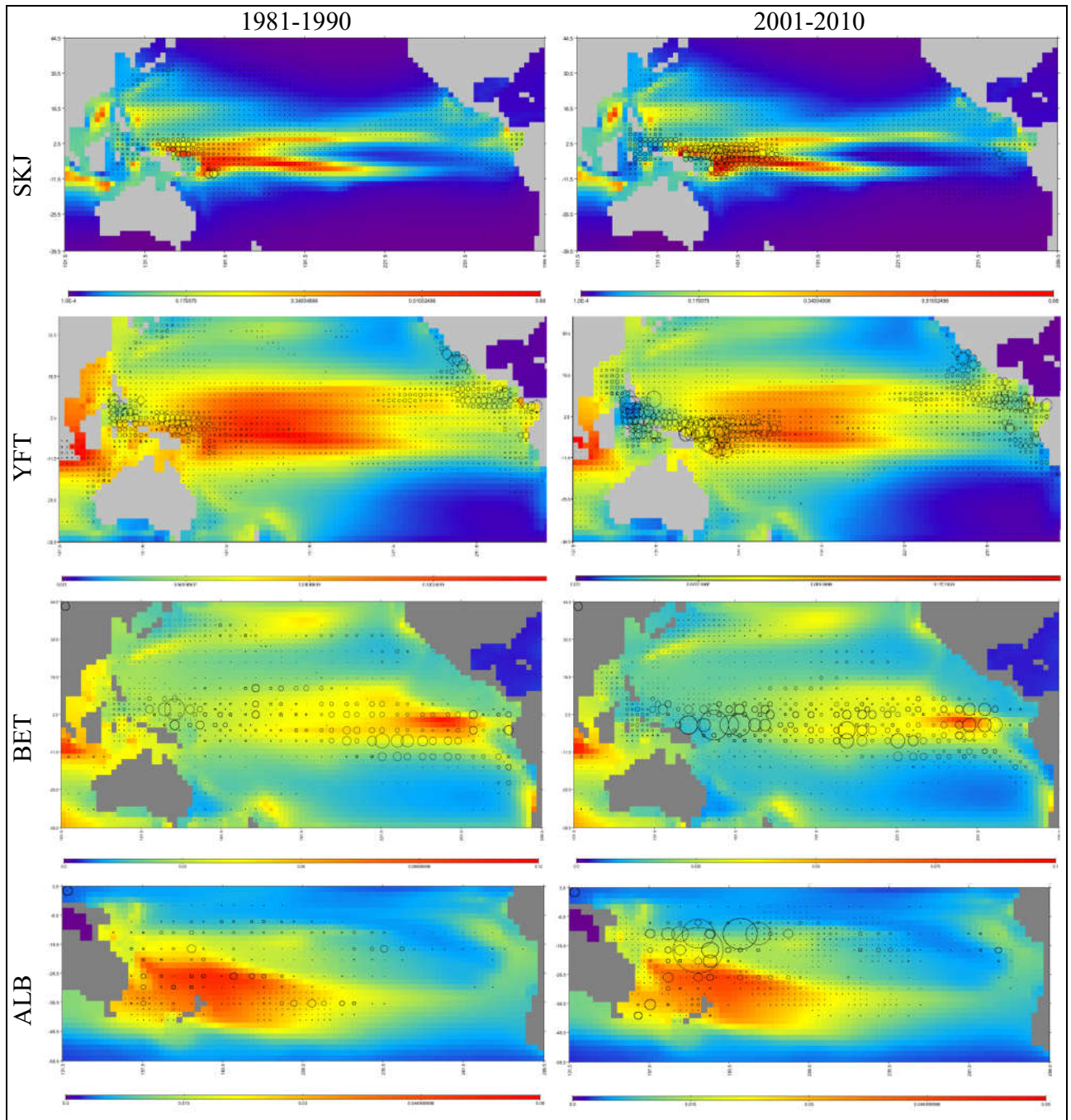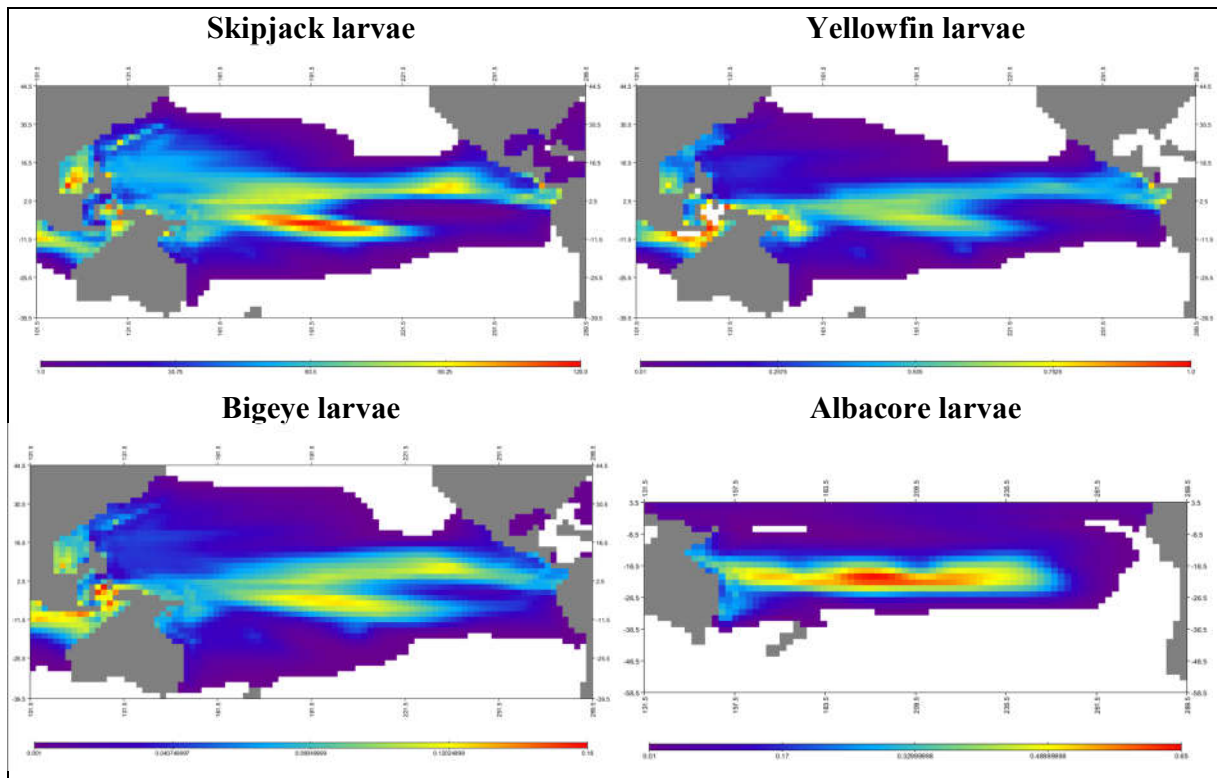
Figure 2: Comparison of predicted distributions for 1st and last decade of the historical time series. Total observed catches are shown, with catch proportional to the size of the circles (same scales between decades).

Figure 3: Mean predicted distributions of tuna larvae densities (nb km⁻²) for 2001-2010.

The thermal habitat of yellowfin is estimated to be wider (13.3°C - 32°C) and the model for this species shows a lack of sensitivity to oxygen with a very low oxygen tolerance threshold value (0.41 mL L⁻¹). The habitat is known to be even wider for bigeye tuna. Adults of this species have well-developed thermoregulation mechanisms and physiological adaptation that confer good tolerance to low dissolved oxygen concentration (Brill 1994; Schaefer and Fuller 2010), allowing them to dive regularly to the deeper lower mesopelagic layer (> 400 m depth). For bigeye tuna, the model estimates a large thermal range with the optimal value at age decreasing from 27°C for the youngest cohorts to 10°C for the oldest. There is also a low threshold oxygen value (0.5 mL L⁻¹), and an increasing contribution of non-migrant lower-mesopelagic micronekton for bigeye tuna compared to the other species. Albacore is much less tolerant to poorly oxygenated waters than bigeye tuna (Sund et al. 1981; Brill 1994) and more limited in its vertical habitat - electronic tagging data indicate that albacore has a preference for the upper mesopelagic layer (Domokos et al. 2007; Williams et al. 2015). Bertrand et al. (2002a) reports that 97.5% of all experimental longline albacore catch in the French Polynesian EEZ occurred in waters with temperatures above 10°C. These observations match well the predicted habitat with a thermal range estimated between 10°C (std. dev. 1.99) and 23.5°C (std. dev. 5.21), a threshold value in dissolved

oxygen concentration of 3.43 mL L^{-1} and a noticeable contribution of upper meso-pelagic micronekton groups to distribution (*Supp. Mat.*, Table B2).

Thus, it is remarkable that the relationships to the different functional groups of prey estimated to compute the feeding habitats, agree well with observations on the feeding ecology and vertical behaviour of tuna (e.g., Sund et al. 1981; Dagorn et al. 2000; Bertrand et al. 2002b; Domokos et al. 2007; Schaefer and Fuller 2010; Schaefer et al. 2011). Skipjack tuna are limited to feeding on the groups present in the epipelagic layer (epipelagic and highly migrant lower-mesopelagic); yellowfin tuna to the epipelagic and upper-mesopelagic layers; bigeye tuna to the upper and lower mesopelagic layers; and albacore to the non-migrant upper-mesopelagic and epipelagic groups. For albacore, however, this habitat is characterized by a marked seasonal change (and thus migration) between the spawning ground in tropical waters and the feeding grounds near Tasmania, New Zealand and the sub-tropical convergence zone (STCZ) in the central Pacific at about 40°S. This is well simulated by the model with a migration controlled by the seasonal change in day length leading to a gradual shift of the thermal preference window towards the optimal spawning temperature range. The resulting movement of adult albacore *"tends to correspond with the seasonal shift in the 23–28°C sea surface temperature isotherm location"* as inferred from monthly trends in longline catch rates by Langley (2004).

The effective average movement rates are computed by combining estimated theoretical rates with predicted values of habitat (diffusion) or habitat gradients (advection). The highest diffusion rates estimated for albacore are somewhat counter-balanced by the seasonal switch of the spawning migration that creates strong habitat gradients around the peak of the spawning season. This peak is predicted to occur in early November in the Southern Hemisphere (i.e., Julian day 115 for the northern hemisphere), and coincides with the peak observed in the gonad index of female albacore (Farley et al. 2013).

For the three other species, which spawn and feed in the tropical waters, the movements are controlled only by the gradient in the feeding habitat. The use of tagging data in the MLE in the application to skipjack tuna (see details in Senina et al. 2018 *submitted*) allows a better estimation of movement, resulting in less diffusion. Note the tagging data were used for bigeye and yellowfin only for the estimation of habitat parameters in the first phases of optimization.

Historical fisheries and biomass distributions

Together, skipjack, yellowfin and bigeye tuna and albacore represent > 90% of the total catch taken by industrial fleets in the Pacific Ocean. Pole-and-line and longline were the first two main fishing gears used by industrial fleets, with pole-and-line targeting small- to medium-size skipjack and yellowfin tuna

in surface waters, and longline targeting larger individual yellowfin and bigeye tuna, and albacore in subsurface waters. The surface fishery also includes boats that use trolling gear to target albacore, and small-scale artisanal fisheries using various fishing gears such as handlines and ring-nets.

After a development phase in the 1970s, purse-seine fishing expanded rapidly at the expense of the pole-and-line fishery. Since the 1990s, the use of fish aggregating devices (FADs) to attract and temporarily retain schools of tuna, has been widely adopted by purse-seine vessels. Today, half of the total purse-seine catch is taken around FADs. The purse-seine and pole-and-line fisheries in surface waters supply the canning industry, while the longline catch is for fresh and frozen markets, including the valuable sashimi market. A concern associated with the use of FADs is the increasing catch of juvenile bigeye tuna - this species is not the target of the surface fishery and has lower productivity than skipjack and yellowfin tuna.

These fisheries are described and listed in *Supp. Mat.* Table A1-4 for each species together with the fit of model predictions to these data (catch and size frequencies of catch). For computational reasons, a compromise is needed between a reasonable number of fisheries and the most homogeneous possible definition according to various criteria (gear, flag, region, period, target species etc, …). Classically, for a given species, the best fits are obtained for fisheries targeting the species over time without switching to a different species and modifying the fishing strategy. For instance, longline fleets targeting bigeye tuna receive a lower score for albacore and yellowfin tuna. Also, since the same purse-seine fishing vessel can fish both on a free school of tuna or a school associated with a FAD, the total fishing effort (number of fishing days in a month in the grid cell of the model) needs to be divided between these two different fisheries defined by different catchability and size selectivity. This can result in a noisy fishing effort, especially considering the high spatial resolution of the model. Nevertheless, each fishery is sufficiently well described to achieve very good prediction of total catch by species over the historical period (1980-2010), with correlation coefficients above 0.8 for each series of total catch. This is essential to account for the increasing fishing mortality over the historical period (1980-2010), and to produce accurate initial conditions of the population structures at the beginning of the projection.

However, the goodness of fit is not high everywhere. For example, satisfactory scores could not be predicted for skipjack based on the fishing effort in the Eastern Pacific Ocean south of 5S and especially in the upwelling zone west of Peru. Since the catch removal method (Senina et al. 2018 *submitted*) shows that there is enough biomass to sustain observed levels of catch in this area, the discrepancy can be attributed to 1) the fishing effort computation methods, which do not consider the changes in target

species, and/or 2) underestimated skipjack biomass in this zone due to poor representation of circulation in the Humboldt upwelling zone that leads to insufficient amount of primary production and hence micronekton biomass. As a result of the misfit in this area, the model catches are too low compared to those observed are predicted during the last decade of historical simulation (Figure 6, EPO).

For yellowfin tuna, there are some low scores both in WCPO and EPO. High yellowfin catches in EPO during the period 2001-2003 can only be predicted by replacing the PISCES primary production by a satellite-derived product and re-running the micronekton model (Lehodey et al. 2017). The optimization for yellowfin with modified forcing resolves high discrepancies between catches (Figure C1) allowing unbiased parameters estimates. However, the simulation with the default INTERIM-NEMO-PISCES forcing was used to initialize the climate change simulations, so the discrepancies for 2001-2003 visible on Figure 7 (EPO) are attributed to the forcing data. In the WCPO, low scores for yellowfin catch are associated with the effort of the Philippine purse-seine fishery in high sea pocket I1 (Figure 1) and with the model predictions in the Indonesian archipelago. Although the effort data in this area are also uncertain, predicted yellowfin density is clearly underestimated by the model. The reason for this is that in the global configuration model (Figure 2, right panel for yellowfin) it is not sustaining the reporting levels of catch. The higher and consistent levels of exploited biomass of yellowfin in the Indonesian archipelago predicted by the Pacific configuration model is then obtained as a result of Neumann (closed on the west) boundary conditions.

For bigeye tuna, good validation scores are achieved for all EPO catches, except during the 1980s, most likely due to the technological changes in longline fisheries. However, since this period was not included in the optimization, it did not bias model parameter estimates. The predicted total WCPO catch of bigeye is too high (Figure 8) in the sub-tropical regions of the western Pacific. The model predicts higher biomass for this area than can be deduced from the spatial distributions of CPUE of the main long-line fishery targeting bigeye tuna (L1). Future optimization runs, with tagging data to improve movement and reduce the estimated high diffusivity for bigeye, and a spatially refined structure of the fishery in L1, are needed to resolve this issue.

Not surprisingly, given the observed trends in fishing effort and catch, the fishing impact is increasing over time (Figure 4). The strongest impact at the end of the time series is on bigeye tuna, with a decrease in adult (spawning) biomass in the range of 50-55% for both the EPO and WCPO, followed by yellowfin tuna (50 and 42% for the EPO and WCPO respectively), albacore (44%) and skipjack tuna (20-25%).

Fishing impact varies spatially, with the strongest decreases occurring in the main fishing grounds (Figure 2).

B. Climate change projections of virgin biomass

Without considering the impact of past and future fishing, the projections achieved with the simulation ensembles show average anomalies increasing with time until the end of the century, and with the trend occurring in opposite directions for the EPO and the WCPO (Figure 4). The widest range of uncertainty is for albacore and skipjack tuna in the 2nd half of the century. In the WCPO, trends of biomass are stable until 2050 and then start to decline, with increasing steepness from bigeye tuna to yellowfin tuna to skipjack tuna. The maximum average decrease over the 21st Century is predicted for yellowfin tuna (-40%) and skipjack tuna (-38%) whereas decreases look like they may be limited to -15 % for bigeye tuna. Opposite trends occur in the EPO, with a projected increase of 40% for skipjack tuna compared to the recent period 2000-2010. However, the difference is lower when compared to the period 1980-2000 that was dominated by a higher frequency of strong El Niño events, predicted to be favourable to skipjack recruitment in this region. The projected increase for yellowfin tuna in the EPO is just above 30%, and 20% for bigeye tuna. For albacore, the ensemble of simulations projects a rapid increase in average biomass of 50%, stabilizing after 2035, but with much associated uncertainty.

The analysis of uncertainty associated with each specific scenario for albacore (Figure E1) indicates that the rapid projected increase in biomass of albacore is due to the very strong effect of the scenario where no change in dissolved oxygen concentration occurs (SO), resulting in a 3-fold increase in mean biomass. When this scenario is removed, the mean biomass of albacore is predicted to remain stable. By comparison with the reference projection (REF), the SO scenario is also favourable for yellowfin in the EPO. The SP scenario for a possible underestimation of primary production in the tropical ocean (primary production increases by 10% in waters above 27°C), has a positive effect on all species, but is most pronounced for bigeye and then yellowfin tuna. Under this SP scenario, the biomass of bigeye tuna increases up to 18 % by the end of the century compared to the reference scenario. The scenario testing the effect of a potential adaptation (ST), with optimal spawning temperature increasing in parallel to the projected warming of surface water (>2° by the end of the century), has positive effect only for skipjack tuna in the WCPO (Figure 4) and would be an unfavourable "adaptation" for all tuna stocks in the EPO.
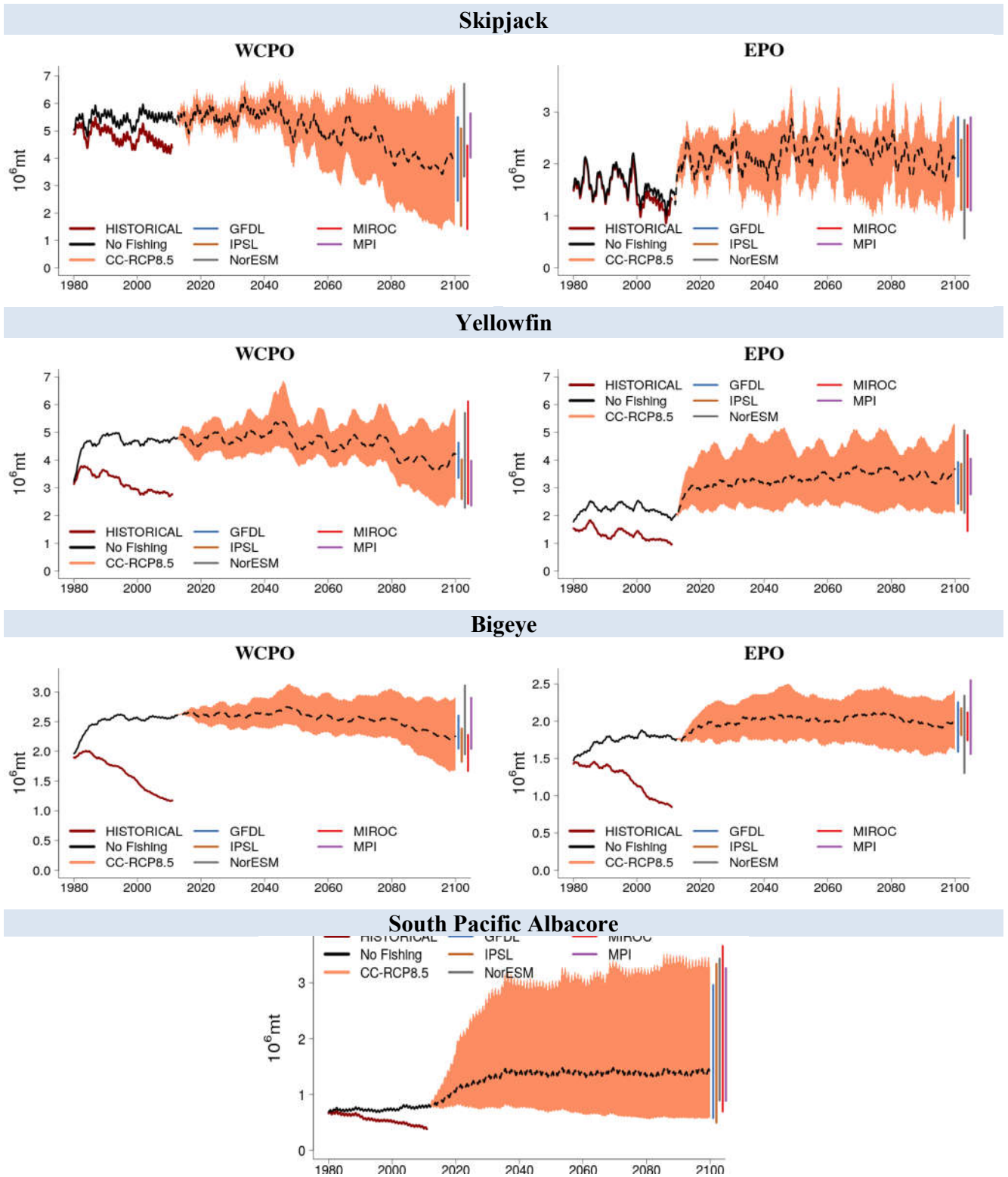
Figure 4: Envelope of predictions computed from simulation ensembles under IPCC RCP8.5 scenario for the western central (WCPO: 120E-150W, 50S-50N) and eastern (EPO: 150W-70W, 50S-50N) Pacific Ocean. The change in total biomass is presented with the average (dotted line) and its envelope bounded by the 5% and 95% quantile values of the simulation ensembles.

Finally, the ocean acidification (scenario PH), tested only for yellowfin tuna, shows that effects will be strongest in the EPO. Despite ocean acidification causing a relatively small additional mortality for larvae (*Suppl. Mat.*, Figure D2), the average accumulated effect on the yellowfin tuna population in the EPO leads to a biomass decrease of 20% compared to the reference scenario.

In absence of fishing, the population trends in the model are mainly driven by larval recruitment resulting from the product of the spawning habitat index value with the local density-dependent effect linked to the adult (spawning) biomass. Therefore, the changes associated with the oxygen scenarios are mainly driven by the better feeding habitat of adult fish, allowing them to occupy an increasing proportion of the favourable spawning habitat and to eventually reach the maximum potential of the population. For albacore, the density decreased over time in the western part of the southern Pacific Ocean, but this was offset by increases in the eastern part (Figure 5). This trend is seen in all simulations with and without oxygen change. For the three other species of tuna, the projected impact of climate change is strongly driven by the spawning habitat through changes in temperature and primary production. For yellowfin tuna in the EPO, the impact is also linked to future oxygen conditions in the adult habitat. Spatial density distributions of skipjack and yellowfin tuna are projected to be the most impacted (Figure 5). The density of skipjack tuna is expected to decrease in the west and slightly increase in the central and east Pacific. Overall, however, total biomass is projected to decline. The biomass of yellowfin tuna is projected to be stable at the basin-scale but there is a clear shift in population density from the western to the central and eastern Pacific. The density distribution of bigeye tuna is expected to decrease slightly and homogeneously throughout its habitat, with very few spatial changes relative to its present-day distribution.

The projected changes in abundance and distribution of all four species have potential impacts for the economies of Pacific Island Countries. For example, by 2050, the eastward shift in distribution and decrease in biomass for skipjack and yellowfin tuna could impact Papua New Guinea (PNG), whereas French Polynesia would have a substantial increase in biomass relative to the 2000 decade. In the second half of the century, the decrease in mean percentage biomass will extend to most other EEZs west of 170°E (FSM, Nauru, Solomon Islands, Palau and Tuvalu) and conversely increase in Vanuatu, Samoa, American Samoa and New Caledonia.
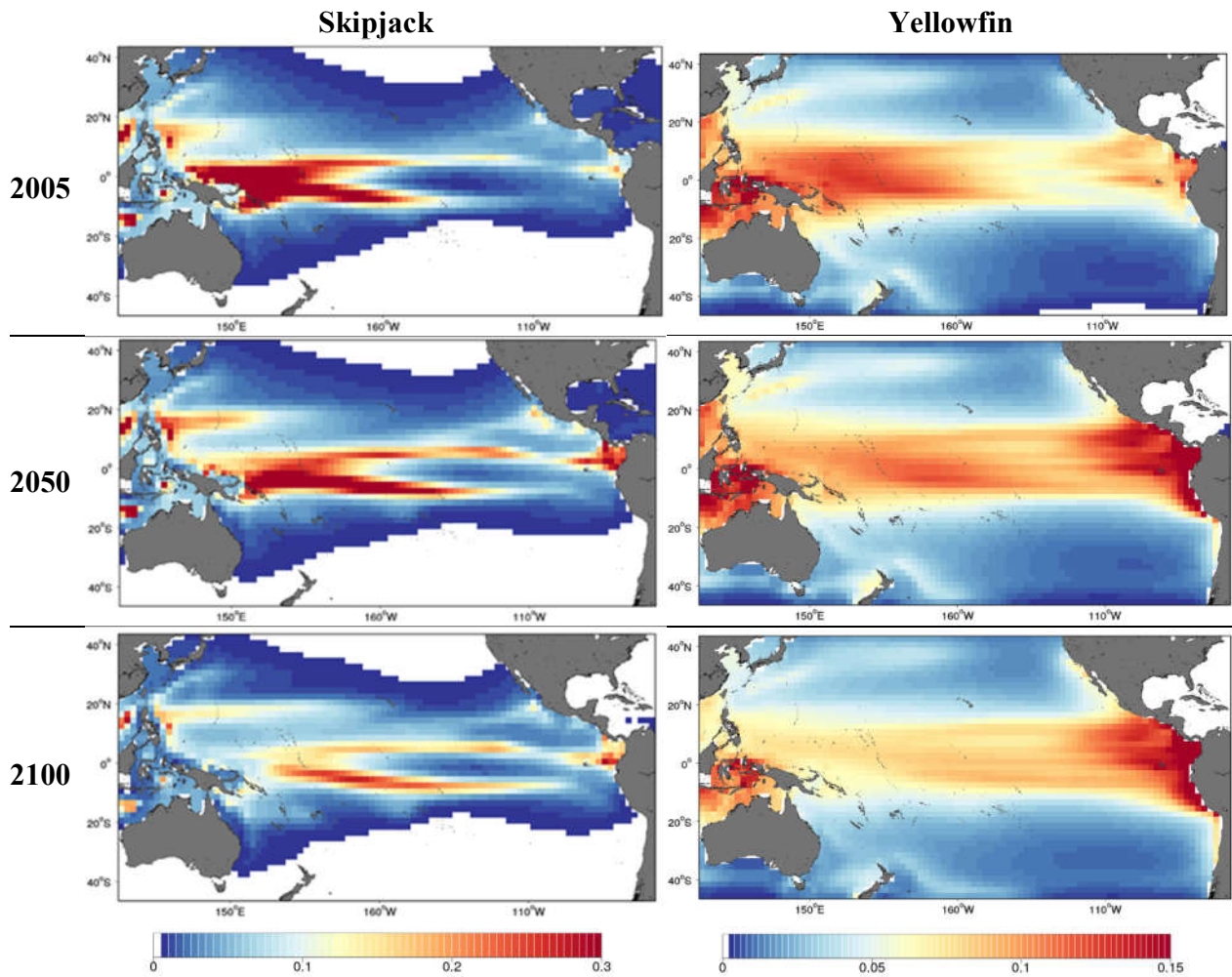
Figure 5: Projected mean distributions of skipjack and yellowfin tuna biomass across the tropical Pacific Ocean under a high emissions scenario (IPCC AR8.5) for 2005 and from the simulation ensembles in the decades centred on 2045 and 2095.

The climate change impact on bigeye tuna is predicted to be much lower and significant only by the end of century, with a maximum average decrease around 20% in Nauru, Tuvalu and New Caledonia. For albacore, consideration needs to be given to the scenarios with and without projected changes in dissolved oxygen concentration (Figure 5; Table 1). With projected changes in oxygen, the largest increases of mean biomass occur in the EEZs of PICTs to the west (Palau, PNG, FSM and Nauru) but decreases of around 15% are expected to occur in the EEZs of Fiji, New Caledonia and Vanuatu EEZs by the end of the century. If no change in dissolved oxygen concentration occurs, large and widespread increases in biomass are expected, with the maximum increase (~200%) shifted slightly to the western-central region in the EEZs of Palau, Marshall Is., Kiribati and FSM.

C. Climate change projections of exploited biomass

If the effects of fishing are considered during the historical period, the impact of climate change alters the declining trend in stock dynamics of all four species, either stabilizing it (bigeye) or switching to increase of exploited biomass (e.g. the biomass with fishing pressure at f equals one) during the first half of the century (skipjack, yellowfin, albacore, see Figures 6-9). The exception is albacore biomass under the scenario without SO (Figure 9, the light brown polygon), where the stock continues to decrease, albeit with a slight slowdown in the rate of decrease. However, the ensemble averages of biomass for all tuna species decline during the second half of the 21st century; together with an increase in uncertainty of predictions. The widest range of uncertainty in the dynamics of the exploited population occurs for albacore and for skipjack tuna at the end of the century.

The envelopes of catches and biomass are qualitatively different for skipjack and yellowfin tuna in the WCPO. Even though the biomass is increasing during the first 40 years, catches start to decline from the beginning of the RCP8.5 simulations. As a result, catches of skipjack are 10% lower at 2050 reference points with respect to the average predicted catch during the decade 2001-2010. For yellowfin tuna, the decline is more moderate (3%), mostly due to the peak following the predicted maximum of biomass at the beginning of the 2040s. Such discrepancy in the dynamics of biomass and catches can be explained by the distribution of reference effort (averaged over the 2001-2010 period), which is not optimal given the changing distribution of adults. Opposite trends occur in the EPO for skipjack and yellowfin catches, with a very substantial increase of 125% and 85% in skipjack catch by 2050 and 2100, respectively, relative to 2001-2010. The corresponding increase for yellowfin tuna catches stabilises at 80% in the mid-century and does not change until 2100.

The envelopes of catches predicted for bigeye and albacore follow closely the dynamics of the biomass during the projection period. The exploited biomass of bigeye in WCPO is predicted to decline by 20% in 2050 and 30% in 2100 in reference to current reference points, whereas a more moderate decline in catches of this species, 10% and 20%, correspondingly, is predicted for the WCPO. In the EPO, the climate change impact on the biomass and catch of bigeye is almost identical, corresponding to no change in 2050 and a small <2% decline during the last decade of the 21st century. For albacore, the average increase of exploited stock biomass stabilises at 25% throughout the 2050-2100 period under the SO scenario, resulting in predicted catches of +20% and +10%, in 2050 and 2100, respectively (Figure 9). Under RCP 8.5 and SO scenario the distribution of albacore shifts eastward to what is expected to be new favourable habitat, leading to the highest density of albacore occurring in the eastern central region (Figure 5) and a decrease in density in the west.

Bigeye   **South Pacific Albacore**
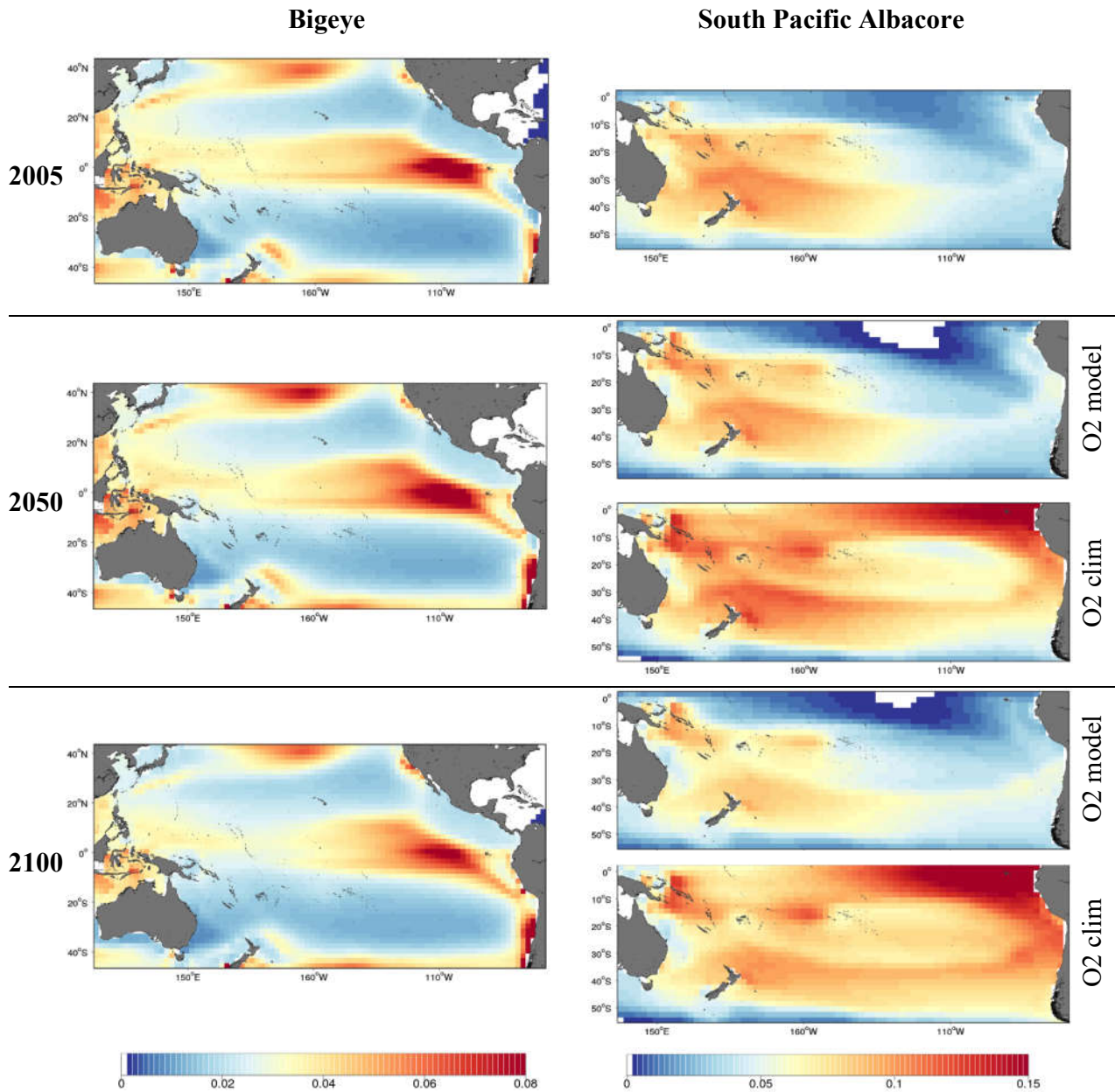
Figure 5 (cont.): Projected mean distributions of bigeye (left) and albacore (right) tuna biomass across the tropical Pacific Ocean under a high emissions scenario (IPCC AR8.5) for 2005 and from the simulation ensembles in the decades centred on 2045 and 2095. For albacore two mean distributions are shown with and without the climatological oxygen scenario.

However, if the main fishing grounds do not follow the biomass distribution, the decrease of albacore biomass in the western region will lead to the decrease in catches. The opposite situation is predicted without SO scenarios - the biomass decreases faster, by 45% in 2050 and 65% 2100, and declines of catches by 30% and 55% by 2050 and 2100, respectively.

With both climate change and fishing impacts driving the dynamics of tuna populations, the analysis of change by region (Table 3) gives a different view from the previous analysis (Table 2) that considers only the impact of climate change. This is due to the different initial conditions in 2010 – for the analysis of the combined impact of fish and climate change, the long-term projection starts from a situation where stocks were already depleted and high catch levels (Figures 6-9). Skipjack tuna catch is predicted to increase in the central EPO (50 to 90% relative to the 2000 decade) but to decrease in almost all EEZs and high seas of the WCPO regions (Table 3). By 2050, a strong decline in catch is expected in Solomon Islands, I1 area, Guam, American Samoa and Cook Islands.

By the end of the century, the decline is predicted to extend to the EEZs of other PICTs, including the current productive fishing grounds of PNG, FSM and Kiribati. For yellowfin tuna, the result is more contrasted. Catch in some areas is expected to increase substantially (American Samoa, Wallis and Futuna, New Caledonia and Cook Islands, I3 and the whole EPO), whereas there is likely to be a marked decline in other areas (Solomon Islands, I1, CNMI, Guam, Samoa, Tokelau, Kiribati and Tuvalu).

The projected catch of bigeye tuna in the WCPO is expected to be relatively stable until 2050, with a maximum decrease of around -15% to -20% for Fiji, PNG, I2 and I8. By the end of the century, a stronger decline in catch, in the range of -15% to -28%, is projected within the EEZs of almost all PICTs (Table 3). The exceptions are small increases in catch in the EEZs of French Polynesia and Pitcairn Is. Declines in catch are also expected to occur in all the international waters of the WCPO Convention Area. In the EPO, a decrease of around -35% is expected in the Northern region but compensated by an increase in the southern region.

For albacore, if we consider the worst case, i.e., removing the scenario SO with no change in oxygen conditions, the catch is project to decrease almost everywhere, with maximum declines > -40 % by 2050 and > -60% in last decade of the century in Fiji, Vanuatu and Wallis and Futuna. With the scenario SO included, the projected decrease in catch is reduced, and increases are projected in Kiribati, Tuvalu and Tokelau. The largest increase, however, is expected in the central and southern EPO.

Table 2: Impact of climate change without fishing. Mean biomass change (%) by area for the decades 2046-2055 (2050) and 2091-2100 (2100) relative to 2001-2010 average. Description of international waters zones are provided in Figure 1.

|	Area	Virgin biomass							
		SKJ		YFT		BET		ALB	
		2050	2100	2050	2100	2050	2100	2050 (-SO)	2100 (-SO)
EEZs west of 170E	CNMI*	48	8	-1	-14	4	-5	-	-
	FSM#	-29	-55	-19	-37	3	-6	196 (32)	188 (22)
	Guam	-5	-30	-16	-30	2	-3	-	-
	Marshall Islands	-17	-31	-12	-31	-3	-12	216 (20)	211 (6)
	Nauru	-8	-51	-16	-44	-4	-23	170 (31)	143 (6)
	New Caledonia	8	49	-9	-25	-5	-18	14 (0)	-3 (-16)
	Palau	-28	-54	-12	-29	4	-6	226 (58)	209 (48)
	Papua New Guinea	-43	-72	-21	-42	-4	-16	72 (35)	64 (28)
	Solomon Islands	-17	-37	-9	-30	-2	-14	62 (24)	46 (8)
EEZs east of 170E	Vanuatu	21	82	-2	-20	-1	-13	20 (4)	2 (-14)
	American Samoa	42	61	23	9	4	-7	41 (9)	36 (-2)
	Cook Islands	16	29	28	18	3	-7	47 (5)	39 (-7)
	Fiji	14	14	6	-14	-1	-16	21 (1)	3 (-16)
	French Polynesia	97	99	43	45	7	0	60 (4)	59 (-6)
	Kiribati	18	-21	7	-17	1	-15	200 (14)	181 (-7)
	Niue	24	15	20	6	3	-9	31 (6)	20 (-6)
	Pitcairn Islands	60	41	55	72	10	7	68 (11)	85 (11)
	Samoa	39	46	20	4	3	-8	36 (7)	29 (-4)
	Tokelau	-14	-24	14	-7	-1	-17	92 (11)	69 (-10)
	Tonga	15	3	13	-5	1	-14	25 (4)	14 (-9)
	Tuvalu	-12	-45	3	-23	-2	-21	93 (13)	66 (-10)
	Wallis and Futuna	26	21	14	-5	2	-11	39 (9)	28 (-6)
IW WCPFC	I1**	-52	-76	-19	-39	0	-12	195 (39)	181 (25)
	I2	-15	-58	-12	-39	-3	-20	132 (23)	108 (2)
	I3	21	-9	-7	-21	3	-3	-	-
	I4	5	-9	1	-17	-4	-14	-	-
	I5	65	45	23	10	2	-7	-	-
	I6	10	5	12	-6	3	-18	-	-
	I7	13	1	20	6	6	-10	27 (5)	17 (-7)
	I8	26	55	3	-17	-1	-15	20 (2)	1 (-17)
	I9	88	165	35	31	2	-5	36 (1)	28 (-14)
	H4	-10	-44	4	-23	-1	-21	127 (16)	96 (-9)
	H5	38	-2	15	-9	1	-15	243 (16)	220 (-5)
IW EPO	EPO-N	29	-9	43	31	12	8	-	-
	EPO-C	80	64	55	61	9	1	332 (19)	390 (12)
	EPO-S	47	51	71	114	20	23	93 (25)	121 (30)

* CNMI = Commonwealth of Northern Mariana Islands
# FSM = Federated States of Micronesia

The increase of fishing effort does not produce a linear increase in catch (Table 4). Despite a 50% increase of effort, the skipjack tuna catch is still predicted to decrease in the EEZs of most PICTs, with the exception of CNMI and Nauru, and FSM and PNG during the first half the century only. In the central EPO, the same 50% increase in fishing effort relative to the 2000 decade provides an increase up to 167% and 109% in the catch of skipjack tuna by 2050 and 2100, respectively. For yellowfin tuna, the higher fishing effort scenario (i.5f) led to ~30% more catch in all the EPO regions than with the average fishing effort scenario (1.0)f. There is also a similar substantial increase in international waters (I3, I5, I6, I8 and H5) and in the EEZs of American Samoa, Wallis and Futuna, Pitcairn Is., New Caledonia, French Polynesia, Cook, Tonga and Fiji. However, this increase cannot compensate for the decline of catch in I1 and I2 or the EEZs of CNMI, Guam, Solomon Islands, Niue, Samoa and Tuvalu. For bigeye tuna the benefit of increasing fishing effort from 1 to 1.5 is very limited or negligible for the EEZs west of 170°E. Elsewhere in the region, increased fishing effort would help maintain the level of catch at the average reference catch for the 2000 decade (Vanuatu, American Samoa, Kiribati and Tokelau) or limit the decline (Fiji and Wallis and Futuna).

For albacore, without the scenario SO, i.e., considering the pessimistic trends, the scenario with 50% increase of fishing effort results in lower catch than with the average fishing effort almost everywhere, due to the nonlinear effect on spawning biomass and recruitment. With the much more optimistic scenario of including SO, large increases in catch are expected to occur in the central and southern EPO. However, the catch is projected to decrease almost everywhere else with maximum impacts (above -40% decline by 2050 and above -60% in last decade of the century) in Fiji, Vanuatu and Wallis and Futuna. With the scenario SO included, the decrease in catch is reduced and there are increases projected in Kiribati, Tuvalu and Tokelau. Even so, the increase compared to the reference scenario is limited. and In many other areas, the effect of increasing effort is likely to be counterproductive.

Skipjack
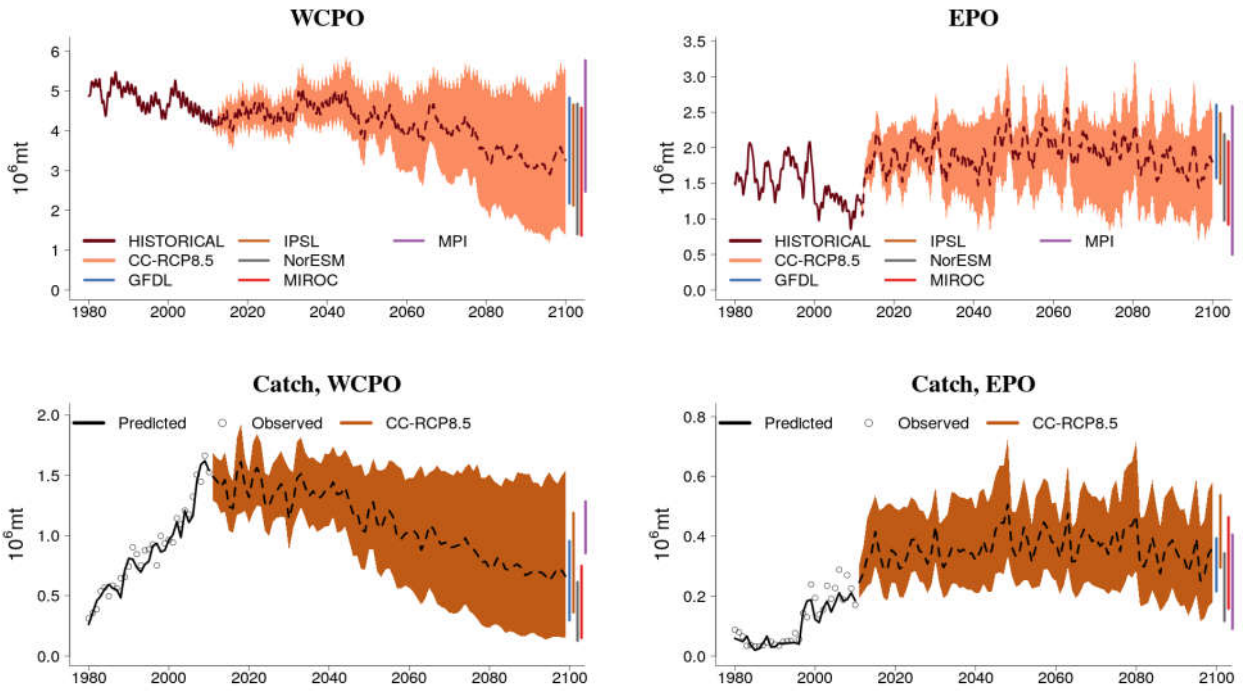
Figure 6: Envelope of predictions for exploited biomass (top) and catch (bottom) of skipjack computed from simulation ensembles under IPCC RCP8.5 scenario for the western central (WCPO) and eastern (EPO) Pacific Ocean. The change in total biomass is presented with the average (dotted line) and its envelope bounded by the 5% and 95% quantile values of the simulation ensembles.

Yellowfin
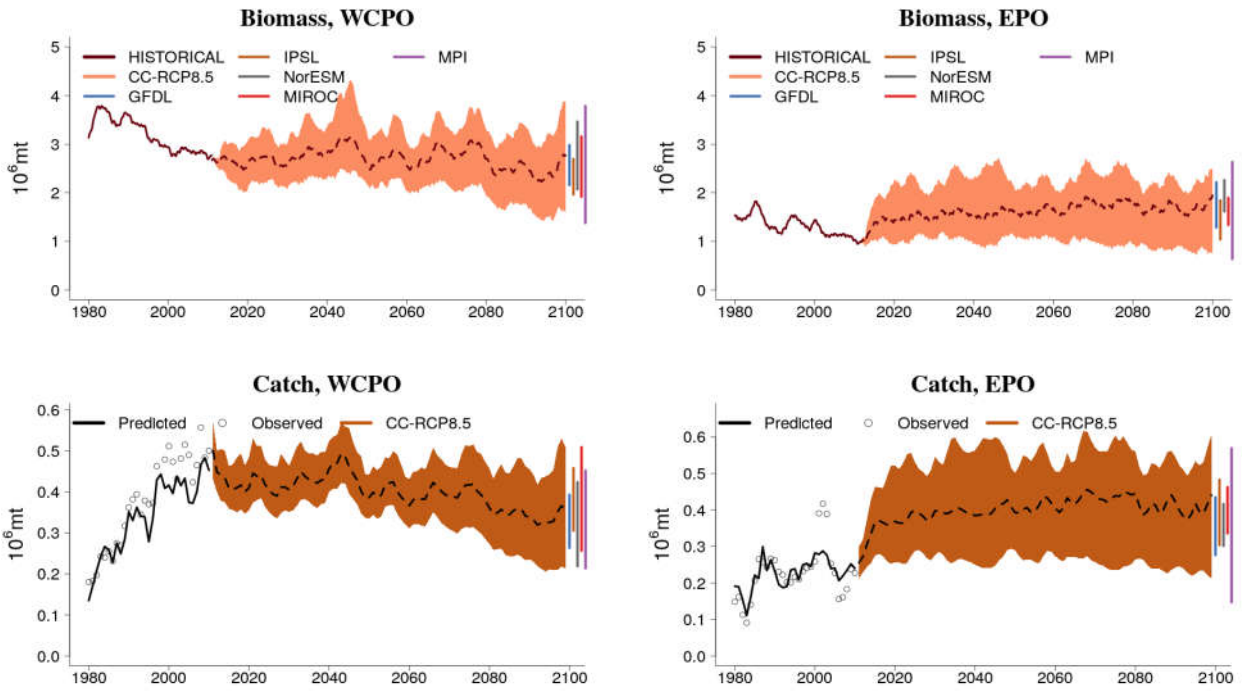
Figure 7: Envelope of predictions for exploited biomass (top) and catch (bottom) of yellowfin computed from simulation ensembles under IPCC RCP8.5 scenario for the western central (WCPO) and eastern (EPO) Pacific Ocean. The change in total biomass is presented with the average (dotted line) and its envelope bounded by the 5% and 95% quantile values of the simulation ensembles.

Bigeye

Figure 8: Envelope of predictions for exploited biomass (top) and catch (bottom) of bigeye computed from simulation ensembles under IPCC RCP8.5 scenario for the western central (WCPO) and eastern (EPO) Pacific Ocean. The change in total biomass is presented with the average (dotted line) and its envelope bounded by the 5% and 95% quantile values of the simulation ensembles.
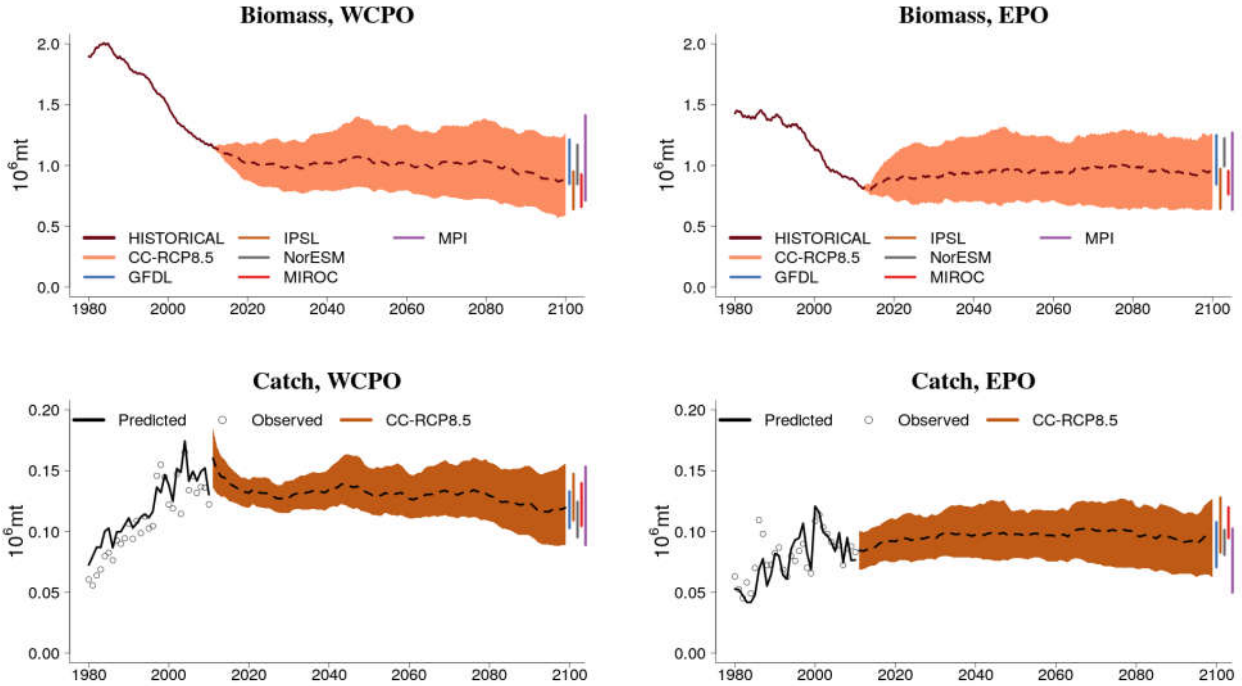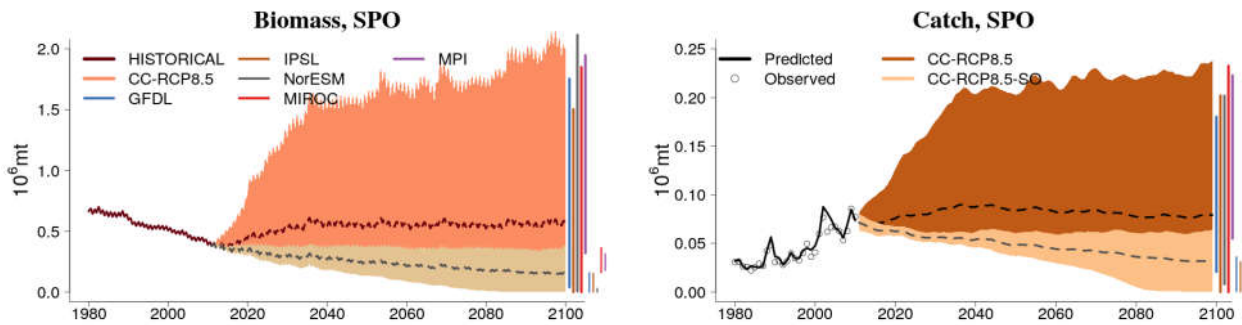
Albacore

Figure 9: Envelope of predictions for exploited biomass (top) and catch (bottom) of albacore computed from simulation ensembles under IPCC RCP8.5 scenario for the southern Pacific Ocean (SPO). The light brown polygon shows the envelope of ensemble simulations excluding SO scenario (climatological oxygen during projection phase). The change in total biomass is presented with the average (dotted line) and its envelope bounded by the 5% and 95% quantile values of the simulation ensembles.

Table 3: Impact of climate change and fishing (1.0f). Predicted catch change (%) by EEZ for the decades 2046-2055 (2050) and 2091-2100 (2100) relative to 2001-2010 average. The catches were computed based on mean effort over 2001-2010 period. Description of International waters zones is provided in Figure 1.

| | Area | Predicted catch | | | | | | | |
| | | SKJ | | YFT | | BET | | ALB | |
		2050	2100	2050	2100	2050	2100	2050 (-SO)	2100 (-SO)
EEZs west of 170E	CNMI*	22	-11	-64	-64	-5	-6	-	-
	FSM#	-9	-44	19	-2	-8	-15	0 (0)	-1 (-1)
	Guam	-100	-100	-38	-41	-2	-4	-	-
	Marshall Islands	-24	-36	-21	-35	-12	-18	-	-
	Nauru	81	-1	52	5	-8	-27	0	-2
	New Caledonia	-100	-100	105	93	-13	-22	5 (-18)	-15 (-41)
	Palau	-13	-39	19	3	-9	-20	-	-
	Papua New Guinea	-10	-60	-7	-30	-16	-26	13 (-17)	1 (-34)
	Solomon Islands	-95	-96	-61	-68	-11	-21	-1 (-34)	-16 (-53)
EEZs east of 170E	Vanuatu	-43	-35	2	-7	-9	-17	-25 (-42)	-40 (-60)
	American Samoa	-73	-69	457	405	-8	-19	-3 (-39)	-11 (-53)
	Cook Islands	-83	-84	91	85	-3	-12	5 (-27)	2 (-39)
	Fiji	-100	-100	9	-1	-18	-28	-22 (-42)	-39 (-62)
	French Polynesia	-69	-67	11	18	9	5	47 (-16)	54 (-26)
	Kiribati	-28	-57	-25	-44	-6	-21	106 (-24)	106 (-40)
	Niue	-	-	-64	-67	3	-8	-23 (-48)	-33 (-63)
	Pitcairn Islands	-	-	151	187	9	9	19 (-22)	24 (-29)
	Samoa	-	-	-94	-94	1	-8	0	-5 (-7)
	Tokelau	-84	-87	-93	-94	-12	-28	37 (-13)	25 (-29)
	Tonga	-100	-100	10	-1	-11	-21	-19 (-36)	-28 (-48)
	Tuvalu	-98	-98	-71	-78	-8	-27	42 (-28)	25 (-45)
	Wallis and Futuna	-98	-99	358	294	-14	-26	-9 (-46)	-19 (-62)
IW WCPFC	I1**	-100	-100	-98	-98	-1	-5		
	I2	-29	-65	-38	-57	-22	-34	66 (-30)	43 (-52)
	I3	-23	-34	78	65	1	-5	-	-
	I4	-5	-29	-4	-21	-7	-16	-	-
	I5	-9	-31	15	5	6	-1	117 (-22)	136 (-34)
	I6	-57	-64	17	4	-2	-15	-	-
	I7	-	-	0	-10	-5	-20	-10 (-23)	-20 (-35)
	I8	-100	-100	253	222	-18	-28	-19 (-41)	-38 (-63)
	I9	-	-	-100	-100	-	-	0 (0)	-4 (-6)
	H4	113	32	7	-21	-12	-39	72 (-34)	54 (-53)
	H5	-59	-72	5	-13	-2	-18	98 (-21)	94 (-37)
IW EPO	EPO-N	-10	-32	64	52	-36	-35	-	-
	EPO-C	91	50	69	70	1	-4	180 (-21)	234 (-30)
	EPO-S	-	-	27	72	20	35	61 (-20)	89 (-25)

* CNMI = Commonwealth of Northern Mariana Islands

FSM = Federated States of Micronesia

Table 4: Impact of climate change and fishing (1.5f). Percentage change in predicted catch by EEZ for the decades 2046-2055 (2050) and 2091-2100 (2100) relative to 2001-2010 average. The catches were computed based on 50% increase of climatological effort. Description of international waters zones are provided in Figure 1.

	Area	Predicted catch							
		SKJ		*YFT*		*BET*		*ALB*	
		2050	2100	2050	2100	2050	2100	2050 (-SO)	2100 (-SO)
EEZs west of 170E	CNMI*	80	31	-62	-62	-3	-4	-	-
	FSM#	23	-23	41	19	-3	-9	0 (0)	-34 (-45)
	Guam	-100	-100	-29	-31	1	-1	-	-
	Marshall Islands	6	-10	1	-15	-1	-6	-	-
	Nauru	138	30	84	29	-5	-23	0 (0)	-35 (-46)
	New Caledonia	-100	-100	165	158	-1	-10	-8 (-32)	-37 (-69)
	Palau	-13	-39	37	22	-5	-17	-	-
	Papua New Guinea	16	-48	2	-20	-15	-25	2 (-29)	-26 (-66)
	Solomon Islands	-93	-95	-53	-60	-4	-14	-14 (-48)	-36 (-76)
EEZs east of 170E	Vanuatu	-18	-6	32	24	2	-6	-35 (-53)	-56 (-79)
	American Samoa	-60	-54	683	616	8	-4	-8 (-48)	-24 (-75)
	Cook Islands	-75	-76	171	163	14	5	4 (-32)	-15 (-66)
	Fiji	-100	-100	49	37	-4	-16	-28 (-51)	-51 (-79)
	French Polynesia	-55	-51	55	66	26	23	57 (-19)	49 (-56)
	Kiribati	-1	-40	-1	-25	7	-9	111 (-31)	100 (-66)
	Niue	-	-	-49	-54	20	8	-27 (-55)	-43 (-80)
	Pitcairn Islands	-	-	248	300	20	20	26 (-24)	20 (-52)
	Samoa	-	-	-91	-92	27	17	0 (0)	-37 (-50)
	Tokelau	-77	-81	-90	-91	11	-9	35 (-18)	3 (-61)
	Tonga	-100	-100	53	39	5	-7	-23 (-43)	-44 (-72)
	Tuvalu	-96	-98	-62	-71	2	-18	35 (-38)	7 (-70)
	Wallis and Futuna	-98	-98	533	450	-1	-14	-16 (-57)	-30 (-80)
IW WCPFC	I1**	-100	-100	-98	-98	-1	-5	-	-
	I2	-9	-55	-28	-48	-20	-31	51 (-45)	22 (-75)
	I3	3	-12	128	117	11	5	-	-
	I4	37	4	32	9	7	-1	-	-35
	I5	35	2	61	47	25	17	138 (-27)	149 (-60)
	I6	-37	-48	56	41	10	-5	-	-
	I7	-	-	37	26	13	-5	-9 (-25)	-37 (-61)
	I8	-100	-100	372	339	-7	-17	-28 (-53)	-52 (-80)
	I9	-	-	-100	-100	-	-	0 (0)	-35 (-47)
	H4	210	91	47	8	5	-26	65 (-45)	40 (-74)
	H5	-40	-58	48	24	15	-2	99 (-28)	81 (-66)
IW EPO	EPO-N	32	-1	93	80	-22	-21	-	-
	EPO-C	167	109	90	93	18	13	233 (-22)	295 (-53)
	EPO-S	-	-	49	107	34	51	88 (-19)	112 (-46)

* CNMI = Commonwealth of Northern Mariana Islands

FSM = Federated States of Micronesia

Part I - Discussion

The modifications to SEAPODYM done during this project have improved the ability of the model to describe the spawning mechanisms, the accessibility to micronekton (prey) functional groups, and seasonal spawning migrations of tropical Pacific tuna species compared to previous optimizations of SEAPODYM (e.g. Senina et al. 2008; Lehodey et al. 2010, 2013, 2015). Importantly, substantial effort has also been devoted to: 1) a quantitative method to estimate parameters with the integration of conventional tagging data in the Maximum Likelihood Estimation approach (Senina et al. 2018 *submitted*); and 2) an alternative method to use catch directly in the likelihood function when fishing effort is not available or not reliable. *A priori* information on total biomass was also added in the likelihood to force the model to reach the best compromise between minimal biomass and good fit to observations. Together with a more realistic environmental forcing, and spatially disaggregated fishing datasets revised to match the total declared catch, these improvements to SEAPODYM have permitted better estimates of model parameters with a better fit to data, and improved and consistent estimates of the distributions and dynamics of these important tuna species. The emergence of key features in the simulations that match those known from the ecology and behaviour of the tuna species is particularly remarkable. Examples include, the relationships between each species and the different vertical layers of the water column and their associated functional groups of prey, and/or predicted spawning grounds and larval distributions. The results for albacore are also notable, given the more complex life cycle of this sub-tropical species, which involves seasonal migrations of adults between feeding and spawning grounds.

The convergence in biomass estimates with independent stock assessment studies (McKechnie et al. 2016 2017; Tremblay-Boyer et al. 2017; Harley et al. 2014, 2015) provides further confidence in the utility of SEAPODYM to simulate the dynamics of tropical Pacific tuna populations under both the fishing pressure and environmental variability that control their abundance and distribution. This validation over the historical period is obviously a necessary condition for projecting the future of tuna dynamics under the impact of strong environmental changes using IPCC scenarios. The agreement between predicted spawning grounds and larval distributions, and current observations and knowledge, is also essential because the early life stages are the most sensitive to the variability in oceanographic conditions, and thus more vulnerable to the impact of climate change. Nevertheless, it is also necessary to consider future ocean acidification. At present, this is difficult because the effects of lower pH on the four tuna species, and the prey organisms that support them, are still largely unknown, and were not included nor needed in the historical simulation. However, the results of recent laboratory research for yellowfin tuna larvae

(Bromhead et al. 2015; Frommel et al. 2016) enabled us to include this effect in the model for this species for the first time. The simulations for yellowfin tuna indicate that ocean acidification has an additional impact on larvae. In the worst scenario, mortality of larvae in the EPO could increase by 10% to 15% at the end of the 21ˢᵗ Century. Over time, the accumulation of the effect of this additional mortality would be expected to produce a significant decrease of the total stock of yellowfin tuna.

In comparison to previous studies (Lehodey et al. 2010, 2013, 2015; Bell et al. 2013), the conclusions about the impact of a high greenhouse gas (GHG) concentration scenario on skipjack and yellowfin tuna remain unchanged, confirming an eastern shift in biomass of both species over time. However, the envelop of projections becomes very wide for skipjack after mid-century. The improvements to SEAPODYM during this study indicate that the impacts of a high GHG emissions scenario on bigeye tuna are likely to be lower than previously estimated. This is essentially due to the revised parametrization of the spawning habitat. With this new optimization, estimates for the spawning temperature function produce a wider and warmer range of favourable spawning habitat for bigeye tuna. For albacore, the sensitivity to oxygen detected in previous work is clearly confirmed. However, the expected shift in the spawning ground of albacore to the south-west identified during a previous study was not confirmed. This is due to the new estimated temperature spawning function, which points to a warmer optimal temperature.

As mentioned in Section B of the Results, the new simulations indicate that the projected impacts of climate change on tropical Pacific tuna species are likely to have strong implications for the economic development of Pacific Island countries, and the management of tuna resources at basin scale. Indeed, the climate change impact seems to have already positively impacted the populationtuna dynamics of the three tropical tuna species (skipjack, yellowfin and bigeye) over the historical period 1980-2010 in the WCPO. The positive trends in biomass appear to have compensated for the increased mortality associated with the increasing fishing effort over that period.

In the first half of the 21ˢᵗ ˢCentury, the biomass of skipjack and yellowfin tuna is projected to remain relatively stable in the WCPO with stable (yellowfin tuna) or slightly decreasing (skipjack tuna) trend in catch. Although the decline in skipjack biomass by 2050 mentioned above affects mainly the PICTs west of 170°W, the skipjack catch is predicted to decrease in most of the EEZs in the WCPO, even with ta 50% increase in fishing effort, with the exception of CNMI. Such decreases in catch would result in less revenue from licence fees for PICTs (unless practical ways can be found to increase the value of catches). The opposite trend is expected in the EPO central region. For yellowfin tuna, a higher biomass is expected

in some EEZs in the central WCPO (east of 170°E), e.g., American Samoa and Wallis and Futuna, and the EPO, leading to large increases in catch proportional to fishing effort. For bigeye and albacore, the impact of climate change is expected to remain limited in the first half of the century, with a very high uncertainty concerning albacore in relation to the projected trend for dissolved oxygen concentration in sub-surface in the EPO.

The larger proportions of skipjack and yellowfin tuna becoming accessible to fishing in international waters (central WCPO and EPO particularly), will make the monitoring and control of industrial tuna fisheries more difficult in the coming decades. Therefore, these results argue for a rapid reinforcement and improvement of fisheries monitoring at basin scale. The historical fishing pressure is estimated to have reduced the adult stocks of the tuna species by 30-55 % by the end of 2010, depending of species and region. The level of fishing has certainly increased since then and may be closer to, or higher than, the optimal sustainable target for (virgin) biomass reduction of -60% (-50% for skipjack) proposed by the regional fisheries management organizations. The reduction in biomass due to fishing is much more than the reductions expected to occur due to climate change in the decades ahead. Thus, the effects of fishing are expected to continue to be the dominant driver of tuna population sizes until at least mid-century.

In the second half of the century, while the envelope of uncertainty is widening, the biomass of skipjack and yellowfin tuna in the WCPO is projected to decrease. Almost all WCPO EEZs and regions are impacted by the expected decline in biomass and catch of these two species (with the same few exceptions for yellowfin tuna listed above). The decrease in biomass of bigeye tuna is likely to slowly continue in the WCPO and lead to a substantial decrease in catch in most WCPO areas and the North EPO that may be partially compensated for by an increase in fishing effort. For albacore, the same uncertainty in dissolved oxygen trends leads to opposite trajectories in biomass and catch. Better monitoring and modelling of future albacore population trends will require better monitoring and modelling of dissolved oxygen concentration, especially to reduce the high levels of uncertainty in current estimates.

The rapid and continuous improvements in the development and validation of Earth Climate models should be used to regularly revisit these conclusions and the overall uncertainty included in the results. In addition, more elaborate methodology needs to be developed to correct the climate model forcings before running the coupled physical-biogeochemical model. Given the sensitivity of the results to the processes controlling the favorability of spawning habitat, and larval survival, a strong research effort

(including *in situ* observations and laboratory experiments) should be dedicated to defining the combined effects of optimal range of spawning temperature and the effect of pH on the simulations. Better monitoring and modelling of future trends in dissolved oxygen concentration and pH will also be essential to reducing the uncertainty associated with this study. Finally, although the use of the last 10-year average distributions of fishing effort allows most of the past, present and future fishing grounds to be approximated , the patterns of intensity of fishing effort will likely change together with the redistributed tuna abundance. The use of fishing fleet models coupled to the tuna spatial dynamics, as simulated in this study, should help to better identify the future productivity and sustainability of Pacific tuna fisheries.

Part II – Introduction

Implications for Government Revenue and GDP

Although the modelling described earlier in this report examined the effects of climate change on the biomass of tropical tuna species in the exclusive economic zones (EEZs) of Pacific Island countries and territories (PICTs) and in high seas areas by 2050 and 2100, this analysis is restricted to the implications of the projections for 2050. There is more uncertainty associated with the projections for 2100 and the implications of the changes projected to occur by 2050 are considered to be more reliable, and substantial enough in their own right, to bring to the attention of policy makers.

The projected changes to the redistribution of biomass of skipjack, yellowfin and bigeye tuna by 2050 presented in Table 2 (based on the response of these species to climate change alone, i.e., without integrating the effects of variation in fishing effort) show two main trends:

1. a decrease in total tuna biomass in the EEZs of PICTs west of 170°E and in international waters (high seas) areas I1, I2 and H4 in (Figure 1); and
2. an increase in biomass in the EEZs of most (but not all) PICTs east of 170°E, and in all other high seas areas.

The effects of the projected changes in total biomass of these tuna species are, in turn, likely to impact on the economic benefits derived by PICTs from their exploitation. The primary economic benefits generated by tuna fisheries for PICTs are government revenues from access and licenses fees, and the contributions that the tuna harvest and processing sectors make to their GDP. It is difficult to assess these impacts because they will depend on a range of factors, including: i) management responses; ii) the impact of the change in biomass on catch, effort and thus the value of access to the waters of a PICT;

and, iii) the impact of the change in distribution of tuna biomass on the level of control that PICTs are able to exert over the fisheries targeting the respective stocks.

Part II - Material and Methods

To comprehensively assess these impacts would require a study far beyond the scope of this paper. A simplified approach has been applied which assumes that changes in government revenue and contributions to GDP will be proportionate to the projected change in biomass. In effect, this assumes that a change in biomass leads to a proportionate change in catch and in turn to proportionate changes in economic benefits. Given the restricted nature of this analysis, the estimates provided are likely to understate those that would be obtained under a more comprehensive analysis and, as such, caution is urged with the use of and reliance upon these figures (note that this caveat also applies due to the uncertainty in the underpinning climate models and projections of changes in biomass).

It should be noted that the analysis is limited to the purse-seine fishery within the waters of 10 PICTs – the nine members of the Parties to the Nauru Agreement (PNA) (FSM, Kiribati, Palau, PNG, Marshall Islands, Nauru, Solomon Islands and Tuvalu and Tokelau) and Cook Islands – where more than 95% of all tuna caught in the waters of PICTs is taken. Further, the analysis used the following methods and assumptions:

- the change in biomass available to the purse-seine fishery was based on the projected (weighted) average percentage change in biomass across all three species combined, calculated using the information in Table 2 and the average percentage of each species in the purse-seine catch during the 5-year period 2013-2017 (i.e., skipjack 76%, yellowfin 20% and bigeye 4%) (see Table 5);
- current government revenues were based on the most recent information (2016) available for the value of licence fees received by PICTs from the purse-seine fishery (FFA 2017) because these fees dominate government revenues from industrial tuna-fishing operations;
- contributions to GDP were based on the contribution of tuna harvesting and/or tuna processing operations to total national GDP; and
- for each PICT, the average percentage contribution of the sector to GDP was derived from information available for the latest 3-year period (2014-2016) (FFA 2017).

It is important to note that although South Pacific albacore supports longline fisheries in several PICTs (Williams and Reid 2018), it has not been included in this analysis due to uncertainty about the effects of changes in dissolved oxygen on future distribution and biomass (see section B of Part I - Results).

Table 5: Projected changes in biomass of skipjack, yellowfin and bigeye tuna in the exclusive economic zones (EEZs) of Pacific Island countries and territories (PICTs), and in the areas of international waters (IW), in the absence of fishing (see Table 2) by 2050. The projected changes in biomass for all species combined is also shown, estimated using a weighted average based on the percentage of skipjack (76%), yellowfin (20%) and bigeye (4%) in purse-seine catches between 2013 and 2017.

PICT/IW	Tuna species			% change in biomass of all species combined
	Skipjack	**Yellowfin**	**Bigeye**	
EEZs west of 170°E				
FSM	-29	-19	3	-26
Marshall Islands	-17	-12	-3	-15
Nauru	-8	-16	-4	-9
Palau	-28	-12	4	-24
Papua New Guinea	-43	-21	-4	-37
Solomon Islands	-17	-9	-2	-15
EEZs east of 170°E				
Cook Islands	16	28	3	18
Kiribati	18	7	1	15
Tokelau	-14	14	-1	-8
Tuvalu	-12	3	-2	-9
WCPFC International waters				
I1	-52	-19	0	-43
I2	-15	-12	-3	-14
I3	21	-7	3	15
I4	5	1	-4	4
I5	65	23	2	54
I6	10	12	3	10
I7	13	20	6	14
I8	26	3	-1	20
I9	88	35	2	74
H4	-10	4	-1	-7
H5	38	15	1	32
EPO International waters				
EPO-N	29	43	12	31
EPO-C	80	55	9	72
EPO-S	47	71	20	51

Part II – Results

A. Projected changes in government revenue

By 2050, climate change is projected to cause a reduction in government revenue from licence and access fees from purse-seine fishing in eight of the 10 PICTs (Table 6, Figure 10). The greatest decrease in real terms is expected to occur in PNG, where a 37% decline in biomass of tuna is associated with a loss of ~USD48 million in government revenue in today's terms. However, this loss is associated with a reduction in the contribution of fishing licence fees to total government revenue from just 2.4% to 1.5%

(0.9%) due to the relatively large size of the economy in PNG. In contrast, the 27% decrease in tuna biomass in the EEZ of FSM, associated with a loss of USD16.3 million, would reduce the contribution of licence fees to total government revenue from 47.2% to 39.9% (7.3%) (Table 6).

For Kiribati and Cook Islands, the two countries which have a significant part or all of their EEZs further to the east than the other eight PICTs (Figure 1), an increase of 15% and 18% in combined biomass of tuna, respectively, is projected by 2050 (Table 5). This would be associated with an increase in the contribution of purse-seine licence fees to total government revenue of 3.5% in Kiribati and 1.4% in Cook Islands (Table 6).

Overall, the reduction of total tuna biomass subject to purse-seine fishing is likely to cause a decline in total annual value of fishing licence revenue across the 10 PICTs from $465 million to $403 million, i.e., at least $60 million (or 13%) per year (Table 6).

The modelling for other PICTs (Table 2), indicates that there is scope for substantial percentage increases in the biomass for some tuna species, e.g., in the waters of French Polynesia and Samoa, where skipjack biomass is predicted to increase by around 40% and 90%, respectively, in 2050. However, in both cases current skipjack biomass and catches are relatively low (there is a ban on foreign fishing in the waters of French Polynesia) and even significant increases in the economic benefits generated from the fishery in these areas are unlikely to offset anything more than a small proportion of the losses suffered by those PICTs that currently provide the main fishing grounds.

B. Projected changes in GDP

The projected effects of climate change on GDP are not as far reaching as the effects on government revenue because in five of the 10 countries the contributions to national GDP derived from harvesting and/or processing tuna are less than 2.5% (Table 7). However, the effects are significant in FSM and Marshall Islands, where the total biomass of tuna within the EEZ is expected to decrease by 26% and 15%, respectively, by 2050, and where 14% of GDP is derived from tuna in FSM and 32% in Marshall Islands (Table 7). The 37% decrease in tuna biomass projected to occur in the EEZ of PNG by 2050 has the potential to reduce the contributions of tuna to national GDP by USD95 million (Table 7). However, this is unlikely to occur because even if the the average tuna catch from the PNG EEZ (370,000 tonnes per year for the period 2013-2017) is reduced by 37% there will still be sufficient tuna within the EEZ to supply the existing (and proposed) national canneries.

The projected increases in tuna biomass in the EEZs of Kiribati and Cook Islands will have little effect on the tuna-related activities contributing to GDP because these activities currently only contribute to national GDP in minor ways (Table 7).

Part II – Discussion

A. Implications for fisheries management

The projected responses to climate change of tropical tuna species summarised in Table 2 have important implications for the management of both the purse-seine fishery and the longline fishery, and for the tuna resources on which PICTs depend so heavily. For skipjack tuna, the mainstay of the purse-seine fishery, the modelling shows that the net effect of climate change is likely to result in decreases in biomass in the EEZs of eight of the 10 countries in Table 5, and increases in most of the international waters. Although the modelling does not examine biomass projections for the three separate areas comprising the EEZ of Kiribati, it is also possible that the projected total increase in biomass of skipjack tuna in Kiribati's waters (Table 2) will occur mainly within the Line Islands, with decreases in biomass available for capture by the purse-seine fishery in the EEZ areas around the Phoenix Islands and Gilbert Islands further to the west.

Thus, over time, the modelling indicates that the WCPFC will need to assume more responsibility for the sustainable management of tropical tuna resources supporting the purse-seine fishery. Conversely, the climate-smart, vessel day scheme management measures implemented by the PNA Office (Aqorau et al. 2018) will likely have jurisdiction over a lower proportion of tropical Pacific tuna resources.
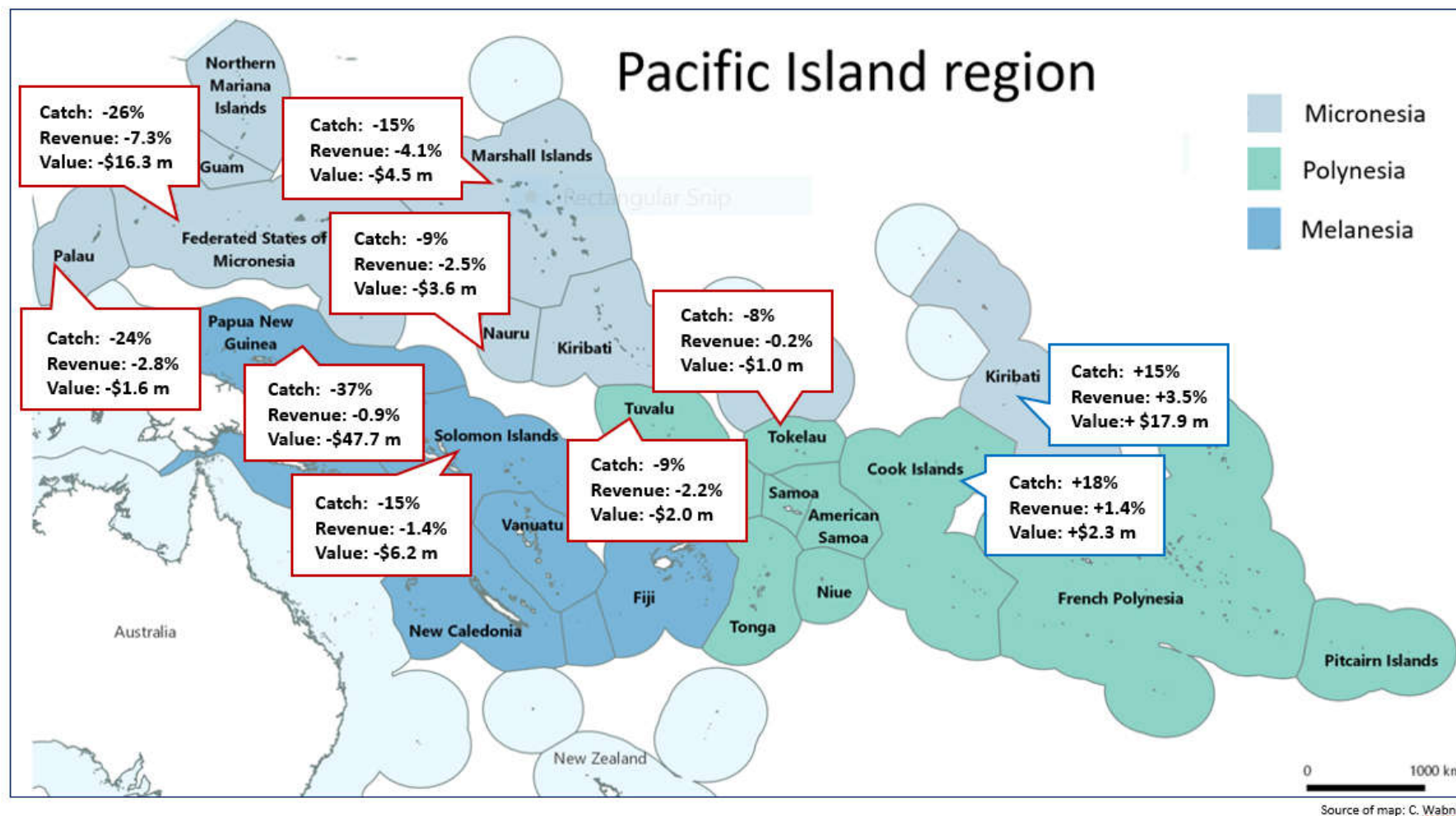
It is difficult to comment on the implications for management of the longline fishery, due to the uncertainty associated with the effects of future dissolved oxygen levels on the biomass of South Pacific albacore as mentioned above. However, with respect to the contribution of yellowfin tuna to longline fisheries, the biomass of this species is projected to decrease in six of the 10 countries listed in Table 5, and increase in adjacent high seas to the east of these EEZs. The projected changes in biomass of bigeye tuna, also important to the longline fishery, within the EEZs of the 10 countries are minor by 2050 (Table 2). Overall, the existing prominence of high seas areas in the management of the longline fishery is expected to continue, and to become even stronger due to the effects of climate change.

Table 6: Projected changes in licence revenue from the purse-seine fishery, in terms of dollar value and as a percentage of all government revenue, in 2050 relative to 2016 due to the effects of climate change on the combined biomass of skipjack (SKJ), yellowfin (YFT) and bigeye (BET) tuna in the exclusive economic zones (EEZs) of 10 Pacific Island countries and territories (PICTs).

PICT (EEZ)	2016			Change (%) in combined biomass of SKJ, YFT & BET tuna by 2050	2050			Change 2016-2050	
	Total Gov't revenue (USD m)	Tuna licence fee revenue (USD m)*	Contribution of licence fees to total Gov't revenue (%)		Total Gov't revenue (USD m)	Tuna licence fee revenue (USD m)	Contribution of licence fees to total Gov't revenue (%)	Tuna licence fee revenue (USD m)	Contribution to total Gov't revenue (%)
EEZ west of 170E									
FSM	133.9	63.2	47.2	-26	117.6	46.9	39.9	-16.3	-7.3
Marshall Islands	64.7	29.2	45.1	-15	60.2	24.7	41.0	-4.5	-4.1
Nauru	56.0	27.8	49.6	-9	53.4	25.2	47.1	-2.6	-2.5
Palau	50.7	6.8	13.4	-24	49.1	5.2	10.6	-1.6	-2.8
Papua New Guinea	5366.7	128.8	2.4	-37	5319.0	81.1	1.5	-47.7	-0.9
Solomon Islands	411.9	41.6	10.1	-15	405.7	35.4	8.7	-6.2	-1.4
EEZ east of 170E									
Cook Islands	143.8	12.8	8.9	18	146.1	15.1	10.3	2.3	1.4
Kiribati	217.5	118.3	54.4	15	235.4	136.2	57.9	17.9	3.5
Tokelau	13.6	13.3	98.0	-8	12.5	12.3	97.8	-1.0	-0.2
Tuvalu	39.0	23.4	60.0	-9	37.0	21.4	57.8	-2.0	-2.2
Total		465.2			403.5				

*Source: FFA 2017

Figure 10: Projected percentage change in the combined catch of skipjack, yellowfin and bigeye tuna in the exclusive economic zones of the 10 Pacific Island countries and territories that produce 95% of the tuna in the Pacific Island region by 2050, together with projected changes in the contributions of licence fees to total government revenue and the value of licence revenue in present-day terms.

Table 7: Projected changes in GDP from the purse-seine fishery and logline fishery in 2050, in terms of dollar value and as a percentage of total national GDP, relative to average values for the period 2014-2016, due to the effects of climate change on the combined biomass of skipjack (SKJ), yellowfin (YFT) and bigeye (BET) tuna in the exclusive economic zones (EEZs) of 10 Pacific Island countries and territories (PICTs).

| PICT (EEZ) | 2016 | | | Change (%) in combined biomass of SKJ, YFT & BET tuna by 2050 | 2050 | | | Change 2014/16-2050 | |
	Average national GDP (2014-2016) (USD m)	Average GDP from tuna (2014-2016) (USD m)*	Contribution of tuna GDP to national GDP (%)		National GDP (USD m)	GDP from tuna (USD m)	Contribution of tuna GDP to national GDP (%)	GDP from tuna (USD m)	Contribution of tuna GDP to national GDP (%)
EEZ west of 170E									
FSM	320	46.1	14.4	-26	308.1	34.2	11.1	-11.9	-3.3
Marshall Islands	187	60.2	32.2	-15	177.7	50.9	28.6	-9.3	-3.5
Nauru	110	0.0	0.0	-9	110.0	0.0	0.0	0.0	0.0
Palau	228	2.4	1.1	-24	227.4	1.8	0.8	-0.6	-0.2
Papua New Guinea	21,872	257.3	1.2	-37	21,776.7	162.0	0.7	-95.3	-0.4
Solomon Islands	1,122	52.1	4.6	-15	1,114.3	44.4	4.0	-7.7	-0.7
EEZ east of 170E									
Cook Islands	374	2.7	0.7	18	374.5	3.2	0.8	0.5	0.1
Kiribati	185	4.6	2.5	15	185.7	5.3	2.8	0.7	0.4
Tokelau	9	0.3	3.5	-8	9.0	0.3	3.2	0.0	-0.3
Tuvalu	37	1.6	4.3	-9	36.9	1.5	4.0	-0.1	-0.4
Total		427.3			303.6				

*Derived from harvesting and/or processing tuna (FFA 2017).

It is important to recognise that inadequate understanding of the stock structure of the tropical Pacific tuna species imposes substantial limitations on our understanding of the implications of climate change for fisheries management. At present, modelling of the effects of climate change on tropical tuna species is restricted to considering each tuna species as a panmictic stock across the Pacific Ocean basin. As explained in the companion World Bank-funded project by SPC and Conservation International on 'Identifying the spatial structure of Tropical Pacific tuna stocks', the implications for management cannot be fully assessed until the stock structure of each species is described. Once that information is available, the response of each self-replenishing population (stock) within the distribution of the species can be better modelled. Only then will it be possible to determine which (if any) stocks: 1) remain entirely within the EEZs of PICTs; 2) span the EEZs of PICTs and high seas areas; 3) occur entirely in high seas areas; or, 4) span the Western and Central Pacific Ocean (WCPO) and Eastern Pacific Ocean (EPO) convention areas.

Depending on the outcome of future research to identify the stock structure of all four tropical Pacific tuna species, the projected eastward movement of tuna, including into high seas areas, may result in a progressive transfer of more management jurisdiction to the Western and Central Pacific Commission (WCPFC) and the Inter-American Tropical Tuna Commission (IATTC). Such a shift may require changes toward more nuanced management arrangements, e.g., PICTs managing some stocks in their own right, and WCPFC and IATTC jointly managing some stocks.

B. Suggested adaptations

A range of possible adaptations have been identified to assist PICTs to reduce the risks of the projected redistribution of tuna biomass to the east to the important contributions that government revenue and GDP to their economies, and capitalise on the opportunities (Bell et al. 2013). The existing suggested adaptations fall into two broad categories – those that are not affected by improved knowledge of stock structure, and those that can only be supported with confidence once the stock structure of each species has been identified and the effects of climate change on each stock has been modelled with greater confidence.

Adaptations to maintain contributions to government revenue

Regardless of improved knowledge of stock structure, one way of insulating PICTs from some of the projected implications of reduced tuna biomass in their EEZs, and the accompanying reduced demand for access by foreign fleets fishing for tuna, would be to find ways to increase the value of tuna catches. Increasing the value of the catch would presumably lead to higher rates for fishing access fees, thereby

helping to maintain present-day licence revenue even though fewer fishing days are sold in the future. Ideally, this adaptation option should be explored as soon as possible because, if successful, it should also provide increased government revenue (and boost GDP) in the nearer term. It is encouraging to see that the Pacific Islands Forum Fisheries Agency and the PNA Office have begun discussions with Iceland (a small island state that has become a world leader in adding value to fish catches) to evaluate the scope for developing improved and new products from tropical Pacific tuna species.

The other possible way of minimising the impact of redistribution of tuna biomass due to climate change on government revenue depends on identifying the stock structure of the four tropical Pacific tuna species and mapping the present-day and future, climate-driven distributions of each stock. Where it can be demonstrated that the majority of the present-day distribution of a stock occurs in the EEZ(s) of PICT(s) and that the majority of the stock will eventually occur on the high seas due to climate change, PICTs will be in a strong position to call for revised management arrangements that continue to give them jurisdiction over those stocks. Due to the existing legal framework that governs fishing on the high seas, this adaptation option will undoubtedly be a long process, and may ultimately depend on the development of broadly accepted principles and practices for loss and damage claims through the United Nations Framework Convention on Climate Change. The immediate adaptation action, therefore, is investment in identifying the stock structure of tropical Pacific tuna and development of improved models to assess the most likely responses of stocks to climate change to lay the groundwork for such negotiations.

Adaptations to maintain contributions to GDP

Although PNG should continue to have access to enough fish to maintain the operations of national tuna canneries as the climate changes (as explained above), the Interim Economic Partnership Agreement (IEPA) between PNG and the European Union (EU) provides an additional level of resilience. If necessary, the global sourcing provisions of the IEPA would enable PNG to acquire tuna from PICTs further to the east and continue to benefit from duty remissions for its canned tuna in European markets. Solomon Islands could also reduce the risk to the operation of its national cannery as the biomass of tuna shifts progressively to the east by signing an IEPA with the EU (or a similar agreement with another market).

Priority adaptations for FSM and Marshall Islands centre around maintaining the transhipping trade in Pohnpei and Majuro that currently supports national GDP. Improved understanding of the stock structure of tropical Pacific Tuna, and the likely redistribution of each stock due to climate change would assist

both countries to understand future operational areas for purse-seine vessels and target incentives for transhipping operations to take place in Majuro and Pohnpei.

Similarly, both Cook Islands and Kiribati would benefit from a better understanding of tuna stock structure and the effects of climate change on stocks. The information would assist these two PICTs to determine the scope for capturing some of the transhipping trade to increase the contribution of tuna to national GDP. It would also assist Cook Islands to explore ways of collaborating with fish processing companies in American Samoa to develop higher-value products from longline-caught tuna for markets in the USA.

In summary, a combination of additional information from future stock structure work, enhanced efforts on climate change modelling and a more sophisticated economic analyses are need in future to provide comprehensive integrated economic advice on climate change adaptations to PICTs.

Acknowledgements and Donors

References

Aires-da-Silva, A. M., Maunder, M. N., Schaefer, K. M., and Fuller, D. W. (2015). Improved growth estimates from integrated analysis of direct aging and tag-recapture data: An illustration with bigeye tuna (*Thunnus obesus*) of the eastern Pacific Ocean with implications for management. *Fisheries Research*, 163:119–126.

Anderson J.J., Gurarie E., Bracis C., Burke B.J., Laidre K.L. (2013). Modeling climate change impacts on phenology and population dynamics of migratory marine species. *Ecological Modelling* 264: 83-97.

Aqaroa T, Bell, J., and Kittinger, J. 2018. Good governance for migratory species. *Science* 361 (6408): 1208-1209.

Aumont O., Ethé C., Tagliabue A., Bopp L., Gehlen M., (2015). PISCES-v2: an ocean biogeochemical model for carbon and ecosystem studies. *Geosci. Model Dev.*, 8, 2465–2513.

Barnett TP, Pierce DW, Achuta Rao KM, Gleckler PJ, Santer BD, Gregory JM, Washington WM (2005). Penetration of human-induced warming into the world's oceans. *Science,* 309: 284–287.

Bell JD, Ganachaud A., Gehrke PC, Griffiths SP, Hobday AJ, Hoegh-Guldberg O, Johnson, JE Le Borgne R, Lehodey P, Lough JM, Matear RJ, Pickering TD, Pratchett MS, Sen Gupta A, Senina I and Waycott M., (2013) Tropical Pacific fisheries and aquaculture will respond differently to climate change. *Nature Climate Change,* 3: 591–599.

Bellenger H., Guilyardi E., Leloup J., Lengaigne M., Vialard J. 2014. ENSO representation in climate models: from CMIP3 to CMIP5. *Climate Dynamics* (42) 7–8: 1999–2018.

Bertrand, A., Josse, E., Bach, P., Gros, P., Dagorn, L. (2002a). Hydrological and trophic characteristics of tuna habitat: consequences of tuna distribution and longline catchability. *Can. J. Fish. Aquat. Sci.* 59: 1002–1013.

Bertrand A., Bard F.-X., Josse E. (2002b). Tuna food habits related to the micronekton distribution in French Polynesia. *Marine Biology,* 140 (5): 1023–1037.

Bindoff, N.L., Willebrand, J., Artale, V., Cazenave, A., Gregory, J., Gulev, S., Hanawa, K. et al. 2007. Observations: oceanic climate change and sea level. In S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller, eds. Climate change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, pp. 385–428. Cambridge, UK, Cambridge University Press. (also available at https://www.ipcc.ch/ publications_and_data/ar4/wg1/en/ch5.html).

Brander, K. (2010) Impacts of climate change on fisheries. *Journal of Marine Systems*, **79**, 389-402.

Brill, R.W., (1994). A review of temperature and O2 tolerance studies of tunas pertinent to fisheries oceanography, movement models and stock assessments. *Fish. Oceanogr.* 3, 204–216.

Caldeira K, Wickett ME (2003) Anthropogenic carbon and ocean pH. *Nature* 425:365.

Cheung W.W.L., Lam V.W.Y., Sarmiento J.L., Kearney K., Watson R., Zeller D., Pauly D. (2010). Large-scale redistribution of maximum catch potential in the global ocean under climate change. *Global Change Biology*, 16: 24-35.

Cheung, W.W.L., Close, C., Lam, V., Watson, R., Pauly, D. (2008) Application of macroecological theory to predict effects on climate change on global fisheries potential. *Marine Ecology Progress Series* 365: 187–197.

Cheung, W.W.L., Frölicher, T.L., Asch, R.G., Jones, M.C., Pinsky, M.L., Reygondeau, G., Rodgers, K.B., Rykaczewski R.R., Sarmiento J.L., Stock, C., and Watson, J. R. (2016). Building confidence in projections of the responses of living marine resources to climate change. – *ICES Journal of Marine Science*, 73: 1283-1296.

Cravatte, S., Delcroix, T., Zhang, D., McPhaden, M. & Leloup, J. (2009). Observed freshening and warming of the western Pacific warm pool. *Clim. Dynam.*, 33: 565-589.

Dagorn L., Bach P., Josse E. (2000). Movement patterns of large bigeye tuna (*Thunnus obesus*) in the open ocean, determined using ultrasonic telemetry. Marine Biology, 136(2): 361-371.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S. and 30 authors, 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.,* 137, 553 – 597.

Domokos, R., Seki, M.P., Polovina, J.J., Hawn, D.R. (2007). Oceanographic investigation of the American Samoa albacore (*Thunnus alalunga*) habitat and longline fishing grounds. *Fish. Oceanogr.*16, 555–572.

Dragon AC, Senina I., Conchon A., Titaud O., Arrizabalaga H. and Lehodey P. (2015). Modeling spatial population dynamics of North Atlantic Albacore tuna under the influence of both fishing and climate variability. *Canadian Journal of Fisheries and Aquatic Sciences*, 72(6): 864-878, 10.1139/cjfas-2014-0338.

Dueri, S., Bopp, L. & Maury, O. (2014) Projecting the impacts of climate change on skipjack tuna abundance and spatial distribution. *Global Change Biology*, doi: 10.1111/gcb.12460.

Duteil, O., F. U. Schwarzkopf, C. W. Böning, and A. Oschlies (2014), Major role of the equatorial current system in setting oxygen levels in the eastern tropical Atlantic Ocean: A high-resolution model study, *Geophys. Res. Lett.*, 41, 2033–2040.

Farley J. H., Williams A.J., Hoyle S.D., Davies C.R., Nicol S. J., (2013). Reproductive Dynamics and Potential Annual Fecundity of South Pacific Albacore Tuna (*Thunnus alalunga*). *PLoS ONE* 8(4): e60577. doi:10.1371/journal.pone.0060577

Farley, J. H., Eveson, P., Krusic-Golub, K., Sanchez, C., Roupsard, F., McKechnie, S., Nichol, S., Leroy, B., Smith, N., and Chang, S.-K. (2017). Age, growth and maturity of bigeye tuna in the western and central Pacific Ocean. WCPFC-SC13-2017/SA-WP-01, Rarotonga, Cook Islands, 9–17 August 2017.

Feely RA, Sabine CL, Lee K, Berelson W, Kleypas J, Fabry VJ, Millero FJ (2004) Impact of anthropogenic CO2 on the CaCO3 system in the oceans. *Science* 305:362–366.

FFA 2017. Economic and Development Indicators and Statistics: Tuna Fisheries of the Western and Central Pacific Ocean. Pacific Islands Forum Fisheries Agency, Honiara, Solomon Islands.

Ganachaud AS, Sen Gupta A, Orr JC, Wijffels SE, Ridgway KR, Hemer MA, Maes C, Steinberg CR, Tribollet AD, Qiu B, Kruger JC. 2011. Observed and expected changes to the tropical Pacific Ocean. In: *Vulnerability of Tropical Pacific Fisheries and Aquaculture to Climate Change*. Bell JD, Johnson JE, Hobday AJ. (eds). Secretariat of the Pacific Community pp. 101–187.

Graham J.B., Dickson K.A. (2004). Tuna Comparative physiology. *The Journal of Experimental Biology* 207: 4015-4024

Harley S.J., Davies N., Tremblay-Boyer L., Hampton J., and McKechnie S. (2015). Stock assessment for south Pacific albacore tuna. 11th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 5–13 Aug 2015, Pohnpei, Federated States of Micronesia. WCPFC-SC11-2015/SA-WP-06-Rev 1: 101 pp.

Harley, S. J., Davies, N., Hampton, J., and McKechnie, S. (2014). Stock assessment of bigeye tuna in the Western and Central Pacific Ocean. WCPFC-SC10-2014/SAWP-01, Majuro, Republic of the Marshall Islands, 6–14 August 2014.

Hawkins, E., and Sutton, R. 2009. The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society*, 90: 1095–1107.

Hazen, E.L., Jorgensen, S., Rykaczewski, R.R., Bograd, S.J., Foley, D.G., Jonsen, I.D., Shaf-fer, S.A., Dunne, J.P., Costa, D.P., Crowder, L.B., Block, B.A., (2012). Predicted habitat shifts of Pacific top predators in a changing climate. *Nature Climate Change:* 3: 234-238.

Langley, A. (2004). An examination of the influence of recent oceanographic conditions on the catch rate of albacore in the main domestic longline fisheries. 17th Standing Committee on Tuna and Billfish. 9–18 August 2004. Majuro, Republic of Marshall Islands. Working Paper SA-4., 101 pp.

Laufkötter C., Vogt M., Gruber N., Aita-Noguchi M., Aumont O., Bopp L., Buitenhuis E., Doney S. C., Dunne J., Hashioka T., Hauck J., Hirata T., John J., Le Quéré C., Lima I. D., Nakano H., Seferian R., Totterdell I., Vichi M., Völker C. (2015). Drivers and uncertainties of future global marine primary production in marine ecosystem models. *Biogesciences*, 12, 6955–6984.

Lehodey P, Senina I, Calmettes B, Hampton J, Nicol S (2013) Modelling the impact of climate change on Pacific skipjack tuna population and fisheries. *Climatic Change* 119:95-109.

Lehodey P., Murtugudde R., Senina I. (2010a). Bridging the gap from ocean models to population dynamics of large marine predators: a model of mid-trophic functional groups. *Progress in Oceanography*, 84: 69–84

Lehodey P., Senina I., Murtugudde R. (2008). A Spatial Ecosystem And Populations Dynamics Model (SEAPODYM) - Modelling of tuna and tuna-like populations. *Progress in Oceanography*, 78: 304-318.

Lehodey P., Senina I., Nicol S., Hampton J. (2015). Modelling the impact of climate change on South Pacific albacore tuna. *Deep Sea Research,* 113: 246–259.

Lehodey P., Senina I., Sibert J., Bopp L, Calmettes B., Hampton J., Murtugudde R. (2010b). Preliminary forecasts of population trends for Pacific bigeye tuna under the A2 IPCC scenario. *Progress in Oceanography.* 86: 302–315

Lehodey, P., Bertignac, M., Hampton, J., Lewis, A.& Picaut, J. 1997. El Niño-Southern Oscillation and tuna in the western Pacific. Nature 389, 715_718.

Lehodey, P., Conchon, A., Senina, I., Domokos, R., Calmettes, B., Jouanno, J., Hernandez, O., and Kloser, R. (2015) Optimization of a micronekton model with acoustic data. – ICES Journal of Marine Science, 72(5): 1399-1412.

Long, M. C., Deutsch C., Ito T. (2016). Finding forced trends in oceanic oxygen, *Global Bio-geochem. Cycles*, 30, 381–397, doi:10.1002/2015GB005310.

Matear, R.J., Chamberlain, M.A., Sun, C. & Feng, M. (2015). Climate change projection for the western tropical Pacific Ocean using a high-resolution ocean model: implications for tuna fisheries. *Deep Sea Research II*, 113: 22–46.

McKechnie S., Hampton J., Pilling G. M., Davies N. (2016). Stock assessment of skipjack tuna in the western and central Pacific Ocean. 12th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 3–11 Aug 2016, Bali, Indonesia. WCPFC-SC12-2016/SA-WP-04: 120 pp.

McKechnie S., Pilling G., Hampton J. (2017). Stock assessment of bigeye tuna in the western and central Pacific Ocean. 13th regular Session of the Scientific Committee of the Western Central Pacific

Fisheries Commission, 9–17 Aug 2017, Rarotonga, Cook Islands. WCPFC-SC13-2017/SA-WP-05_Rev1: 149 pp.

Nye J.A., Link J.S., Hare J.A, Overholtz W.J. (2009). Changing spatial distribution of fish stocks in relation to climate and population size on the Northeast United States continental shelf. *Mar. Ecol. Prog. Ser.,* 393: 111–129.

Payne, M. R., Barange, M., Cheung, W. W. L., MacKenzie, B. R., Batchelder, H. P., Cormon, X., Eddy, T. D., Fernandes, J. A., Hollowed, A. B., Jones, M. C., Link, Jason S., Neubauer, P., Ortiz, I., Queiros, A. M., J. R. Paula (2016). Uncertainties in projecting climate-change impacts in marine ecosystems. *ICES Journal of Marine Sciences.*

Pörtner HO, Karl DM, Boyd PW, Cheung W, Lluch-Cota S, Nojiri Y, Schmidt DN, Zavialov PO, Alheit J, Aristegui J, Armstrong C, Beaugrand G, Belkovich V, Bowler C, Brewer P, Church M, Cooley SR, del Monte-Luna P, Edwards M, Flint M, Follows MJ, Frölicher T, Fulton EA, Gattuso JP, Hoegh-Guldberg O, Hofmann EE, Knoll AH, Levin LA, Menzel L, Moloney CL, Perry RI, Poloczanska ES, Roberts JM, Rost B, Sarmiento JL, Sedlacek J, Storch D, Wiencke C, Wittmann AC (2014). Ocean Systems. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Pages 411-484. Cambridge University Press.

Ramon D., Bailey K. (1996). Spawning seasonality of albacore, *Thunnus alalunga*, in the South Pacific Ocean. *Fish. Bull.* U.S., 96: 725–733.

Schaefer K.M., Fuller D.W., (2010). Vertical movements, behaviour, and habitat of bigeye tuna (*Thunnus obesus*) in the equatorial eastern Pacific Ocean, ascertained from archival tag data. *Mar. Biol.* 157: 2625-2642.

Schaefer, K. M., Fuller, D. W. Block, B. A. (2011). Movements, behaviour, and habitat utilization of yellowfin tuna (*Thunnus albacares*) in the Pacific Ocean off Baja California, Mexico, determined from archival tag data analyses, including unscented Kalman filtering. *Fisheries Research* 112: 22 - 37.

Schmidtko S., Stramma L., Visbeck M. (2017). Decline in global oceanic oxygen content during the past five decades. *Nature* 542: 335–339.

Senina I., Lehodey P., Sibert J., Hampton J. (*in review*). Integrating tagging and fisheries data in fish population dynamics model. *Canadian Journal of Aquatic and Fisheries Sciences.*

Senina I., Lehodey P., Calmettes B., Nicol S., Caillot S., Hampton J. and P. Williams (2016). Predicting skipjack tuna dynamics and effects of climate change using SEAPODYM with fishing and tagging data. WCPFC, 12th Regular Session of the Scientific Committee, Bali, Indonesia 3–11 August 2016, WCPFC-SC12-2016/EB WP-01: 71 pp. http://www.wcpfc.int/node/27443

Senina I., Sibert J., Lehodey P. (2008). Parameter estimation for basin-scale ecosystem-linked population models of large pelagic predators: application to skipjack tuna. *Progress in Oceanography*, 78: 319-335.

Sharp, G. D. and Dizon, A. E. (1978). *The Physiological Ecology of Tunas.* New York: Academic Press.

Sibert, J., Senina, I., Lehodey, P., Hampton, J., (2012). Shifting from marine reserves to maritime zoning for conservation of Pacific bigeye tuna (*Thunnus obesus*). *Proc. Natl. Acad. Sci.* USA 109(44), 18221–18225.

Steinacher, M., Joos, F., Frölicher, T.L., Bopp, L., Cadule, P., Cocco, V., Doney, S.C., Gehlen, M., Lindsay, K., Moore, J.K., Schneider, B., Segschneider, J., (2010). Projected 21st century decrease in marine productivity: a multi-model analysis. *Biogeosciences* 7: 979–1005.

Sund, P.N., Blackburn, M., Williams, F., (1981). Tunas and their environment in the Pacific Ocean: a review. *Oceanogr. Mar. Biol. Ann. Rev.,* 19, 443–512.

Taylor K.E., Stouffer R.J., Meehl G.A. (2011). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, 93: 485–498.

Tremblay-Boyer L., McKechnie S., Pilling G., J. Hampton J. (2017). Stock assessment of yellowfin tuna in the western and central Pacific Ocean 13th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 9–17 Aug 2017, Rarotonga, Cook Islands. WCPFC-SC13-2017/SA-WP-06_Rev1: 125 pp.

Wexler J, Margulies D, Scholey V. (2011). Temperature and dissolved oxygen requirements for survival of yellowfin tuna, *Thunnus albacares*, larvae. *J. Exp. Mar. Biol. Ecol.* 404: 6372.

Wild, A. and Hampton, J. (1994). A review of the biology and fisheries for skipjack tuna, *Katsuwonus pelamis*, in the Pacific Ocean. *FAO Fisheries Technical Paper* (FAO) 336(2):1–51.

Williams A.J., Allain V., Nicol S. J., Evans K.J., Hoyle S.D., Dupoux C., Vourey E., Dubosc J., (2015). Vertical behavior and diet of albacore tuna (*Thunnus alalunga*) vary with latitude in the South Pacific Ocean. *Deep-Sea Research II*, 113: 154-169.

Williams, P., Terawasi, P. & Reid, C. 2017. *Overview of tuna fisheries in the Western and Central Pacific Ocean, including economic conditions – 2016.* 13th Scientific Committee Regular Session, WCPFC-SC13-2017/GN-WP-01. 66 pp. (also available at https://www. wcpfc.int/node/29889).

Supplementary Material

A. Datasets used for model optimization and fishing mortality estimates

Catch data used in optimization of SEAPODYM are monthly spatially-disaggregated catch data at resolution varying from 1 degree (typically for surface gears as purse seine and pole and line) to 5 degrees squares. Size frequencies of catch are aggregated on quarterly time steps at resolutions of 1, 5, 10 or 20 degrees squares. For tagging data, only the recapture data available since 2008 are used. More details on the optimization approach and these datasets can be found in Senina et al. (2008, 2015, 2016, 2017) and Lehodey et al. (2014, 2017).

References:

Frommel, A., Margulies, D., Wexler, J., Stein, M., Scholey, V., Williamson, J., Bromhead, D., Nicol, S., and Havenhand, J. (2016). Ocean acidification has lethal and sub-lethal effects on larval development of yellowfin tuna, *Thunnus albacares*. Journal of Experimental Marine Biology and Ecology. 482. 18-24. 10.1016/j.jembe.2016.04.008.

Harley, S. J., Davies, N., Hampton, J., and McKechnie, S. (2014). Stock assessment of bigeye tuna in the Western and Central Pacific Ocean. WCPFC-SC10-2014/SAWP-01, Majuro, Republic of the Marshall Islands, 6–14 August 2014.

Harley S.J., Davies N., Tremblay-Boyer L., Hampton J., and McKechnie S. (2015). Stock assessment for south Pacific albacore tuna. 11th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 5–13 Aug 2015, Pohnpei, Federated States of Micronesia. WCPFC-SC11-2015/SA-WP-06-Rev 1: 101 pp.

Lehodey P., Senina I., Murtugudde R. (2008). A Spatial Ecosystem And Populations Dynamics Model (SEAPODYM) - Modelling of tuna and tuna-like populations. Progress in Oceanography, 78: 304-318.

Lehodey P., Senina I., Titaud O., Calmettes B., Conchon A., Dragon A-C., Nicol S., Caillot S., Hampton J, Williams P. (2014). Project 62: SEAPODYM applications in WCPO. 10th regular session of the Scientific Steering Committee, 6-14 August 2014, Majuro, Republic of the Marshall Islands. WCPFC-SC10-2014/EB-WP-02 Rev 1. https://wcpfc.int/node/18976

Lehodey P., Senina I., Calmettes B., Dessert M., Nicol S., Hampton J., Smith N., Gorgues T., Aumont O., Lengaigne M., Menkes C., Gehlen M. (2017). Modelling the impact of climate change including ocean acidification on Pacific yellowfin tuna. 13th Scientific Committee of the western Central Pacific Fisheries Commission, Rarotonga, Cook Islands, 9-17 August 2017. Working Paper WCPFC-SC13-2017/EB-WP-01, 26 pp. https://www.wcpfc.int/node/29559

McKechnie S., Hampton J., Pilling G. M., Davies N. (2016). Stock assessment of skipjack tuna in the western and central Pacific Ocean. 12th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 3–11 Aug 2016, Bali, Indonesia. WCPFC-SC12-2016/SA-WP-04: 120 pp.

McKechnie S., Pilling G., Hampton J. (2017). Stock assessment of bigeye tuna in the western and central Pacific Ocean. 13th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 9–17 Aug 2017, Rarotonga, Cook Islands. WCPFC-SC13-2017/SA-WP-05_Rev1: 149 pp.

Senina I., Sibert J., Lehodey P. (2008). Parameter estimation for basin-scale ecosystem-linked population models of large pelagic predators: application to skipjack tuna. Progress in Oceanography, 78: 319-335.

Senina I., Lehodey P., Calmettes B., Nicol S., Caillot S., Hampton J. and Williams P. (2015). SEAPODYM application for yellowfin tuna in the Pacific Ocean. 11th Regular Session of the scientific committee, Pohnpei, Federated States of Micronesia, 5-13 August 2015, WCPFC-SC11-2015/EB-IP-01: 66 pp. https://www.wcpfc.int/node/21726

Senina I., Lehodey P., Kiyofuji H., Masujima M., Hampton J., Smith N., Williams P. (2017) Skipjack Japan Impacts of Recent High Catches of Skipjack on Fisheries on the Margins of the WCPFC Convention Area. 13th Scientific Committee of the western Central Pacific Fisheries Commission, Rarotonga, Cook Islands, 9-17 August 2017. Working Paper WCPFC-SC13-2017/SA-WP-07, 42 pp. https://www.wcpfc.int/node/29520

Senina I., Lehodey P., Calmettes B., Nicol S., Caillot S., Hampton J. and P. Williams (2016). Predicting skipjack tuna dynamics and effects of climate change using SEAPODYM with fishing and tagging data. WCPFC, 12th Regular Session of the Scientific Committee, Bali, Indonesia 3–11 August 2016, WCPFC-SC12-2016/EB WP-01: 71 pp. http://www.wcpfc.int/node/27443

Tremblay-Boyer L., McKechnie S., Pilling G., J. Hampton J. (2017). Stock assessment of yellowfin tuna in the western and central Pacific Ocean 13th regular Session of the Scientific Committee of the Western Central Pacific Fisheries Commission, 9–17 Aug 2017, Rarotonga, Cook Islands. WCPFC-SC13-2017/SA-WP-06_Rev1: 125 pp.

Table A1: Definition of Pacific Skipjack fisheries and fishing data used in basin scale optimization experiments performed for Pacific Ocean domain (PL: pole-and-line; PS: purse seine).

ID	Description	Nation	Resolution	Time period
P1	PL sub-tropics	Japan	1°, month	1972 - 2012
P21	PL	Japan	1°, month	1972 - 1982
P22	PL	Japan	1°, month	1982 - 1990
P23	PL	Japan	1°, month	1990 - 2012
P3	tropical PL	Pacific Islands	1°, month	1970 - 2012
S4	PS sub-tropics	Japan	1°, month	1970 - 2012
S5	PS Anchored FADs, WCPO	ALL	1°, month	1967 - 2012
S6	PS	Philippines, Indonesia	1°, month	1986 - 2010
S7	PS Free swimming school, WCPO	ALL	1°, month	1967 - 2012
L8	LL, WCPO	ALL	5°, month	1950 - 2012
L9	LL, Domestic fisheries	Philippines, Indonesia	5°, month	1970 - 2011
S10	PS Anchored and Drifting FADs, EPO	ALL	1°, month	1996 - 2013
S11	PS LOGs, EPO	ALL	1°, month	1996 - 2013
S12	PS Animal acossiations, EPO	ALL	1°, month	1996 - 2013
S13	PS Free swimming school, EPO	ALL	1°, month	1996 - 2013
S14	PS Unknown Log, EPO	ALL	1°, month	1996 - 2013
P15	PL EPO	ALL	5°, month	1972 - 2008

Table A2: Definition of Pacific Yellowfin fisheries and fishing data used in basin scale optimization experiments performed for the Pacific Ocean domain.

| ID	Description	Nation	Resolution	Time period
L1	LL targeting BET and YFT	Japan	5°, month	1950 - 2014
L2	LL targeting BET and YFT	Korea	5°, month	1962 - 2014
L3	LL targeting BET and YFT	Chinese Taipei	5°, month	1958 - 2014
L4	LL targeting BET and YFT	China	5°, month	1988 - 2015
L5	LL targeting BET and YFT	USA	5°, month	1991 - 2015
L6	LL targeting BET and YFT	Philippines, Indonesia, Vietnam	5°, month	1952 - 2014
L7	LL targeting BET and YFT	Australia, New Zealand	5°, month	1983 - 2014
L8	LL targeting BET and YFT	Pacific Islands	5°, month	1970 - 2012
S9	PS Free swimming school, WCPO	ALL	1°, month	1967 - 2014
S10	PS Drifting FADs and LOGs, WCPO	ALL	1°, month	1968 - 2014
S11	PS Anchored FADs, WCPO	ALL	1°, month	1979 - 2014
S12	PS Animal association, WCPO	ALL	1°, month	1968 - 2014
S13	PS Dolphin schools, EPO	ALL	1°, month	1959 - 2012
S14	PS Free swimming school, EPO	ALL	1°, month	1958 - 2014
S15	PS Drifting FADs and LOGs, EPO	ALL	1°, month	1959 - 2014
P16	PS Pole-and-line	ALL	1°, month	1950 - 2014
O17	Domestic fisheries	PH-ID	5°, month	1970 - 2014

Table A3: Definition of Pacific Bigeye fisheries and fishing data used in basin scale optimization experiments performed for the Pacific Ocean domain.

ID	Description	Nation	Resolution	Time period
L1	LL traditional BET, YFT target	Japan, Korea, Chinese Taipei (DWFN)	5°, month	1950-2014
L2	LL shallow night	China, Chinese, Taipei	5°, month	1958-2014
L3	LL targeting albacore	Chinese Taipei, Vanuatu (DWFN), Korea, Japan	5°, month	1958-2014
L4	LL Pac. Is.	US (Am.Sam) Fiji, Samoa, Tonga, NC, FP, Vanuatu (dom.); PNG, Solomon	5°, month	1988-2015
L5	LL Hawaii	US Hawaii)	5°, month	1991-2015
L6	LL targeting BET & YFT	Indonesia, Vietnam	5°, month	1969-2014
L7	LL targeting BET & YFT	Australia, New Zealand	5°, month	1984-2015
L8	LL targeting BET & YFT	All	1°, month	1982-2015
S9	PS WCPO, free school	All	1°, month	1967-2014
S10	PS WCPO, FAD & LOG	All	1°, month	1968-2014
S11	PS WCPO anchored FADs	All	1°, month	1979-2014
S12	PS WCPO associated	All	1°, month	1968-2014
S13	PS EPO schools	All	1°, month	1959-2012
S14	PS EPO FAD	All	1°, month	1968-2012
P15	Pole-and-Line	All	1°, month	1950-2014
O16	Domestic fisheries	PH-ID	5°, month	1970-2014

Table A4: Definition of South Pacific Albacore fisheries and fishing data used in basin scale optimization experiments performed for the South Pacific Ocean domain.

ID	Description	Nation	Resolution	Time period
L1	LL distant-water. 140°E-210°E; 20°S-65°S	Japan	5°, month	1952-2012
L2	LL distant-water. 140°E-250°E; 0°S-65°S	Korea	5°, month	1962-2012
L3	LL distant-water. 140°E-250°E; 0°S-65°S	Ch. Taipei	5°, month	1964-2012
L4	LL domestic fleet	Australia	5°, month	1985-2015
L5	LL domestic fleet	New Caledonia	5°, month	1984-2015
L6	LL targeting Alb	ALL	5°, month	1955-2012
L7	LL targeting Alb	New Zealand	5°, month	1989-2015
T8	Troll	New Zealand, United States	5°, month	1986-2014
G9	Driftnet	Japan, Chinese Taipei	5°, month	1983-1991
L10	LL 200°E-290°E; 10°S-20°S LL 210°E-290°E; 20°S-65°S	Japan	5°, month	1957-2012
L11	LL domestic fleet	American Samoa, Samoa	5°, month	1998-2015
L12	LL tropical distant water: 140°E-160°W; 0-10°S	Japan	5°, month	1952-2012
L13	LL targeting Alb	Fiji, Korea, Vanuatu, Cook Australia, New Zealand	5°, month	1990-2015
L14	LL domestic fleet targeting Alb	French Polynesia	5°, month	1993-2015
L15	LL China Taipei	Fiji, Tonga, Taipei	5°, month	1983-2014
L16	Offshore domestic LL: 140°E-110°W; 0°-65°S	Fiji, China, Taipei	5°, month	1997-2015
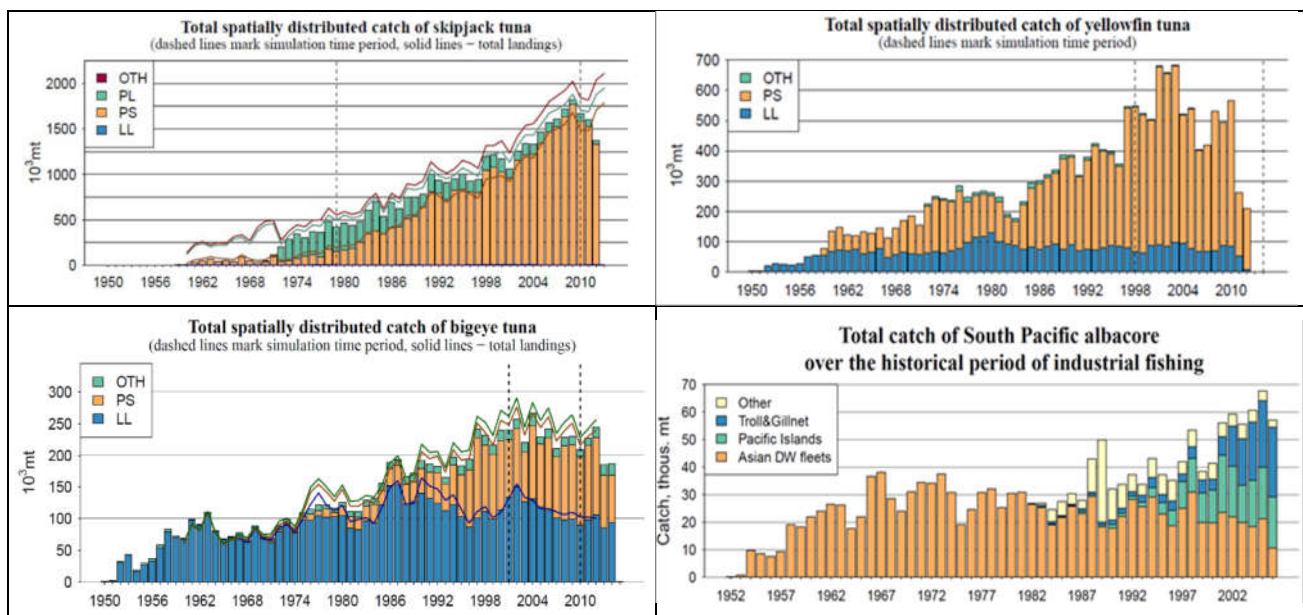
Figure A1: Comparison of total annual catches from spatial fishing datasets used in this study for model optimization and fishing mortality estimates with total nominal catch declared from port landings.
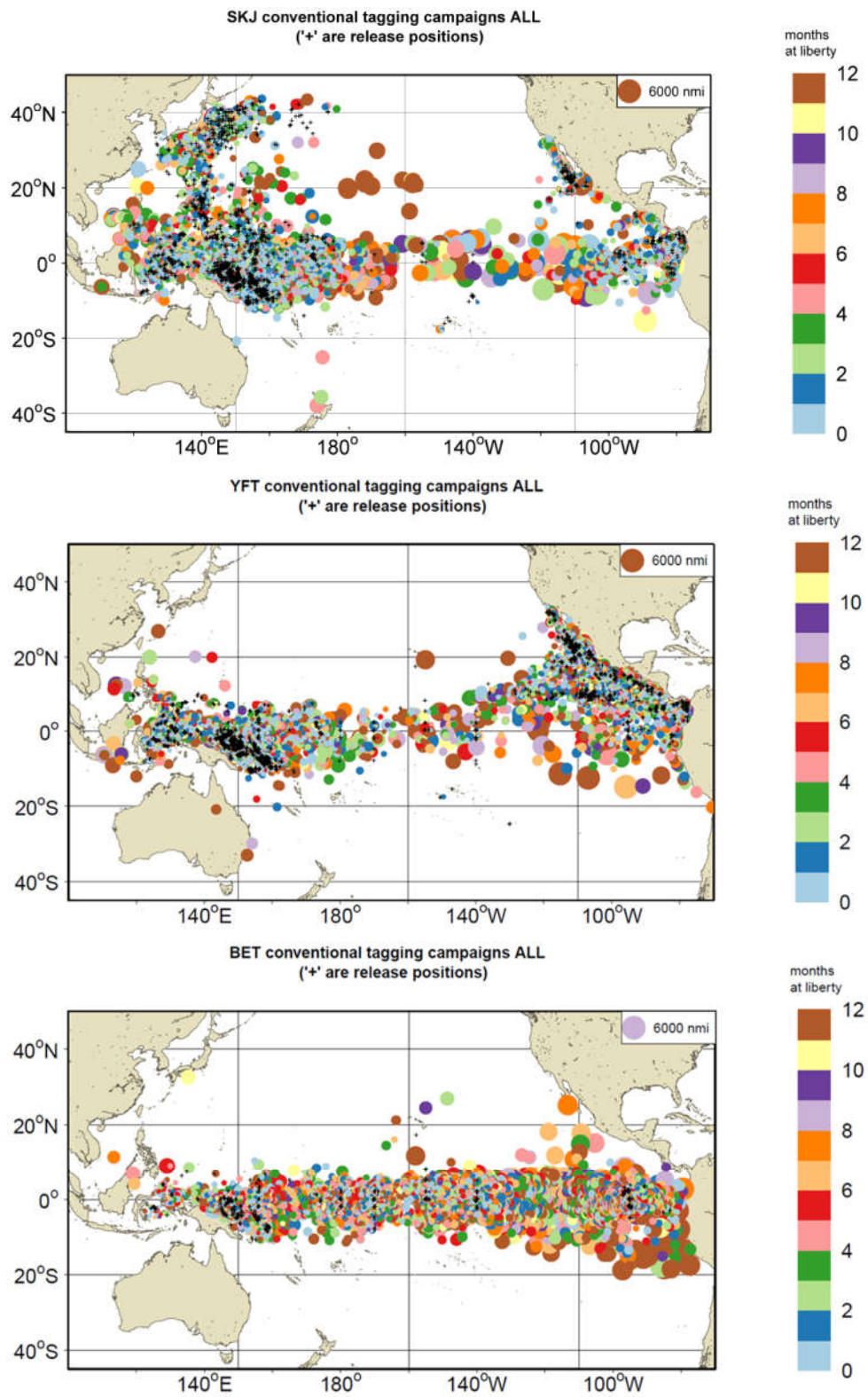
Figure A2: Release-recapture tagging data used in model optimisation (from top to bottom: skipjack, yellowfin and bigeye tuna).

B. Model parameterization

Table B1: Population structure based on independent information, for skipjack, yellowfin, bigeye and albacore (McKechnie et al. 2016, 2017; Tremblay-Boyer et al. 2017; Harley et al. 2014, 2015).

Description	SKJ	YFT	BET	ALB
Maturity				
Age at 1st maturity (mo)	11	20	36*	54
Age structure (number of monthly cohorts)				
Larvae	1	1	1	1
Juvenile	2	2	2	2
Immature	8	17	33	51
Adults	25	38	46	94
Last cohort	36+	58+	82+	148+

*Age at y=0.5 from the maturity ogive
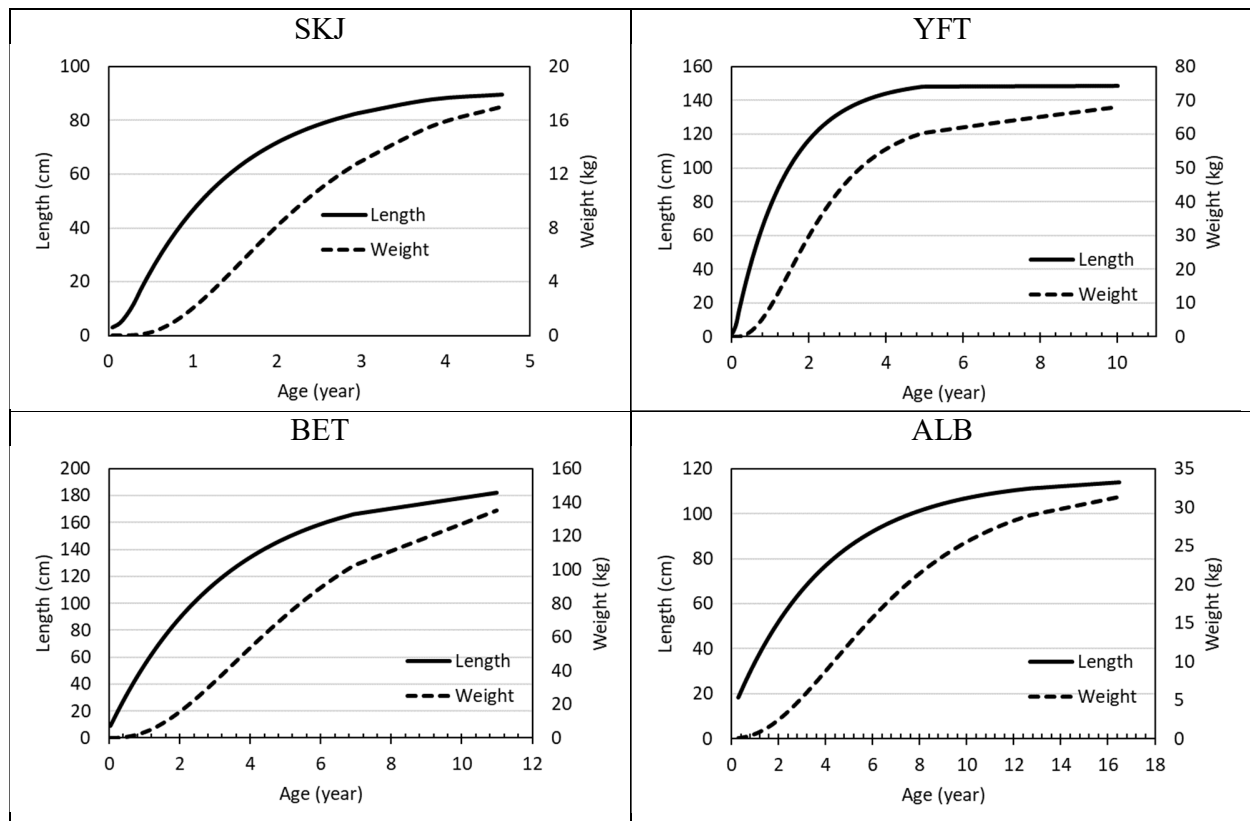
Figure B1: Growth functions (size and weight by age) for skipjack, yellowfin, bigeye and albacore, (McKechnie et al. 2016, 2017; Tremblay-Boyer et al. 2017; Harley et al. 2014, 2015).

Table B2: Parameter estimates for the four Pacific tuna species skipjack (SKJ), yellowfin (YFT), bigeye (BET) and albacore (ALB). Parameter with "[" or "]" were estimated at their lower or upper boundary correspondingly. The dash indicates that the parameter is not effective and could not be estimated.

Parameters estimated by the model		Unit	SKJ	YFT	BET	ALB
Reproduction						
σ_0*	Std. dev. in temperature Gaussian function at age 0 based on SST	^oC	1.49	1.85	2.99	3.170
T_0*	Optimal SST for larvae	^oC	[28.50	28.94	26.5*	27.985
α_P	Prey encounter rate in Holling (type III) function	day^{-1}	0.0006	0.78	0.10075	0.00025
α_F	Gaussian mean parameter predator-dependent function	$g\ m^{-2}$	2.31	0.21	[0.075	1.00087
β_F	Gaussian shape parameter in predator-dependent function	-	1.53	0.91	1.159	2.178
R	Reproduction rate in the Beverton-Holt function	mo^{-1}	0.04	0.051	0.00403	0.00318
b	Slope value in the Beverton-Holt function	$nb\ km^{-2}$	0.16	10*	16.05	1.5
Natural mortality						
$\bar{m}_p$	predation mortality rate at age 0	mo^{-1}	0.25*	0.1*	0.05*	0.05*
β_p	slope coefficient in predation mortality	mo^{-1}	0.07	0.18	0.299	0.01083
$\bar{m}_s$	senescence mortality at age 0	-	0.005	0.00026	0.03893	0.0004
β_s	slope coefficient in senescence mortality	-	1.14	1.15	[-0.249	0.8000
ε	Coefficient of variability of mortality rate with habitat index	-	[0	2.07	0.1499]	1.7491
Feeding habitat						
T_0	Optimal temperature (if Gaussian function), or temperature range for the first young cohort	^oC	31.1]	32.0	29.99]	23.50
σ_0	Std. Err. Of the temperature function for the 1st young cohort	^oC	1.50	[1.50	5.499]	1.99]
T_K	Optimal temperature (if Gaussian function), or temperature range for the oldest adult cohort	^oC	26.0]	13.3	[10.0	11.862
σ_a	Std. Err. of the adult temperature function at maximum age	^oC	1.948		6.499]	5.206
γ	Slope coefficient in sigmoid oxygen function	-	0.0001	0.00015	0.000112	[1.0e-05
$\hat{O}$	Threshold value in sigmoid oxygen function	$mL \cdot L^{-1}$	3.76	0.41	0.504	3.427
eF_1	contribution of epipelagic micronekton	-	4]	0.37	4.94e-15	2.999]
eF_2	contribution of upper mesopelagic micronekton	-	0.05*	0.35	0.6487	3.591
eF_3	contribution of upper migrant mesopelagic micronekton	-	0.897	0.351	0.05*	2.87e-05
eF_4	contribution of lower mesopelagic micronekton	-	0.0*	0.0*	0.398	0
eF_5	contribution of lower migrant mesopelagic micronekton	-	0.0*	0.0*	0.05*	0
eF_6	contribution of lower highly migrant mesopelagic micronekton	-	4]	0.35	0.3467	4.05e-15
Seasonal migration						
J_m	Spawning season peak	Julian d	-	-	-	125
ρ_{cr}	day to night threshold ratio to mark spawning season	d	-	-	-	1.0521
Movement						
V_{max}	Maximal sustainable speed	$B.L.\ s^{-1}$	0.5	[0.7	[0.35	0.952
a_V	Slope coefficient in allometric function for maximal speed	-	0.43	[0.85	0.750	0.45*
σ	Weighting coefficient of maximal theoretical diffusion rate	-	4.8	0.03	1.367	5.49]
c	Slope coefficient of the diffusion-habitat function	-	0.93	0.3*	0.5*	1.2006
Fisheries						
q_f	Catchability coefficient of fishery f	-				
s_f	Minimal target (if sigmoid) or mean fish length (if Gaussian function) of fishery f	Cm		3 or 4 parameters by fishery		
d_f	Selectivity slope coefficient (if sigmoid function) or width (if Gaussian function) of fishery f	-				
h_f	Selectivity for the last age-class ((if asymmetric Gaussian function)	-				

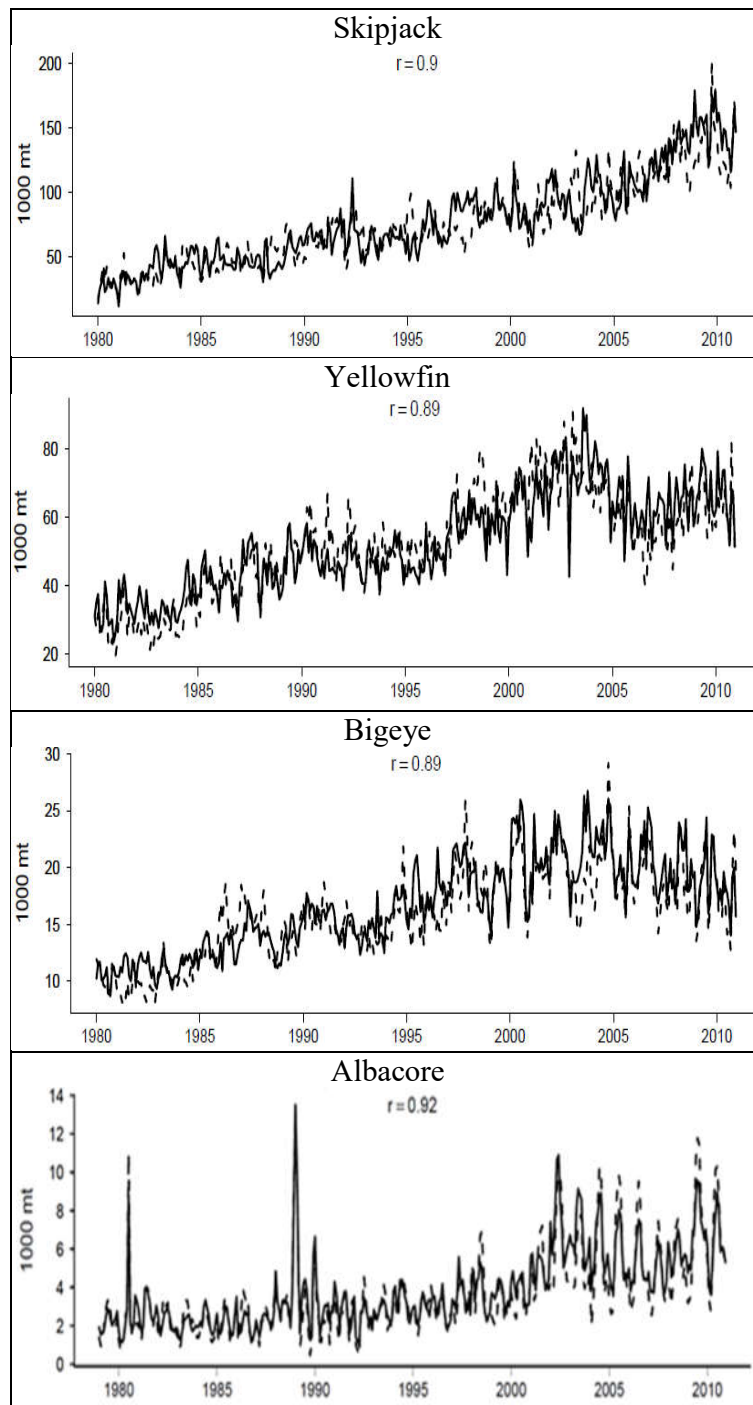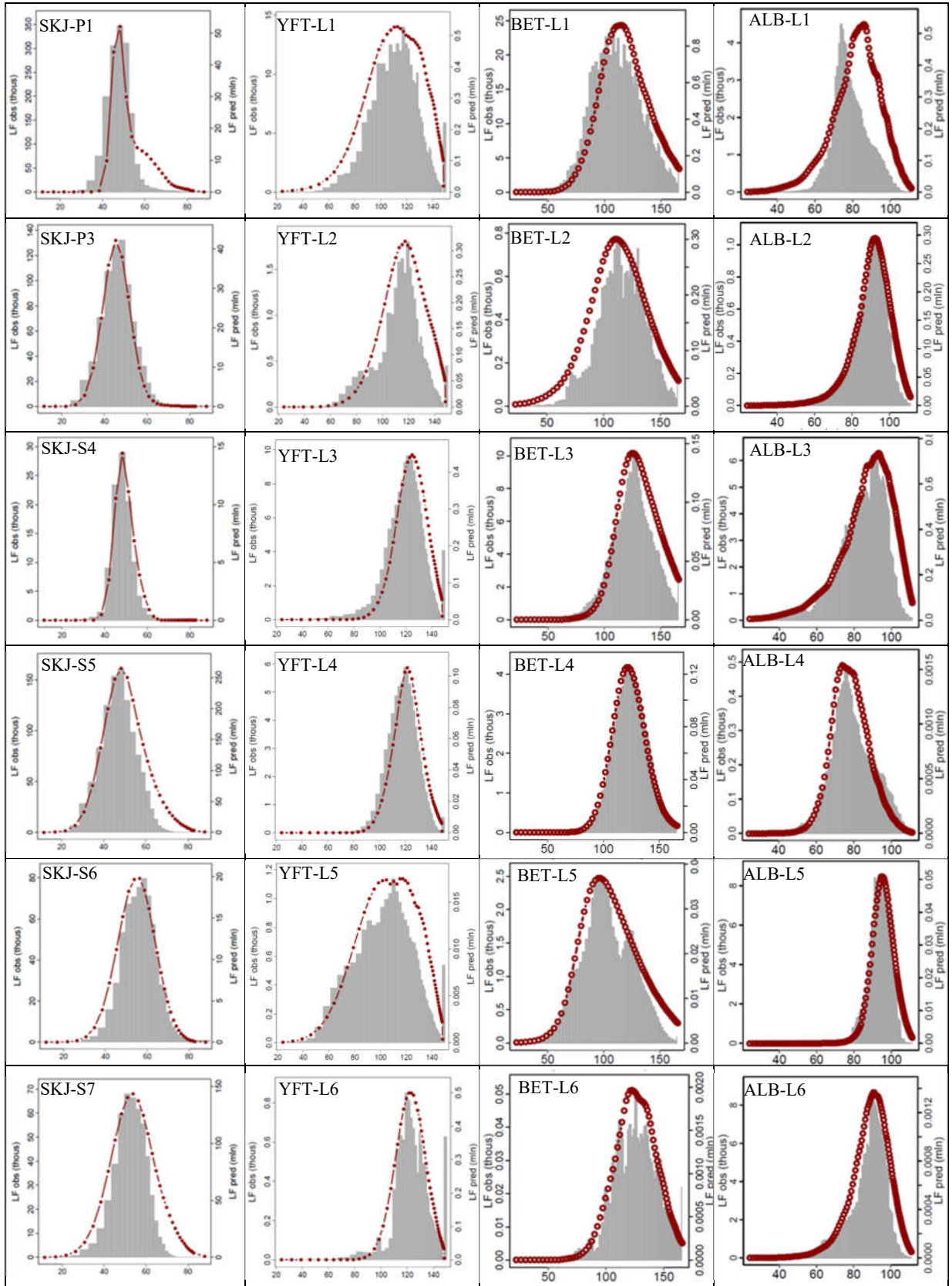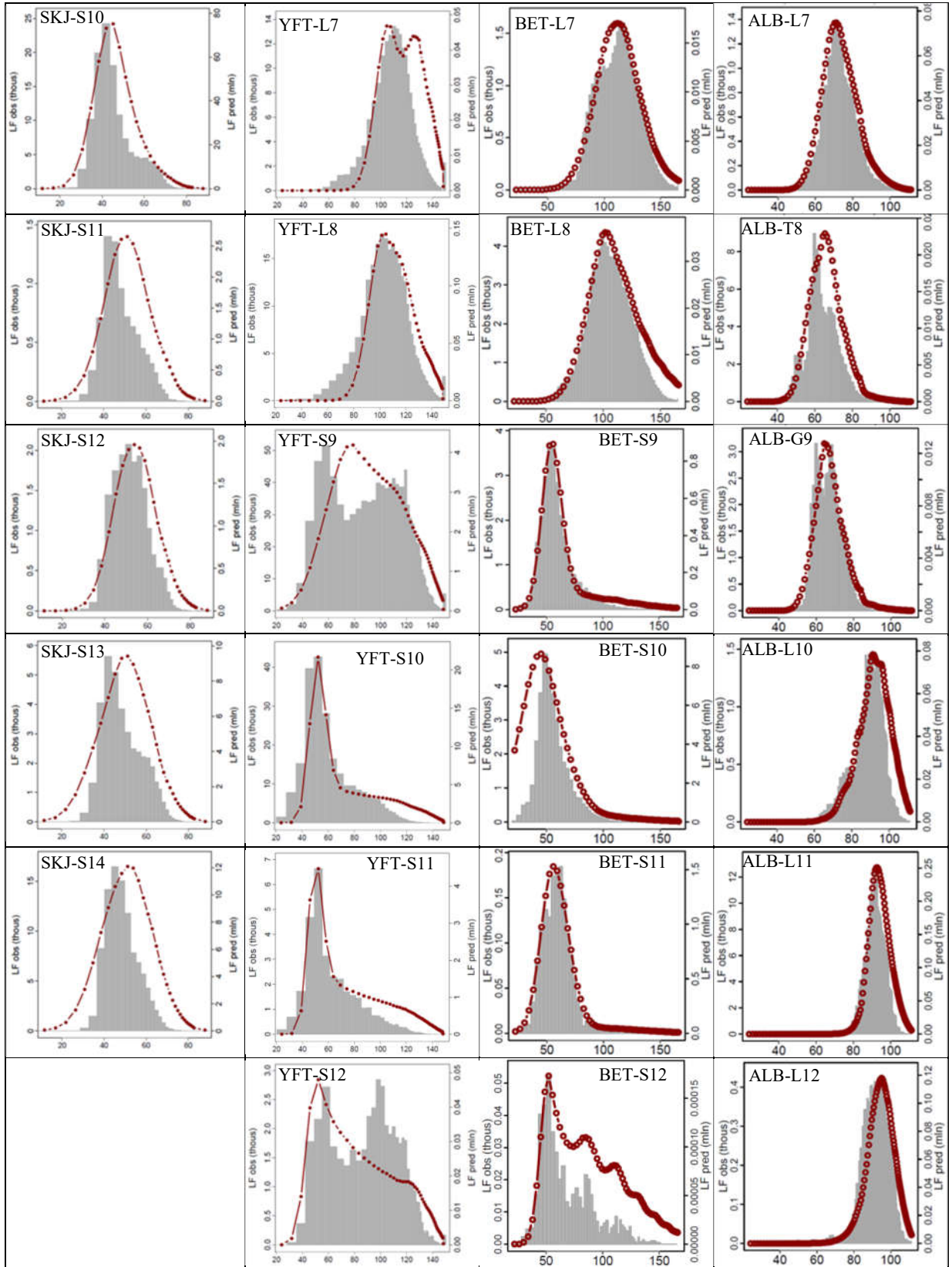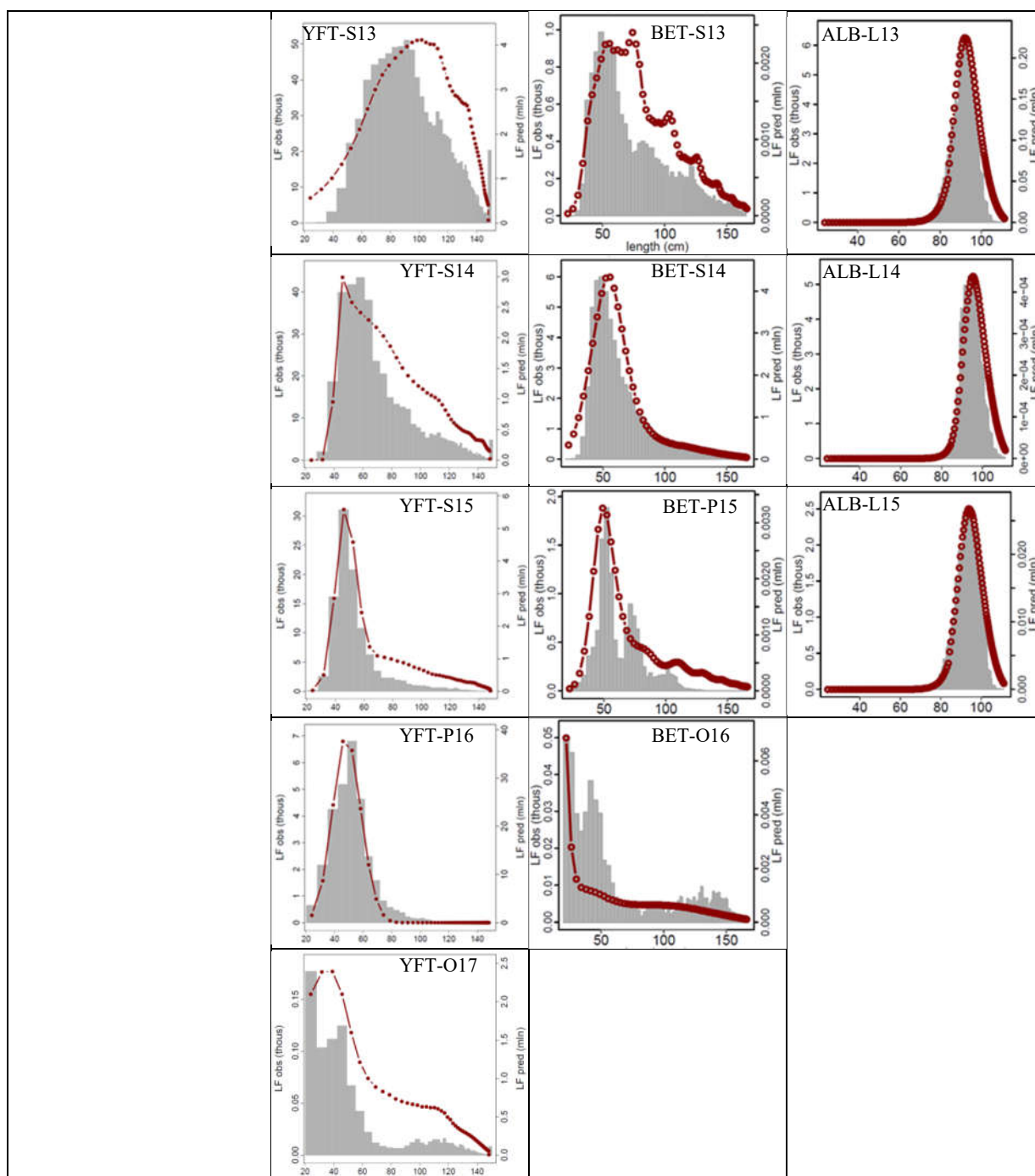## C. Fit to Pacific Ocean fishing data for the four tuna species

**Figure C1: Time series of predicted (continuous line) vs observed (dashed line) total monthly catch.**

Figure C2: Composite (all time periods combined) observed (histograms) and predicted (line) catch at length for all fisheries with samples for the four Pacific tuna species (SKJ: skipjack; YFT: yellowfin; BET: bigeye; ALB: albacore. See tables A2-A5 for fisheries definitions.

63

D. Ocean acidification effect on juvenile yellowfin tuna

Impact of ocean acidification on the life history of tuna was incorporated to the natural mortality curve. The parameterisation of the functional response to pH level is based on the experimental study described in Frommel et al. (2016). The decrease in pH level was found to significantly reduce larval survival by 64% and 70% at pH 7.3 and 6.9 respectively during the first 7 days. For higher pH levels there are statistically insignificant results with a mean reduction of survival at pH = 7.6 by 27% (mean reduction of 27% with a range of 6% increase down to 49% decrease). It is therefore assumed that additional mortality due to pH is effectively null when pH is above this value. According to these findings, the monthly mortality rates of larvae in SEAPODYM were increased with decreasing pH. It is assumed that the survival rates observed after 7 days in laboratory experiments under different pH conditions are constant over the 1st month of development, i.e., during the SEAPODYM larval stage. This seems a conservative assumption since the impact can be expected to decrease with size/age. Then, an additional monthly mortality coefficient related to pH is derived from the observed reduction in survival rate due to pH conditions. For instance, a 70% decrease in larvae survival at pH 6.9 results in an additional monthly mortality coefficient of 1.2.

Three scenarios are tested with different shapes of the functional relationship to consider the uncertainty of acidification impact at higher pH levels. The scenarios are based on the mortality rates estimated at three different pH values by Frommel et al. (2016), considering that at pH 7.6 the result is statistically insignificant:

- S1 (solid line in Fig. D1) – the mean scenario based on the three mean values of mortality observed in the experimental study;
- S2 (dashed curve on Fig. D1) – a high sensitivity scenario to ocean acidification, also implying that pH could have already have an impact in the Eastern Pacific equatorial zone where pH values below 8.0 are regularly observed (Bromhead et al. 2015); and
- S3 (dotted line on Fig. D1) – a low sensitivity scenario to ocean acidification with the lowest reduction at pH 7.6.
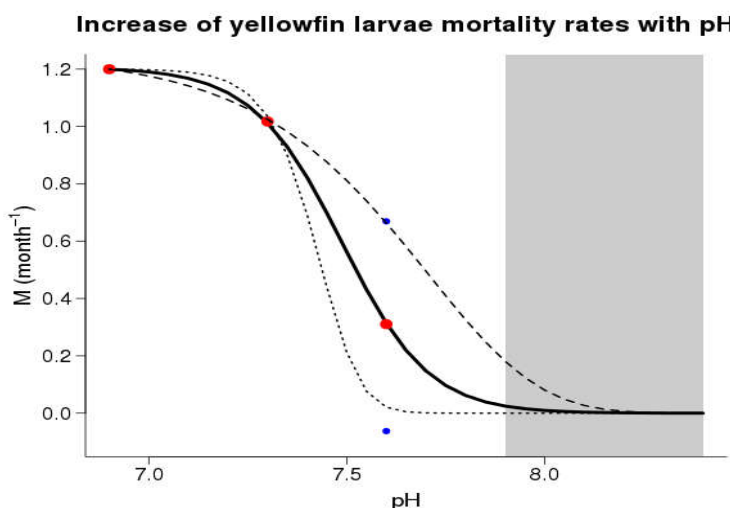
Figure D1: Change in additional monthly mortality rates of yellowfin larvae deduced from experimental results (Frommel et al. 2016) corresponding to 70%, 64% and 27% (red points) decrease in larvae survival during first 7 days of life at pH value of 6.9, 7.3, 7.6 respectively. The solid line shows the analytical function implemented in SEAPODYM based on these three mean values (scenario S1). Two other curves (dashed, S2 and dotted, S3) are high and low sensitivity scenarios. The shaded area corresponds to the historical pH values in the ocean.

The predicted additional impact of ocean acidification during the 21st Century is minor (Fig. D2). There is no impact at all when considering the low sensitivity scenario (S3). Very small effect appears by the end of the Century in the eastern equatorial Pacific Ocean with the intermediate scenario S1. The high sensitivity scenario (S2) shows a stronger negative impact on larvae recruitment in the same area, with

anomalies reaching locally -10% in 2050 and -15% in 2100. Interestingly it shows also a visible but small impact for the end of the historical period.
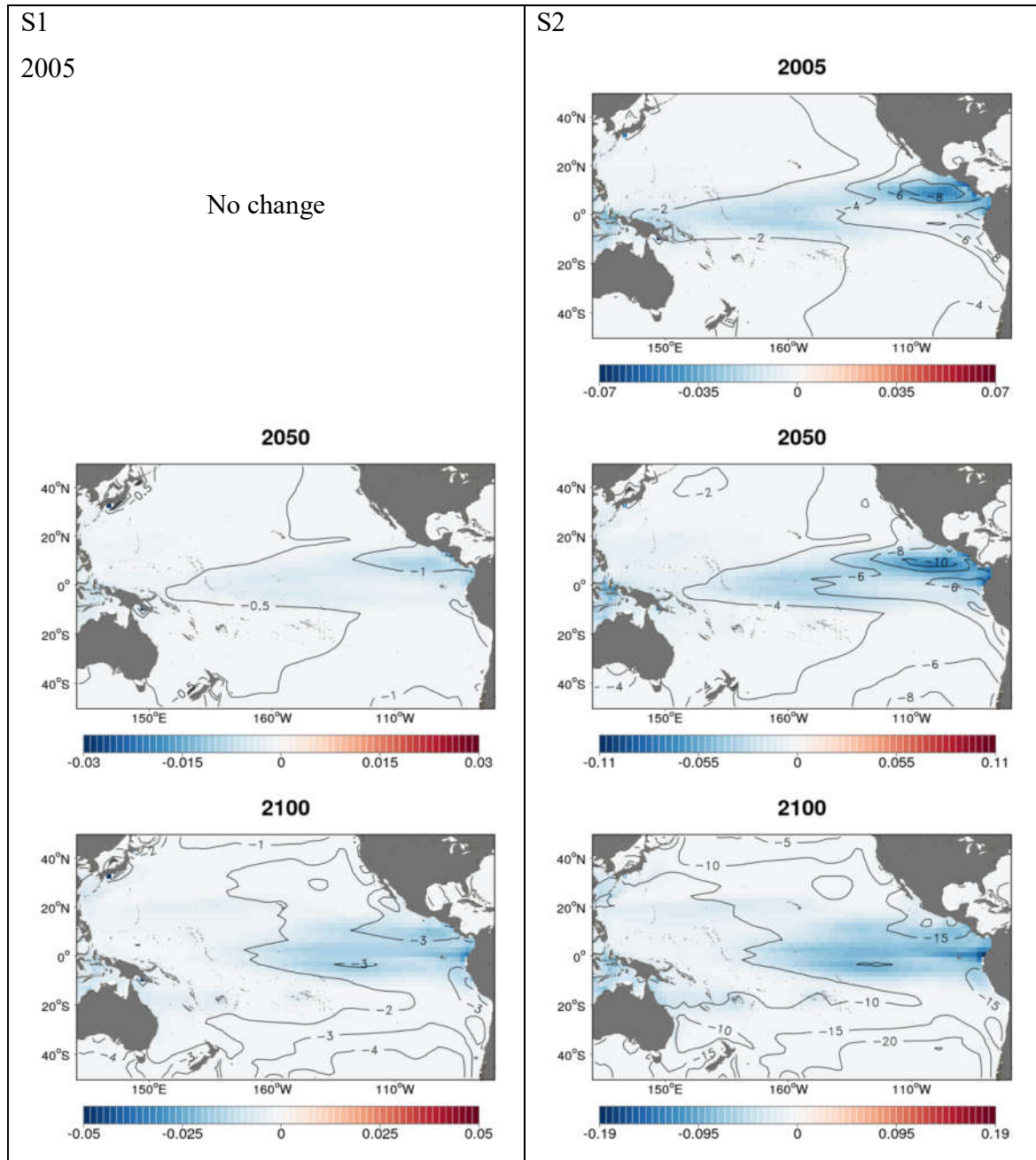
Figure D2: Change in yellowfin larval density due to ocean acidification effects included in SEAPODYM, in 2050 (average 2046-2055) and 2100 (average 2090-2099) for intermediate scenario S1 and high sensitivity scenario S2. There is no change for scenario S3. The colour maps show the average biomass change since 2005 projected to occur under a high emissions scenario (RCP8.5) with five different atmospheric forcings generated by Earth Climate models. Isopleths gives the relative percentage change in biomass with respect to 2005, i.e. 100*(B$_{year}$ − B$_{REF}$)/B$_{REF}$.
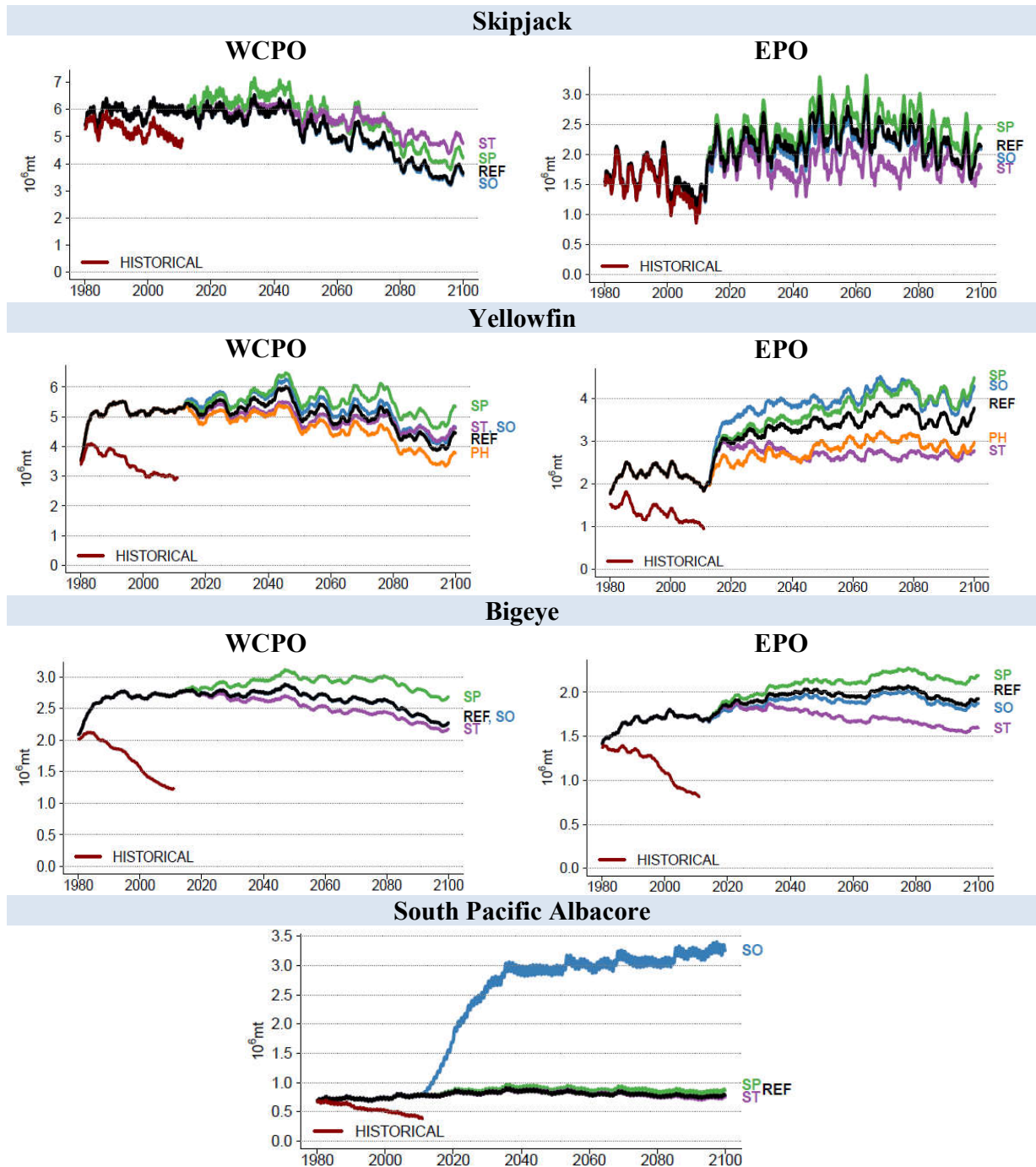
Figure E1: Mean projection (5 forcings) by scenario exploring uncertainty in primary production (SP), change in optimal spawning temperature (ST), no change in dissolved oxygen concentration (SO) and ocean acidification scenario (PH) compared to the reference projection (REF).