Predicting past and future of Tunas

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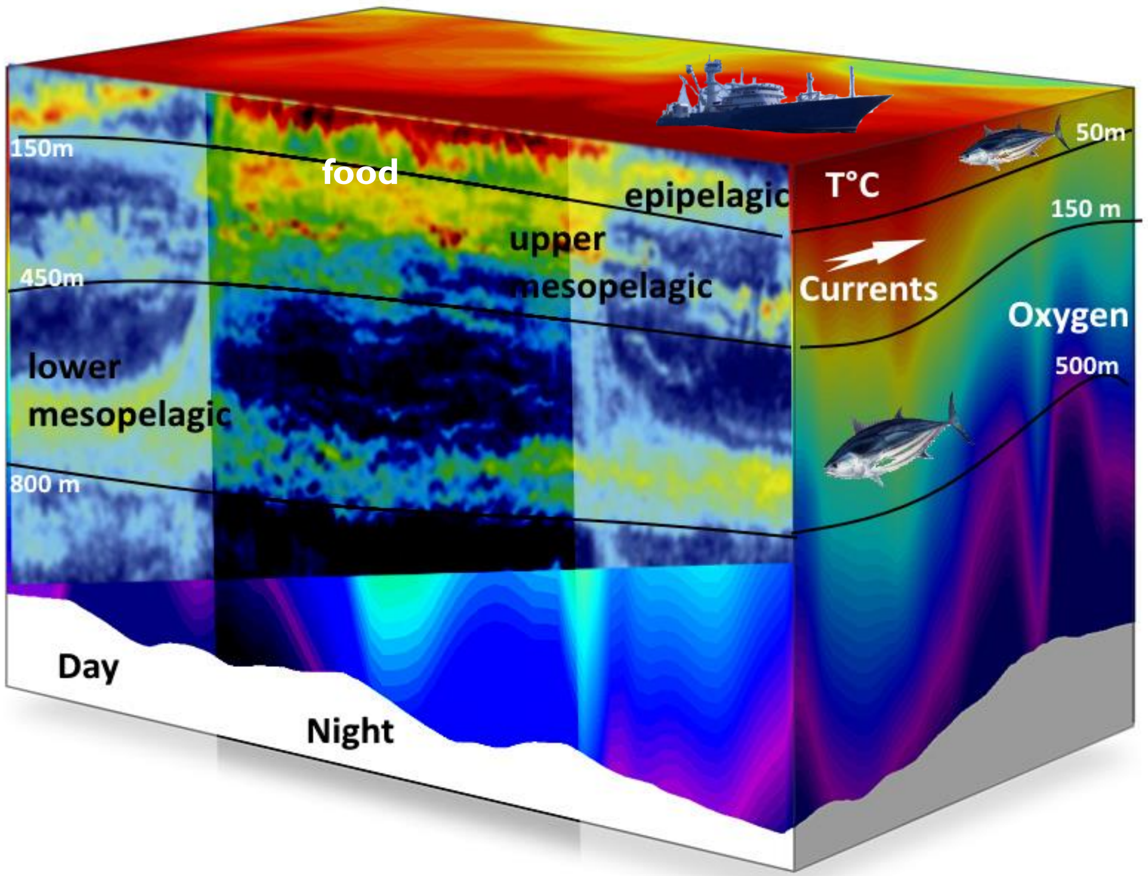
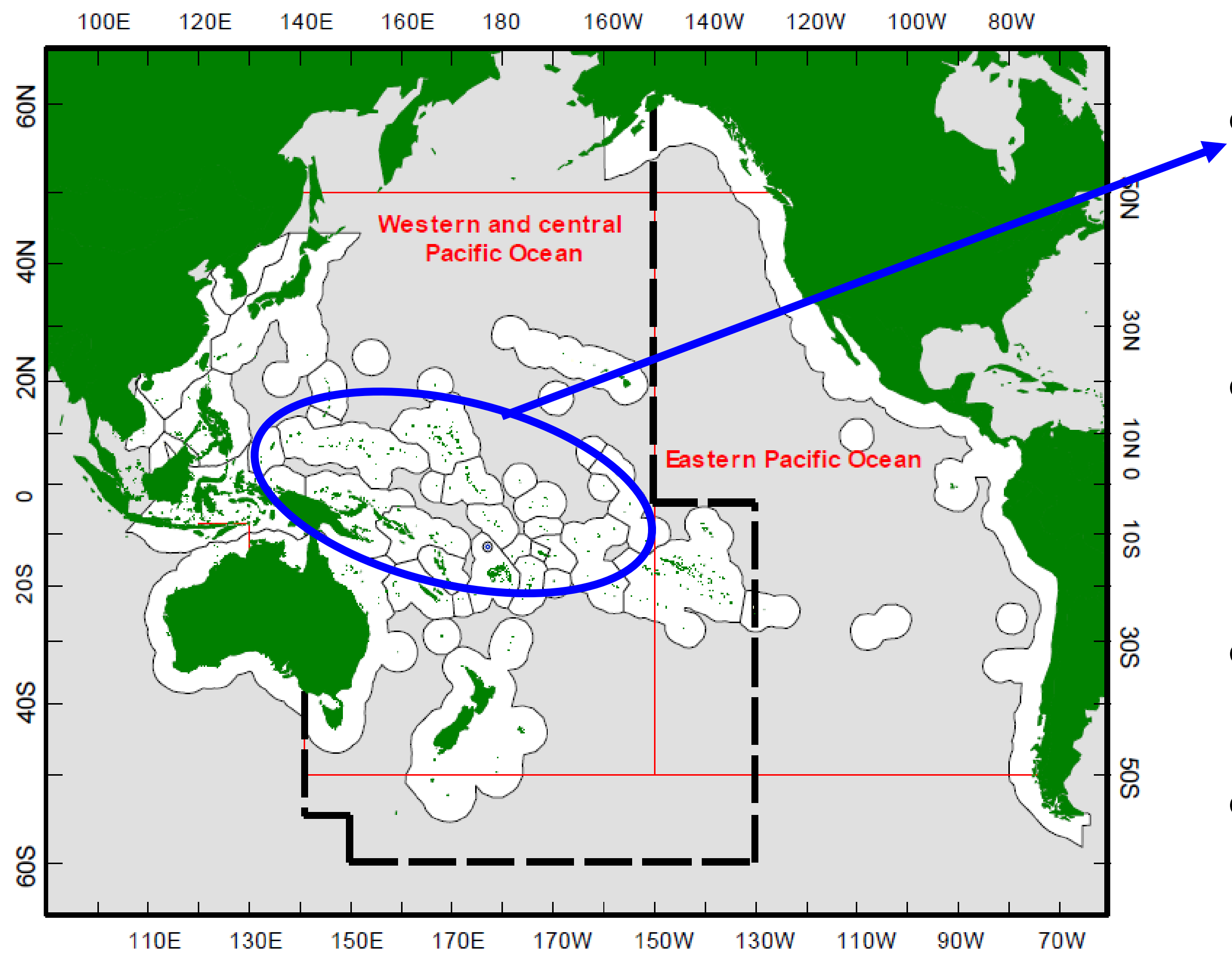


SPC: Inna Senina, Simon Nicol, John Hampton
MOi: Karen Guihou, Julien Temple-Boyer, Angelique Melet
CLS: Olivier Titaud, Guillaume Briand

Tuna Fisheries within the Pacific Islands



- 1.4 million tonnes annual catch
- $2.5 billion annual catch landed value
- $500+ million revenue
- 17,000 jobs

ENSO influence on tuna distribution and abundance

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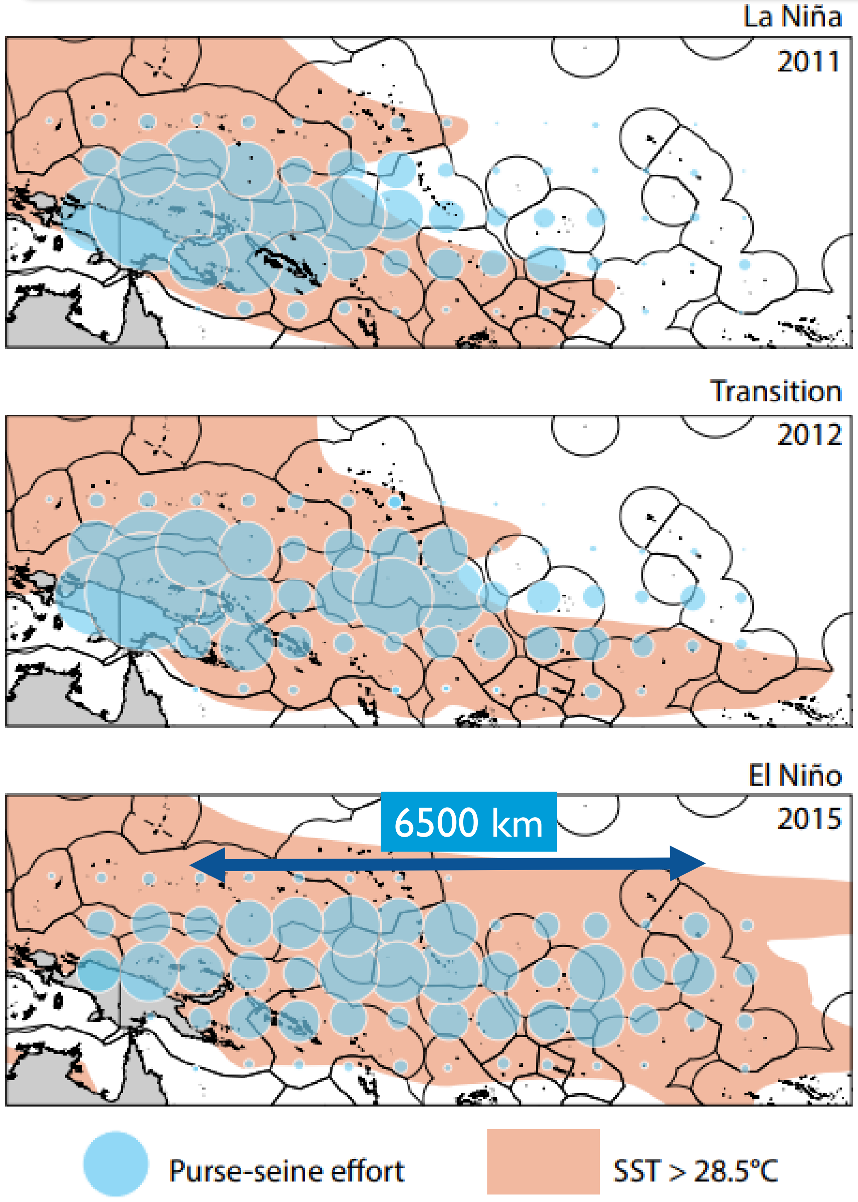
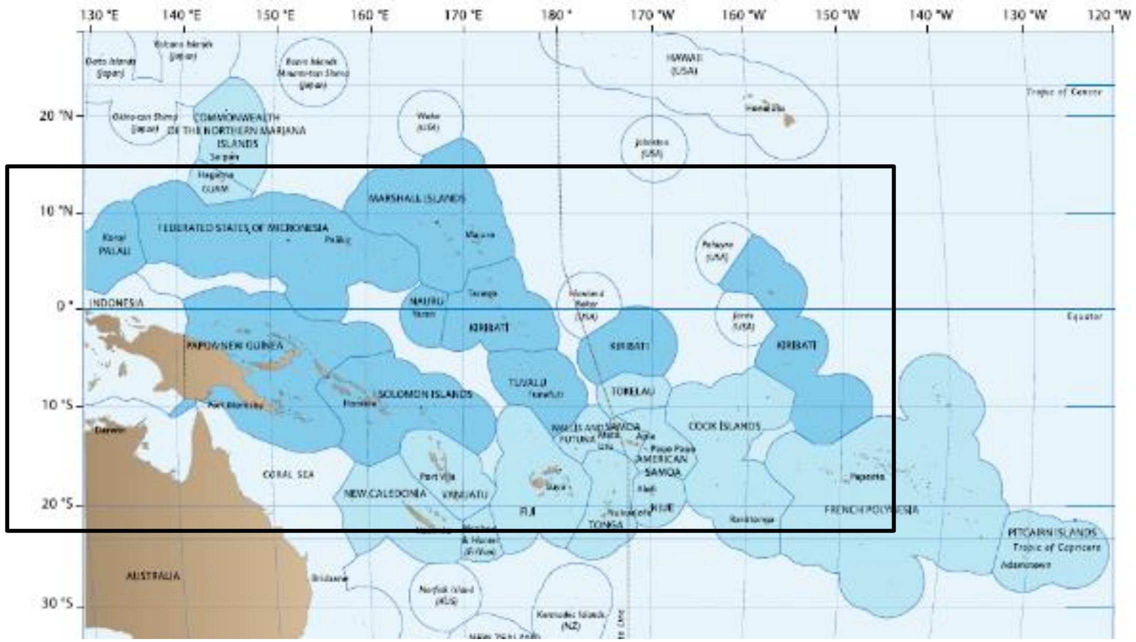
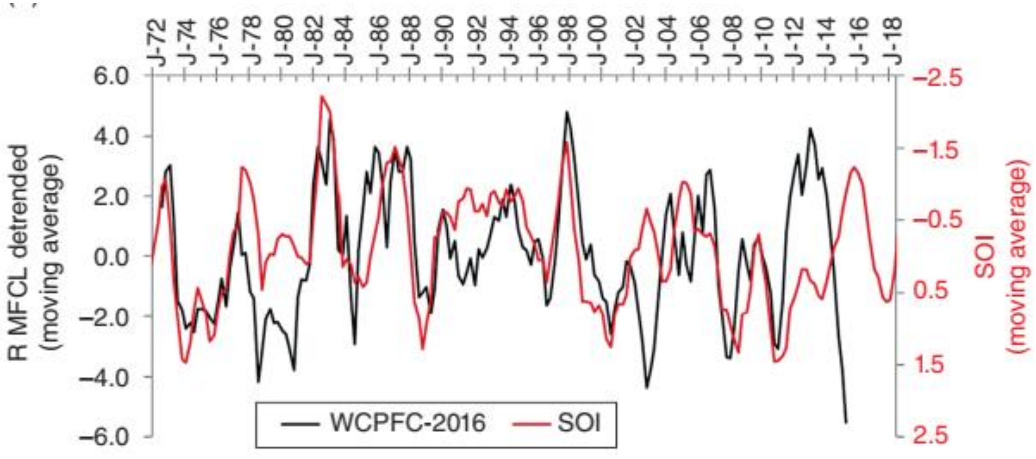




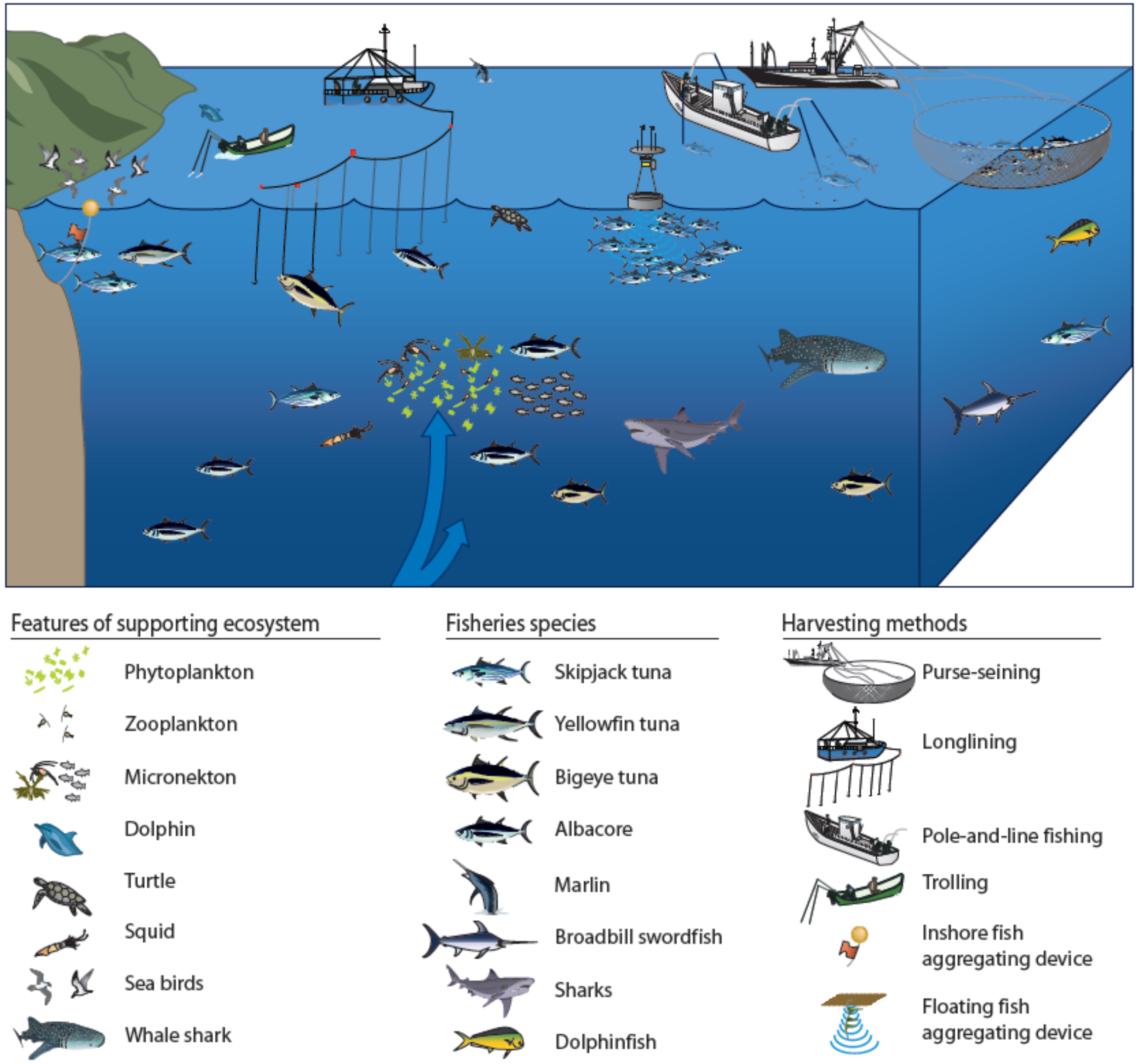
PNA
Parties to the Nauru Agreement



Skipjack recruitment index from stock assessment model (WCPFC 2016) and Southern Oscillation Index (Lehodey et al 2020; Geophysical Monograph 253)

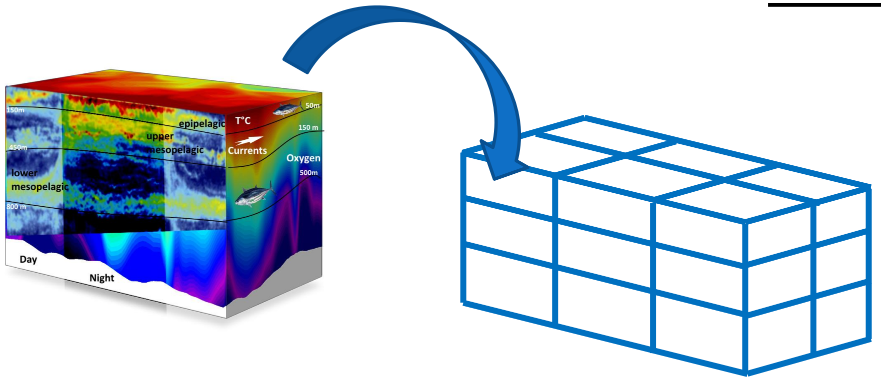
To predict future impacts of climate change on tuna, we need a numerical model to simulate:

1. tuna population dynamics
2. Influence of key environmental variables
3. Impact of fishing
4. Validation based on history of tuna stocks and fisheries
5. Scenarios for the future



Spatial Ecosystem And Population Dynamics Model (SEAPODYM)

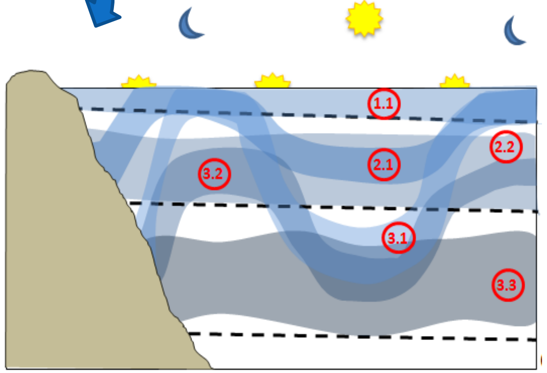
INPUT: PHYS + BIOGEO



2D - 3-layer environment

3 layers:
- Temperature,
- Currents,
- Dissolved O2 (pH, …)

2D fields:
- Total Primary production
- Euphotic depth



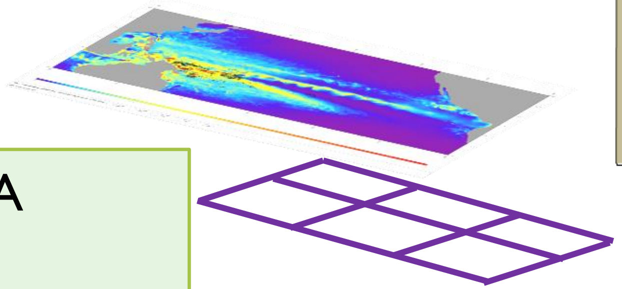
I – SEAPODYM-LMTL

Modeling of Low (zooplankton) and Mid-Trophic Levels (6 groups of micronekton)

Key variables as forage species of larvae to adult fish (tuna), while micronekton is predator of tuna eggs and larvae!

habitats + movements
Integrated over
day-night conditions
in the 3 vertical layers

2D – Habitat and population dynamics
Density by cohort (N or biomass) by km^2
Catch by size by fleet by grid cell

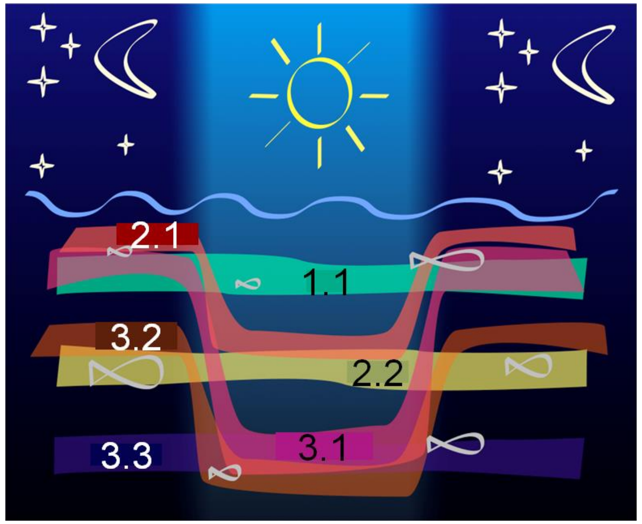


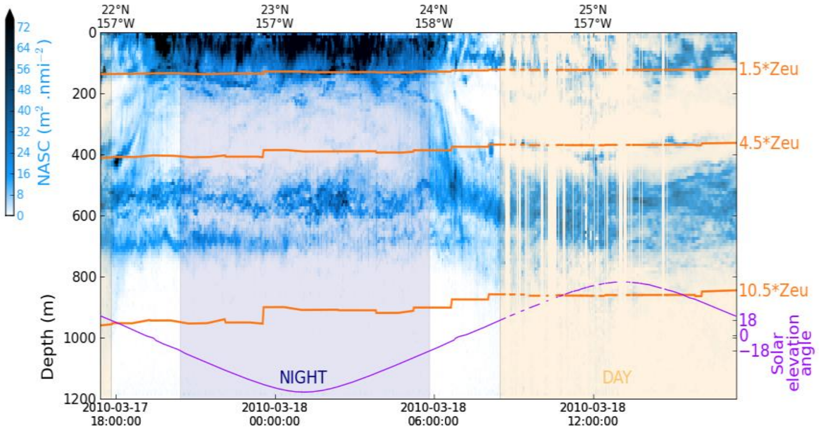
2- SEAPODYM-TUNA

Modeling of Species Habitats population dynamics and fisheries (Migratory Age-Structured Stock)

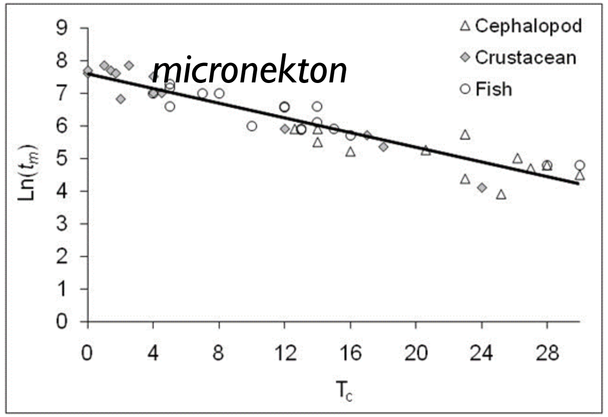
SEAPODYM LMTL

Using **temperature**, oceanic **currents and primary production** (sat. or mod.), the model SEAPODYM-LMTL simulates spatio-temporal dynamics of one zooplankton and 6 micronekton functional groups, according to their diel vertical migration behavior in 3 vertical layers (epi-, upper meso- and lower meso-pelagic).

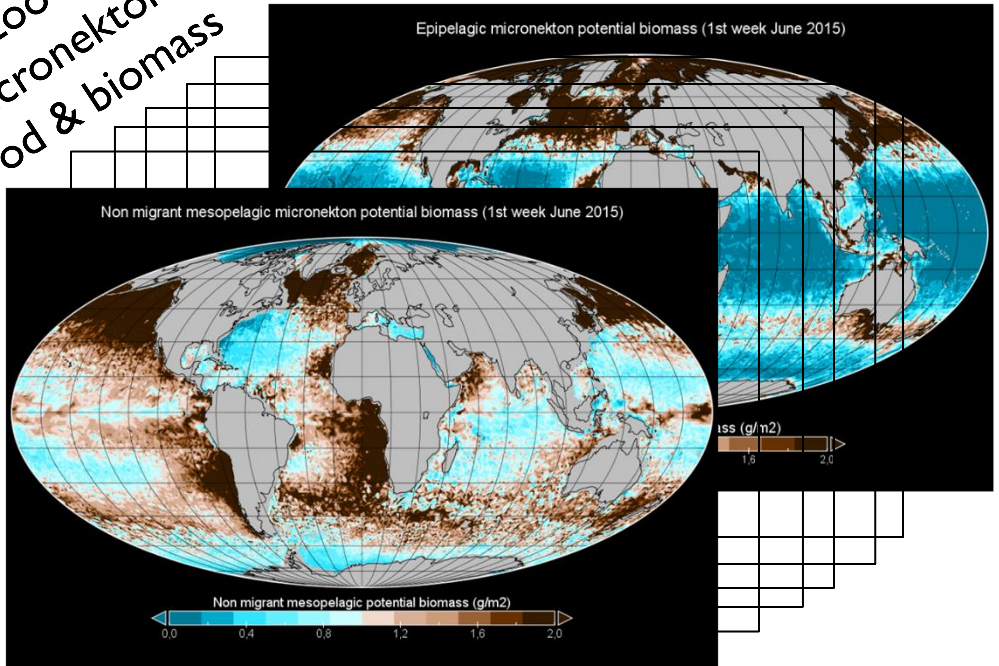




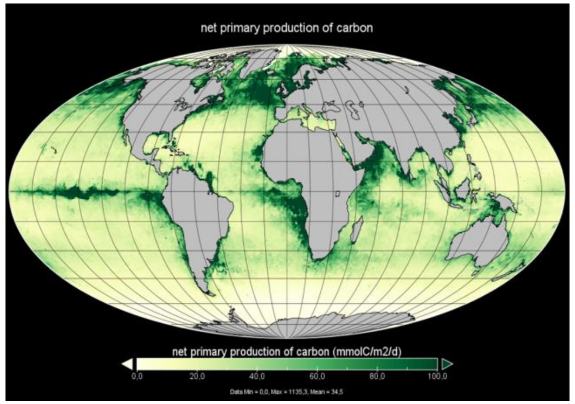
Time of development until maturity vs temperature



Zoo & micronekton Prod & biomass



E

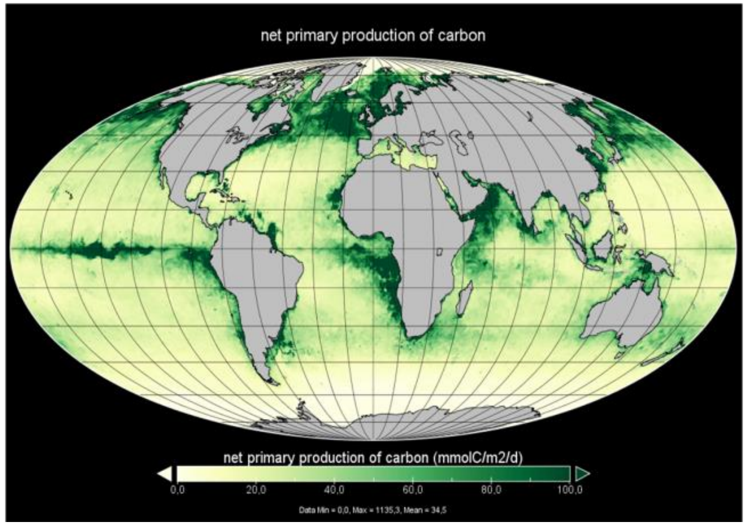


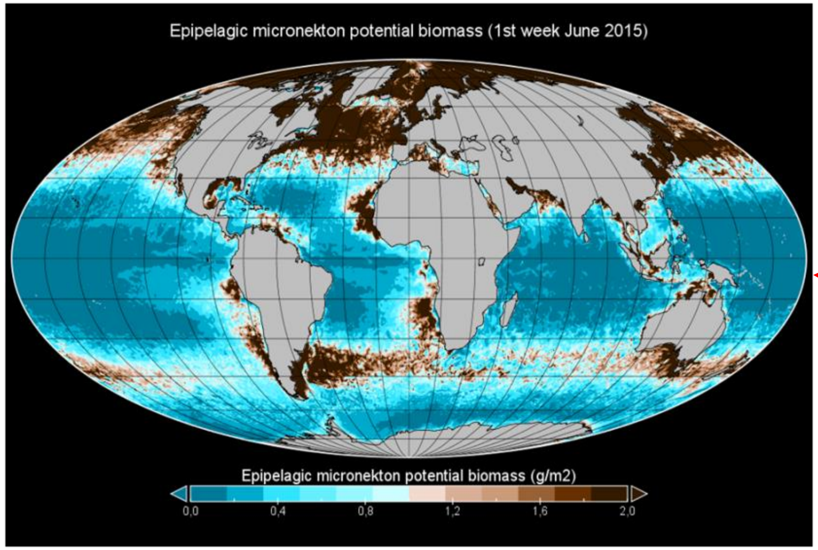
Primary Prod.

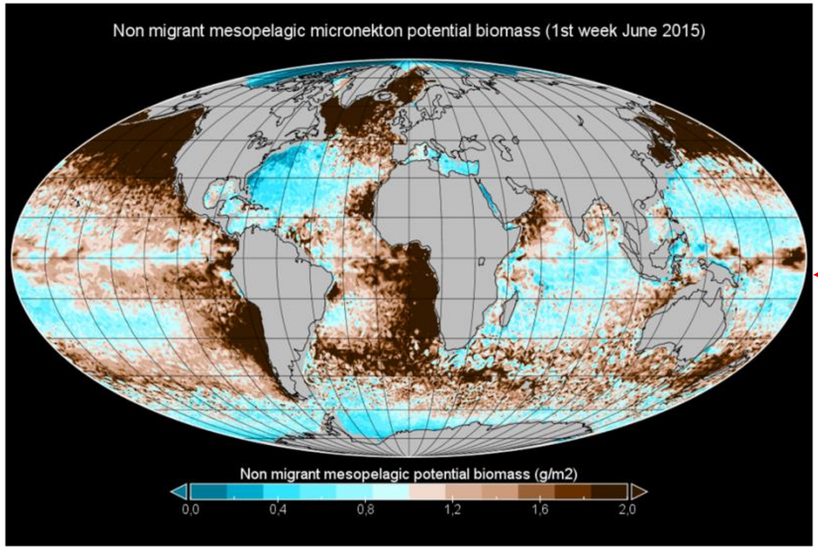
Ref: Lehodey et al. 1998; *Fish. Oceanog.*; 2010, *Progr. Oceanog.*; 2015, *ICES J Mar Sci*; CMEMS: QUID document

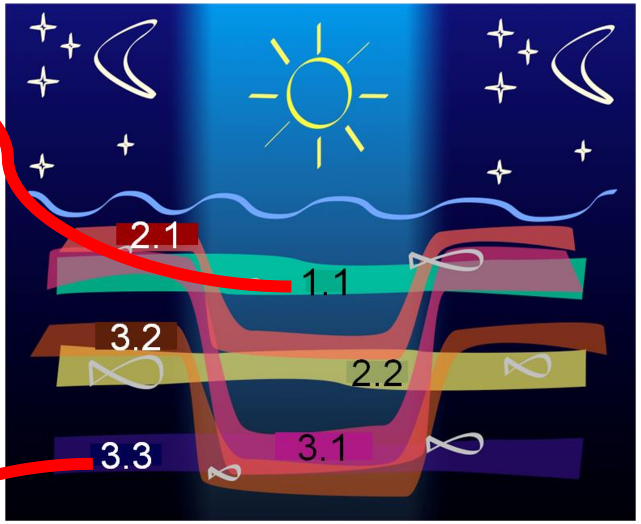
SEAPODYM LMTL

The relationship to temperature can create large spatio-temporal shifts between the source (PP) and the resulting biomass.

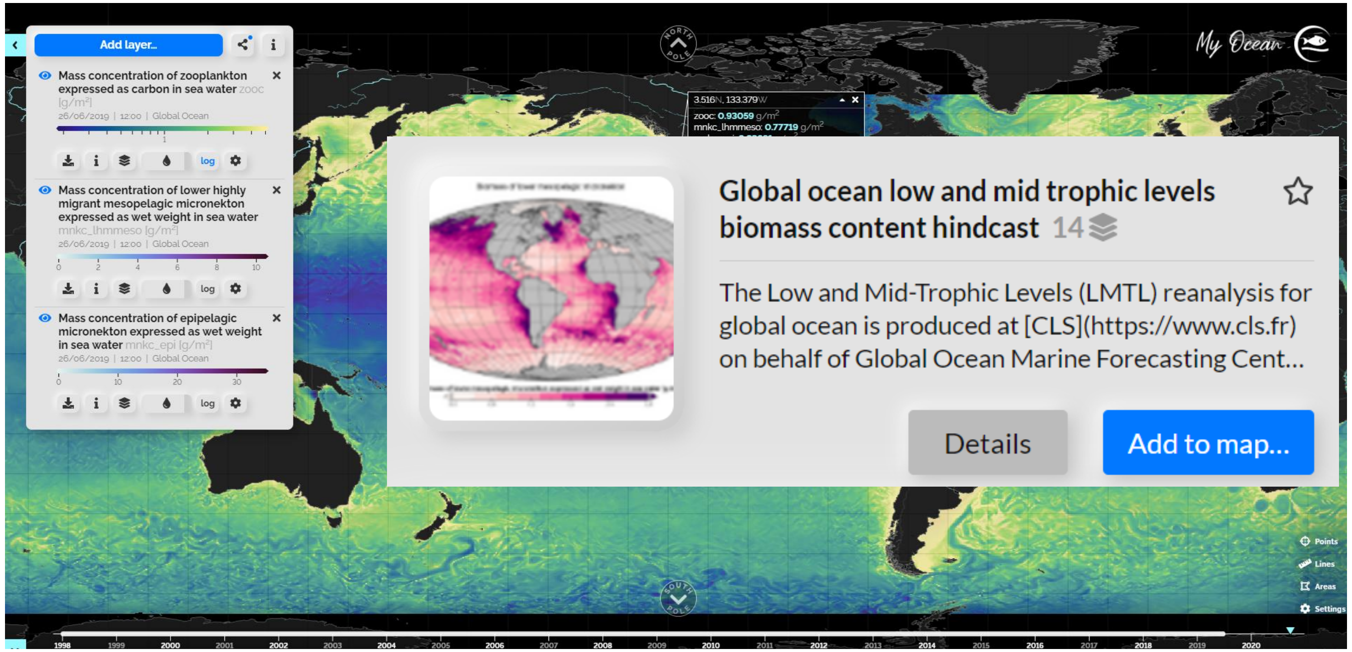








SEAPODYM LMTL



https://marine.copernicus.eu/

Case studies on large marine species habitat/behaviour using Zpk and Mnk:

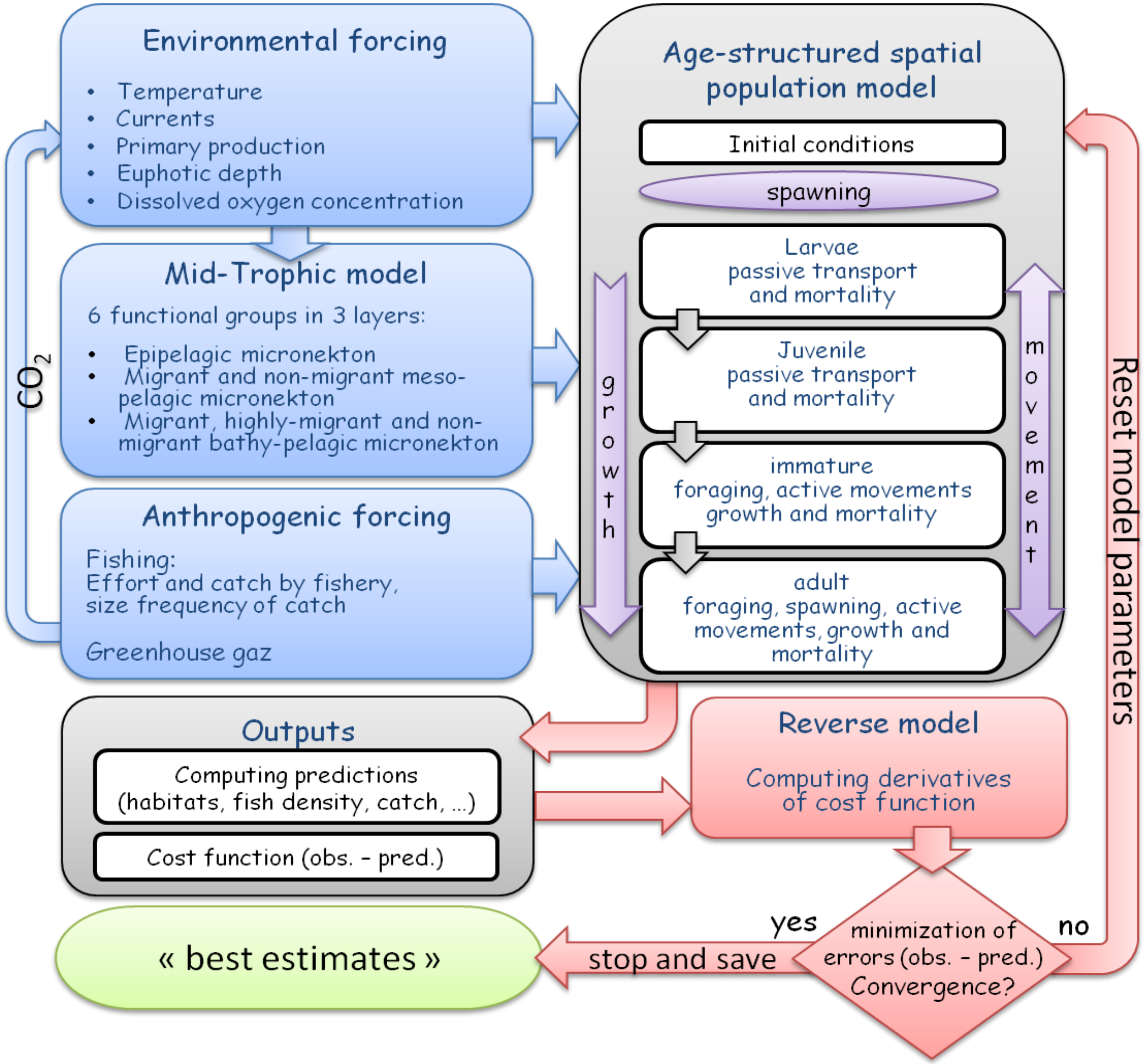
- Pérez-Jorge et al. (2020). Environmental drivers of large-scale movements of baleen **whales** in the mid-North Atlantic Ocean. Diversity and Distributions, 26(6): 683-698.
- Green et al. (2020). Modelled mid-trophic pelagic prey fields improve understanding of marine **predator foraging behaviour.** *Ecography, 43(7): 1014- 1026.*
- Romagosa et al. (2020). Differences in regional oceanography and prey biomass influence the presence of foraging odontocetes at two Atlantic seamounts. ***Marine Mammal** Science,* 36(1): 158-179.
- Lambert et al. (2014) Predicting **Cetacean** Habitats from Their Energetic Needs and the distribution of Their Prey in Two Contrasted Tropical Regions. PLoS ONE 9(8): e105958.
- Abecassis et al. (2013) A Model of Loggerhead Sea **Turtle** (*Caretta caretta*) Habitat and Movement in the Oceanic North Pacific. PLoS ONE 8(9): e73274. doi:10.1371/journal.pone.0073274

SEAPODYM FISH

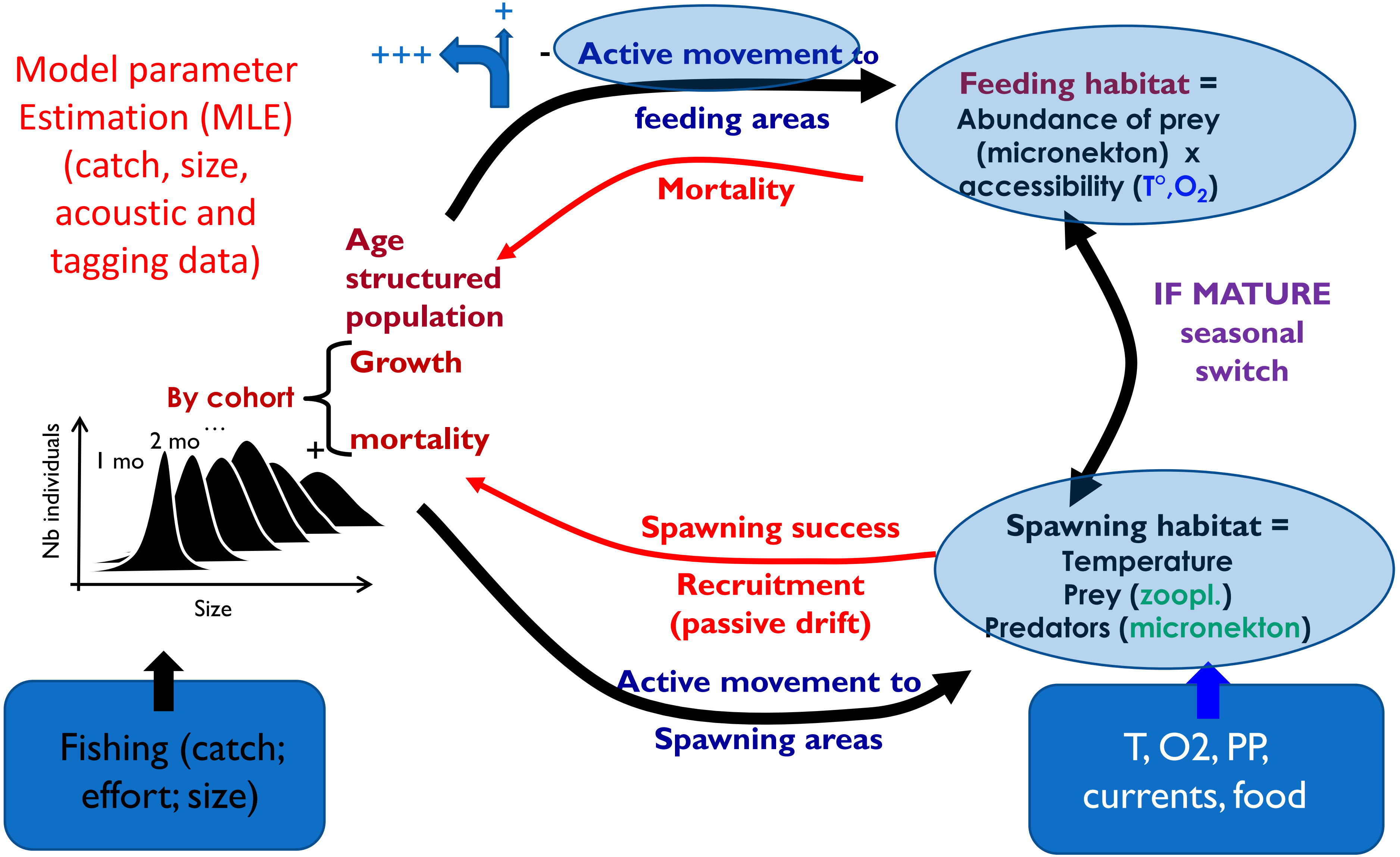
- ➢ SEAPODYM is forced by environmental variables (temperature, currents, primary production, euphotic depth and dissolved oxygen) to predict tuna prey distributions and spatial dynamics of tuna population

- ➢ As in stock assessment model, a robust statistical approach (Maximum likelihood Estimation) using spatialized fishing data provide estimates of key parameters (population & fisheries)

References: Lehodey et al 2003, 2008; Senina et al 2008; 2020; see list of papers in www.seapodym.eu



SEAPODYM FISH

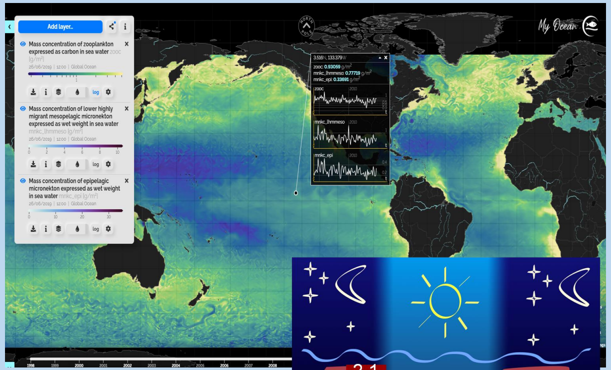


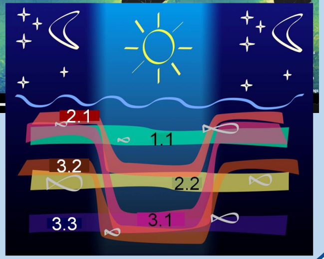
SEAPODYM FISH

HABITATS

Bio-physical environment:

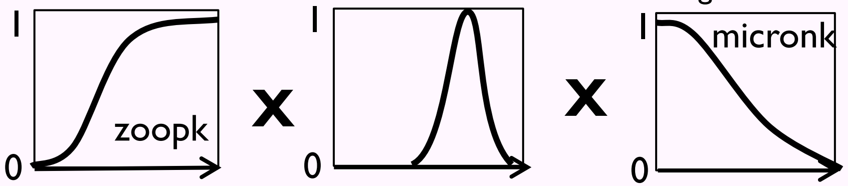
- Temperature
- Currents
- Dissolved oxygen
- Euphotic depth
- Primary production
- Zooplankton (1 group)
- Micronekton (6 groups)





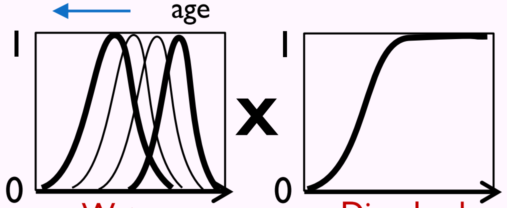
$$F = \begin{pmatrix} F_{11} & 0 & 0 \\ F_{21} & F_{22} & 0 \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

Spawning habitat H_s



$$H_s = f_1(prey)\, f_2(T°)\, f_3(predator)$$

Feeding habitat H_a



Accessibility at age *a* in layer z $= \Theta_{az}$

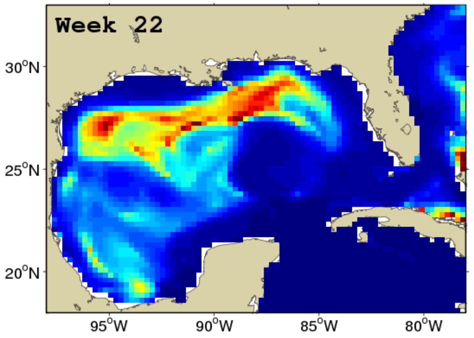
$$\theta_{azz'} = \delta\, \Theta_{az} + (1\text{-}\delta)\, \Theta_{az'}$$

day night

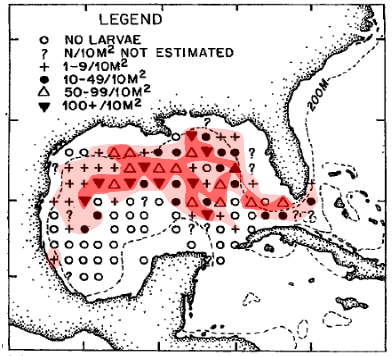
Accessibility to Forage group $F_{zz'}$

$$H_a = \frac{2}{\pi} \operatorname{atan}\left(\frac{\pi}{2} \sum_{z=0}^{z=2} \sum_{z'=0}^{z'=z} \theta_{azz'} \times F_{azz'}\right)$$

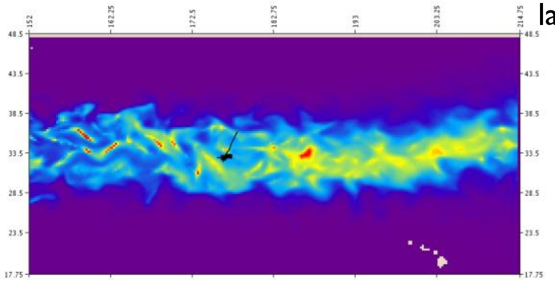
scaling [0-1]



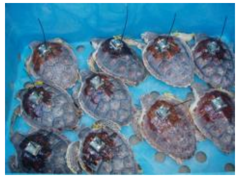
Predicted bluefin larvae density



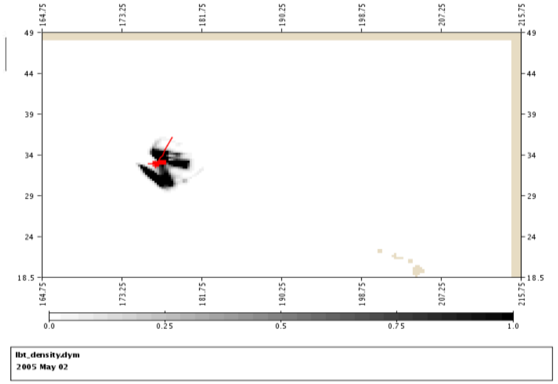
Observed bluefin larvae density



<= Predicted habitat and observed tracks



Loggerhead turtle (Abecassis et al 2012)

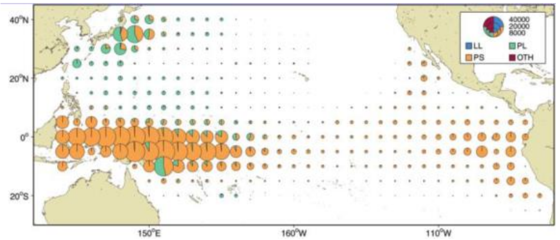


<= Predicted movement and observed tracks

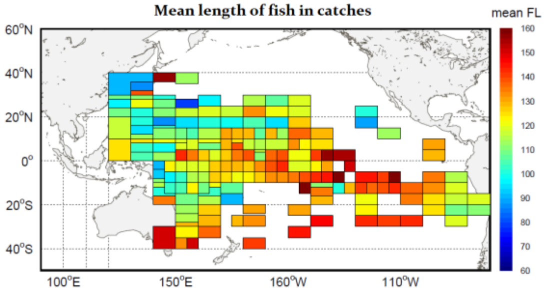
SEAPODYM FISH

APPLICATIONS

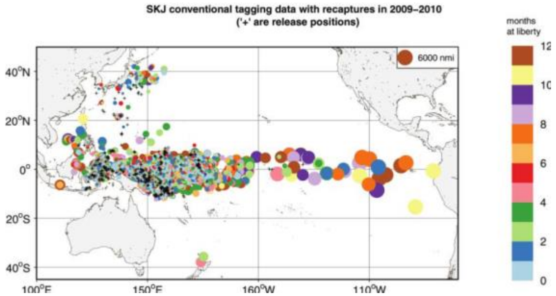
Catch by fleet



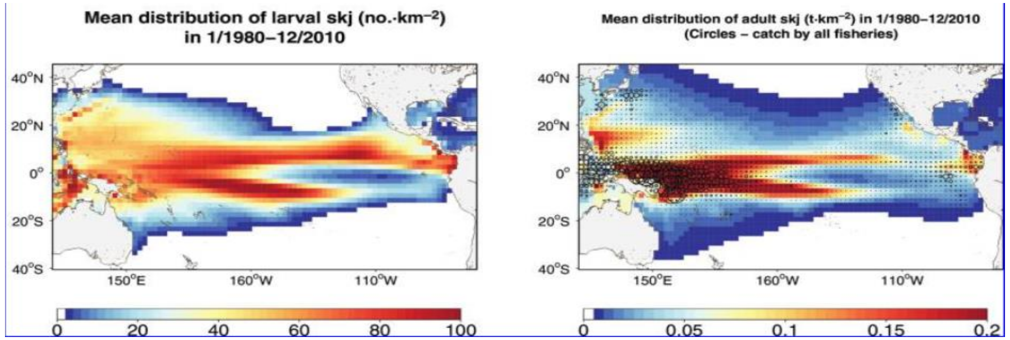
Size frequency of catch



Tagging data



Reference parameterisation (~ reanalysis)



θ	Description
Spawning habitat and reproduction	
σ_0	Standard deviation in temperature Gaussian function at age 0, °C
T_0^*	Optimal surface temperature for larvae, °C
α_P	Prey encounter rate in Holling (type III) function, day^{-1}
α_F	Log-normal mean parameter predator-dependent function, $g \cdot m^{-2}$
β_F	Log-normal shape parameter in predator-dependent function
R	Reproduction rate in Beverton–Holt function, $month^{-1}$
b	Slope parameter in Beverton–Holt function, $no. \cdot km^{-2}$
Natural mortality	
$\overline{m}_p$	Predation mortality rate at age 0, $month^{-1}$
β_p	Slope coefficient in predation mortality
$\overline{m}_s$	Senescence mortality rate at age 0, $month^{-1-\beta_s}$
β_s	Slope coefficient in senescence mortality
ϵ	Variability of mortality rate with habitat index $M_H \in \left[\frac{M}{(1+\epsilon)}, M(1+\epsilon)\right]$
Feeding habitat	
T_0	Optimal temperature for the first young cohort, °C
T_K	Optimal temperature for the oldest adult cohort, °C
σ_K	Standard deviation in temperature Gaussian function at age K, °C
b_T	Allometric power coefficient for thermal preferences at age
γ	Slope of the oxygen function in layer accessibility
$\hat{O}$	Critical value of dissolved oxygen in the layer, $mL \cdot L^{-1}$
E_{11}	Contribution of epipelagic forage to the habitat index
E_{22}	Contribution of mesopelagic forage
E_{21}	Contribution of migrant mesopelagic forage
E_{33}	Contribution of lower mesopelagic forage
E_{32}	Contribution of migrant lower mesopelagic forage
E_{31}	Contribution of highly migrant lower mesopelagic forage
Movement	
V	Velocity at maximal habitat gradient and A = 1, body lengths $(BL) \cdot s^{-1}$
A	Slope coefficient in allometric function for tuna velocity
σ	Multiplier for the theoretical diffusion rate $\frac{\overline{V}^2 \Delta T}{4}$
c	Coefficient of diffusion variability with habitat index

Model parameters (+ 3 to 4 parameters by fishery for q and s)

Senina I., Lehodey P., Sibert J., Hampton J., (2020) Improving predictions of a spatially explicit fish population dynamics model using tagging data. *Can.J. Aqu. Fish. Sci.*, 77(3): 576-593

SEAPODYM FISH

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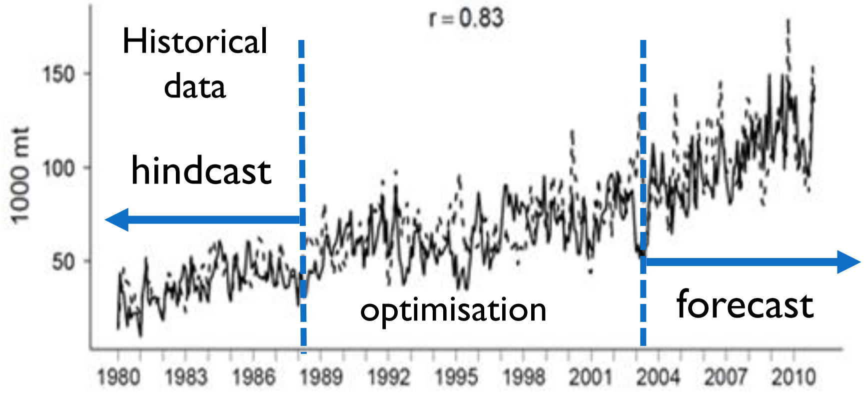
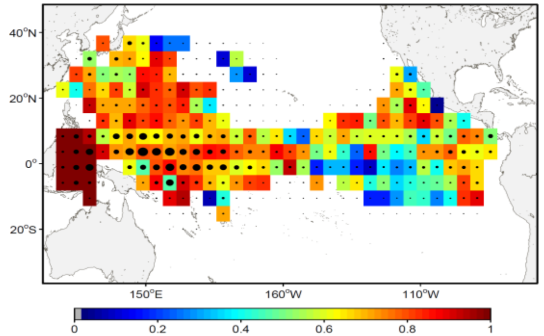
APPLICATIONS

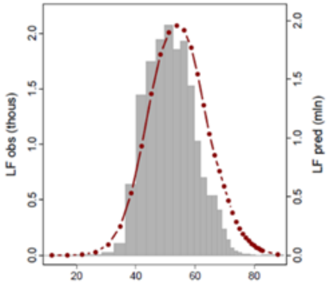
Validation

Persistence of the fit (obs/pred) outside calibration window

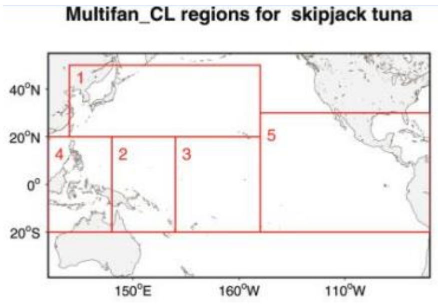


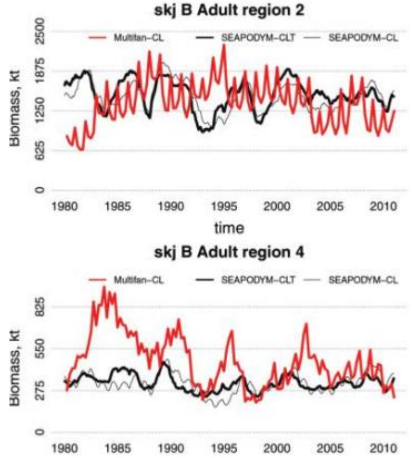
Fit to data: correlation, errors, residuals (bias, trend)



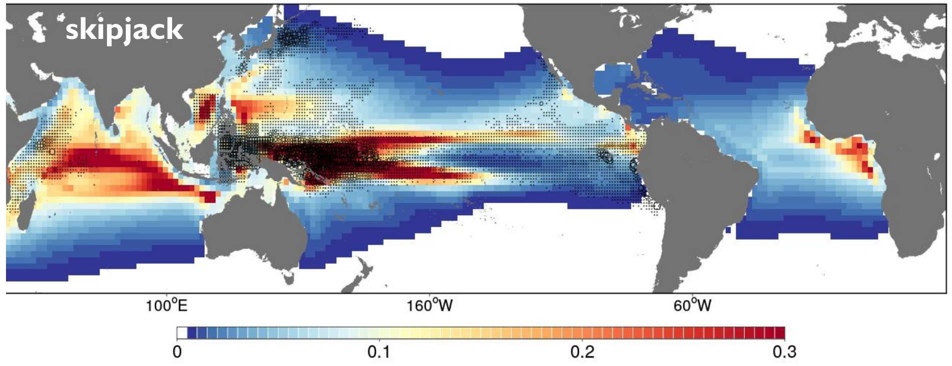


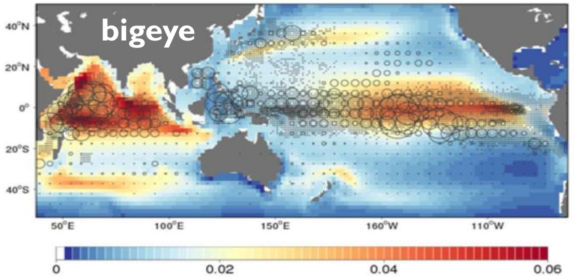
Model inter-comparison





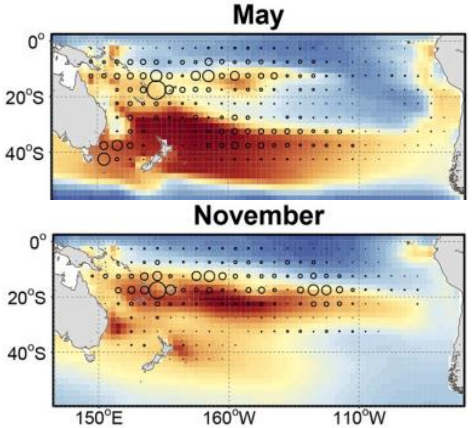
Invariance of parameters



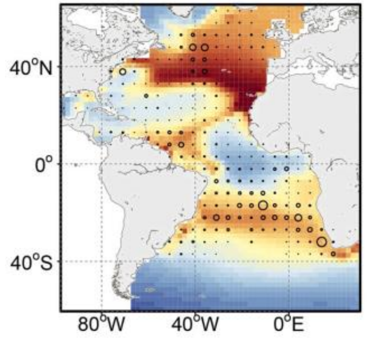


Lehodey et al (2018). Operational modelling of bigeye tuna (*Thunnus obesus*) spatial dynamics in the Indonesian region. Mar. Pol. Bull., 131: 19-32.

Senina et al. (2020). Quantitative modelling of the spatial dynamics of South Pacific and Atlantic albacore tuna populations. Deep Sea Res. 175, 104667



albacore



SEAPODYM FISH

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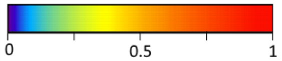
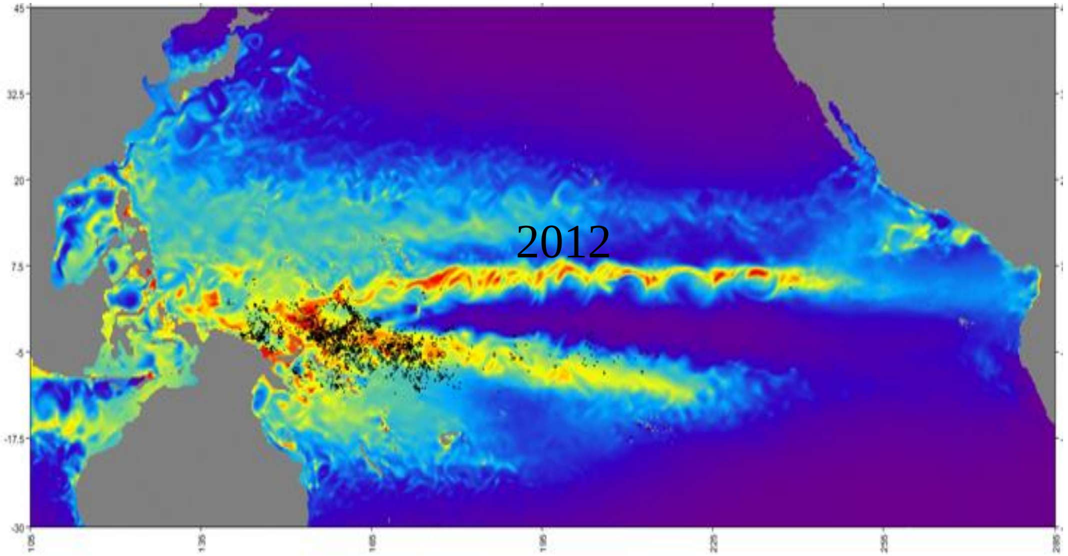
Pacific Community
Communauté du Pacifique



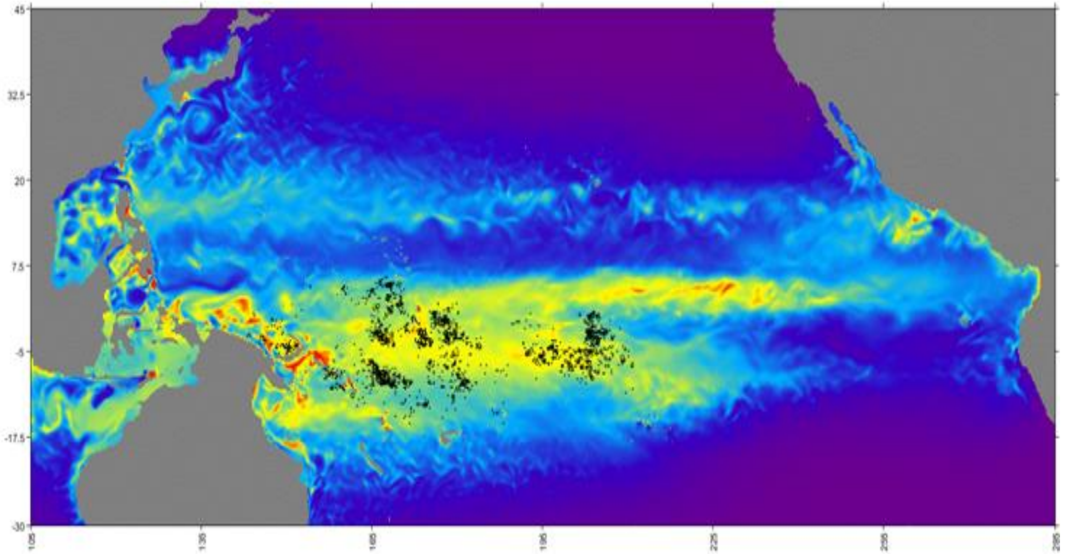
APPLICATIONS

Fisheries vs Environment

Mid-Dec 2007 (La Niña)



Mid-Dec 2015 (El Niño)



Predicted skipjack density (t/ km2) and observed catch (black circles)

Fishing / management scenarios
What if … ?

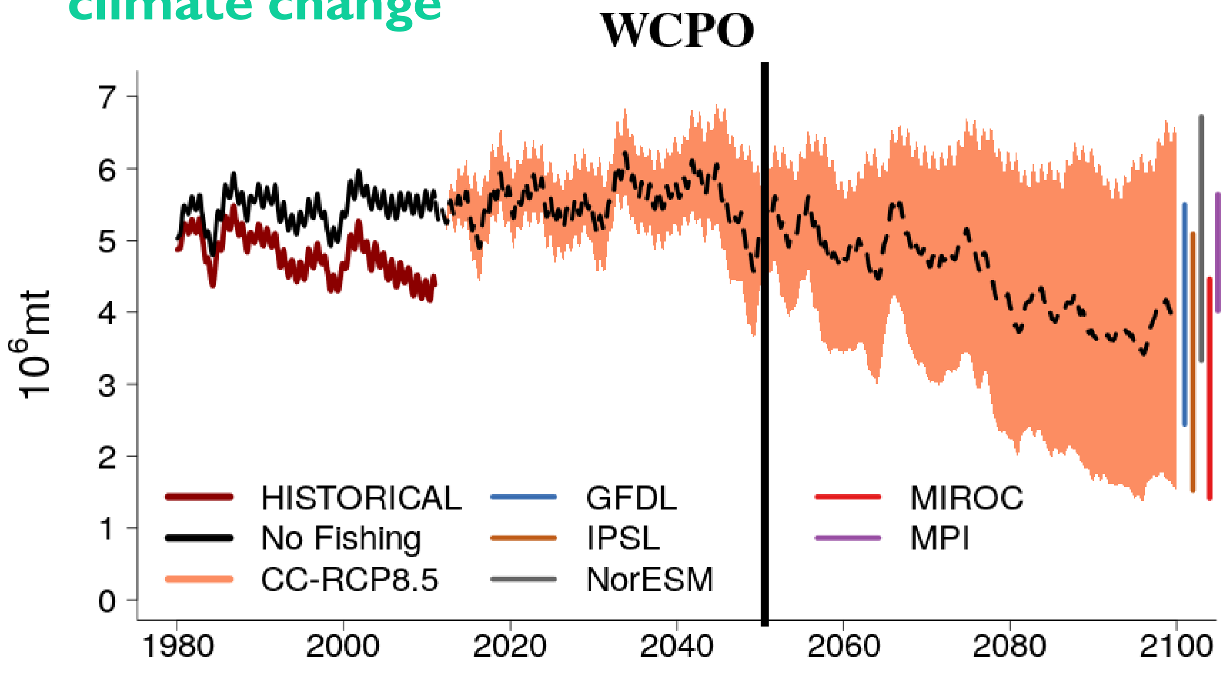
Ex.: Sibert J, Senina I, Lehodey P, Hampton J (2012). Shifting from marine reserves to maritime zoning for conservation of Pacific bigeye tuna (*Thunnus obesus*). *PNAS* 109(44): 18221-18225.

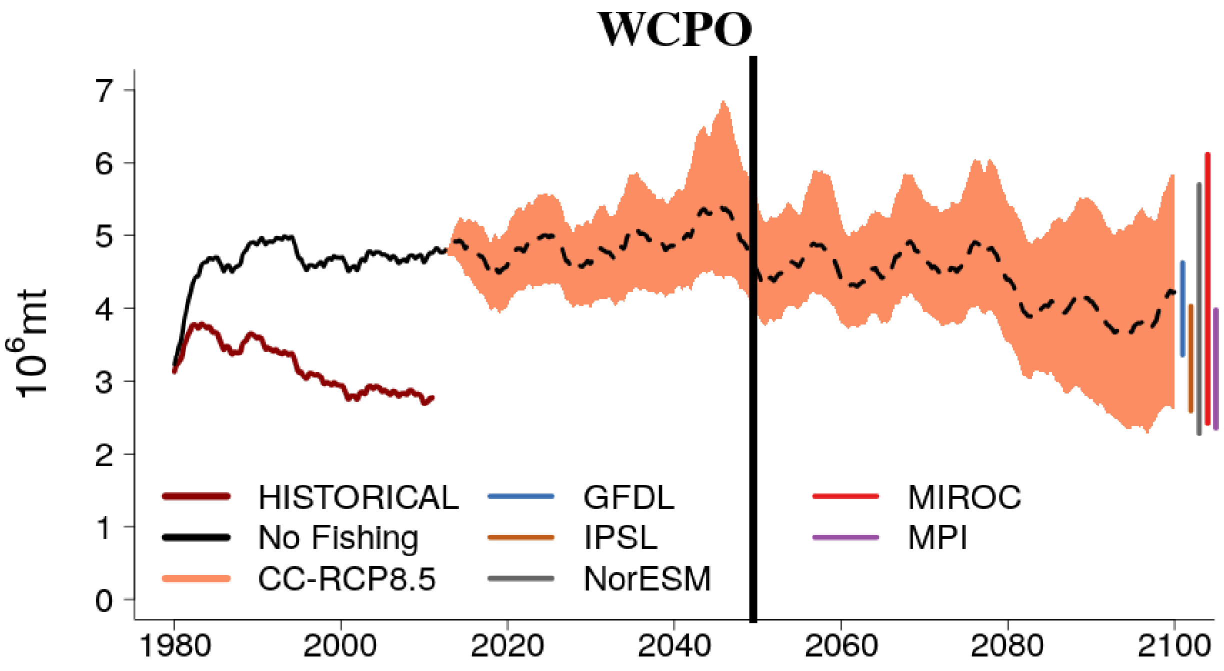
SEAPODYM FISH

APPLICATIONS

Impact of climate change

Impact of climate change on virgin biomass without fishing

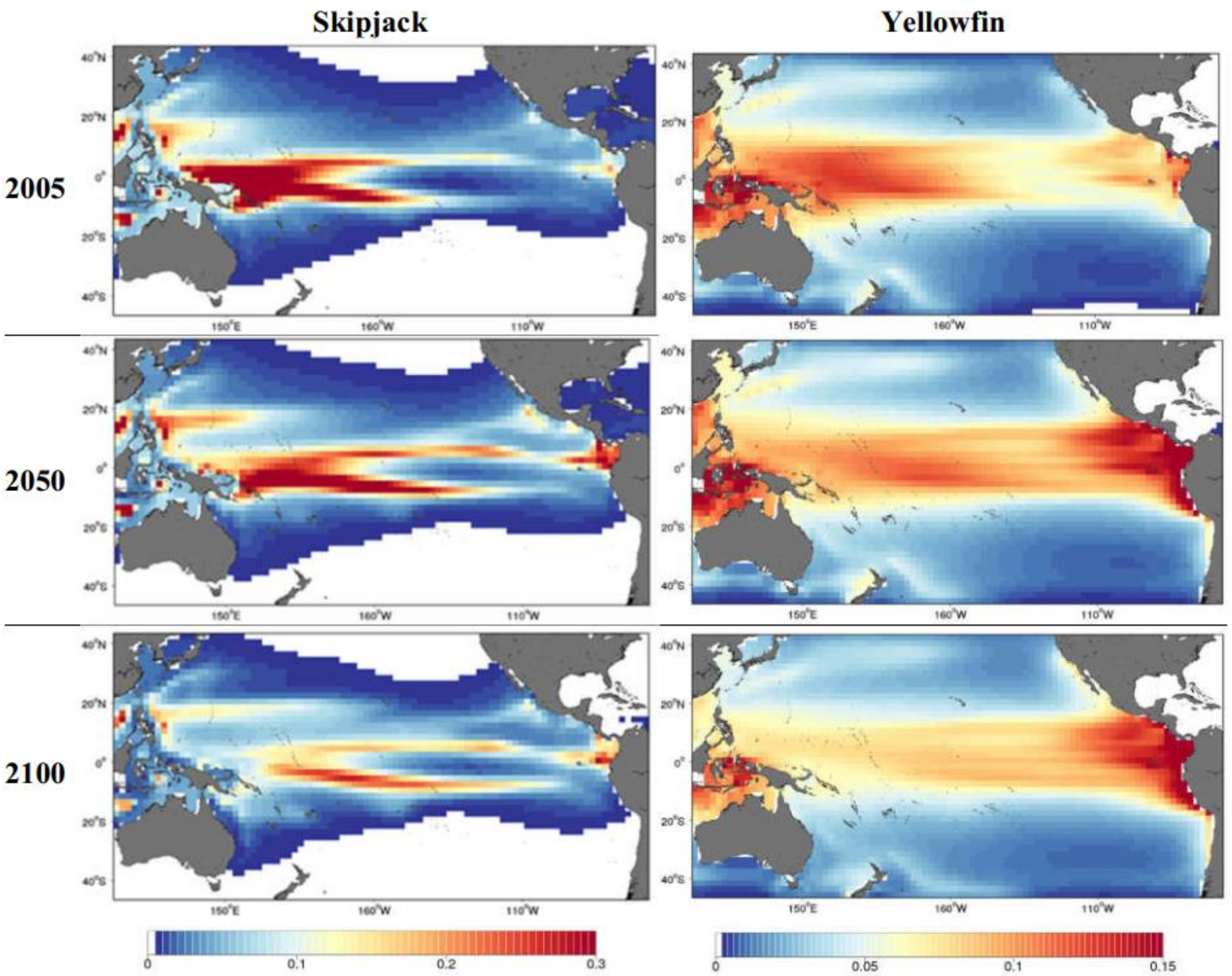




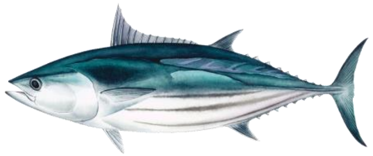
SEAPODYM FISH

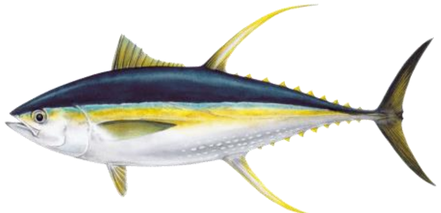
APPLICATIONS

Impact of climate change



RCP8.5





SEAPODYM FISH

APPLICATIONS

Tuna-dependent Pacific Island economies

- Government revenues derived from tuna-fishing access fees varies between 4% and 84%
- Where tuna is the dominant primary industry the revenue varies between 30% and 84 %

nature sustainability
ANALYSIS
https://doi.org/10.1038/s41893-021-00745-z
Check for updates
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Pathways to sustaining tuna-dependent Pacific Island economies during climate change

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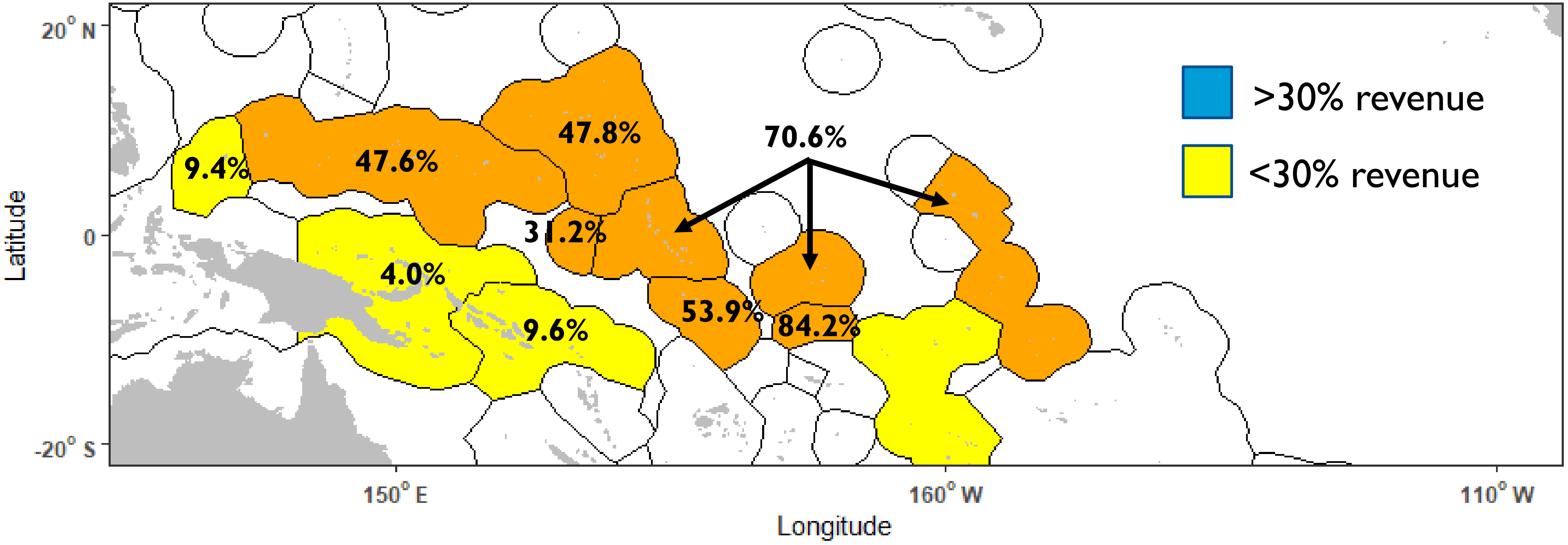
srupt the economies of Pacific Small Island Developing States (SIDS)
tuna fishery. Here we show that by 2050, under a high greenhouse
f three tuna species in the waters of ten Pacific SIDS could decline by an
ater proportion of fish occurring in the high seas. The potential implica-
average decline in purse-seine catch of 20% (range = −10% to −30%),
s fees of US$90 million (range = −US$40 million to -US$140 million)
6 (range = −8% to −17%) for individual Pacific SIDS. Redistribution
5) is projected to reduce the purse-seine catch from the waters of
6 to +9%), indicating that even greater reductions in greenhouse gas
provide a pathway to sustainability for tuna-dependent Pacific Island
DS negotiating within the regional fisheries management organization
m tuna, regardless of the effects of climate change on the distribution



SEAPODYM FISH

PERSPECTIVES

- FAO-SPC project ongoing preliminary study + New project end of 2022
  - Revise parameterisation of 4 main tuna species in the Pacific with new forcing ERA5-NEMO-PISCES
  - Run ensemble simulation CMIP6 models / scenarios
  - Extend to Indian and Pacific Oceans
- NECCTON (EU HORIZON) Jan 2023
  - New application to small pelagic species (PhD): Anchovy Bay of Biscay
  - Tuna case study (Impact of large High Seas MPA)
- SPC funding
  - Revised mechanisms (PhD thesis), mixed layer, oxygen
- Consortium SPC-CLS-MOi
  - Release on Github / open source
  - Other species: Atlantic Mackerel (CLS; Guillaume Briand); Swordfish…