Forecasts of future ocean state and potential application to tuna availability

Jason R. Hartog,[1] J. Paige Eveson,[2] Thomas Moore[2], Kylie L. Scales[3], Toby Patterson[2], Shane Baylis[2], Bernadette Sloyan[2], Ash Williams[2], Claire M. Spillman[3], Grant Smith[4] and Alistair J. Hobday[2]

Background

Commercially valuable species targeted by Australian longline fisheries (bigeye tuna, *Thunnus obesus*; yellowfin tuna, *Thunnus albacares*; albacore tuna, *Thunnus alalunga*; striped marlin, *Kajikia audax*; broadbill swordfish, *Xiphias gladius*) have a wide distribution in the southwest Pacific, but the influence of ocean state and variability on their distribution, abundance and phenology is poorly understood. A recently completed research project funded by the Fisheries Research and Development Corporation (FRDC) and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) sought to investigate the influence of oceanographic conditions on these species' distributions.

A key project result is that sub-surface ocean state variables are important in explaining the distribution of catches. Previous work has focused on surface variables such as sea-surface temperature, which have historically been available in seasonal forecast models and Earth System models such as those included in the Intergovernmental Panel on Climate Change Coupled Model Intercomparison Project (CMIP). However, modelled sub-surface variables are now becoming increasingly available and have revealed their importance for predicting these target species' distributions.

Reanalysis of past conditions

Catch and effort data for the five target species from 13 nations and territories across the southwest Pacific region (Cook Islands; French Polynesia; New Caledonia; New Zealand; Norfolk Island; Samoa; Solomon Islands; Tokelau; Tonga; Tuvalu; Vanuatu; Fiji and Australia) were provided by the Western and Central Pacific Fisheries Commission (WCPFC) and Australian Fisheries Management Authority (AFMA). Using this data, we investigated a suite of modelling techniques to assess the influence of ocean state variables in explaining variability in catch rates. Boosted regression trees (BRTs) were considered to perform best; full details of this modelling approach can be found in a soon to be published FRDC report[5] and a manuscript currently in preparation (Scales et al. in prep). The catch and effort data were aggregated by month and 0.25-degree latitude/longitude grid cell for the years 2008–2020. For each of the five target species, boosted regression trees (BRTs) were used to model the observed catch in each 0.25-degree grid cell in each month, assuming a Poisson distribution. The number of hooks was included as an offset and the selected ocean variables as predictors. Data from 2008–2015 were used to train the BRT models, and 2016–2020 data were used for testing and validation.

During the project two different reanalysis products were used: CSIRO's CAFE60 ocean reanalysis (O'Kane et al 2021a, O'Kane et al 2021b), and the Bureau of Meteorology's ACCESS-S (Australian Community Climate and Earth-System Simulator-Seasonal) ocean reanalysis. The benefit of using these products is that all the ocean state variables are on the same spatial grid, and the data assimilation schemes ensure that there are values at all locations for all time points in the historical period. As ACCESS-S is an operational service provided by the Bureau, we will focus on this reanalysis and forecast system.

ACCESS-S

ACCESS-S is the Bureau of Meteorology's operational coupled ocean-atmosphere seasonal prediction system. ACCESS-S1 (version 1) (Hudson et al. 2017) was operationalised in August 2018 and then upgraded to ACCESS-S2 (version 2) (Wedd et al., in review) in October 2021. This study uses ACCESS-S2. The ocean model is eddy-permitting, with a 0.25-degree resolution and 75 depth layers, with the top 1-metre layer representing sea surface temperature. Ocean model initial conditions are created using a weakly coupled data assimilation scheme, which assimilates in situ profiles of temperature and salinity observations (Wedd et al. in review). The resulting gridded ocean data reanalysis was used in this study to provide input subsurface data for training the BRT models.

Choice of study regions

The southwest Pacific domain was partitioned into four regional sub-domains based on the time-mean ratio of eddy kinetic energy to mean kinetic energy (EKE/MKE, Figure 1a). This was generated from BRAN2020, an eddy-resolving, near-global ocean reanalysis (Chamberlain et al. 2021), and subsequently used to identify boundaries between regions dominated by mesoscale eddies or mean currents.

[1] CSIRO Oceans and Atmosphere, Hobart, Australia. Jason.Hartog@csiro.au
[2] CSIRO Oceans and Atmosphere, Hobart, Australia.
[3] Global-Change Ecology Research Group, University of the Sunshine Coast, Queensland, Australia.
[4] Bureau of Meteorology, Melbourne, Victoria, Australia
[5] https://www.frdc.com.au/project/2017-004

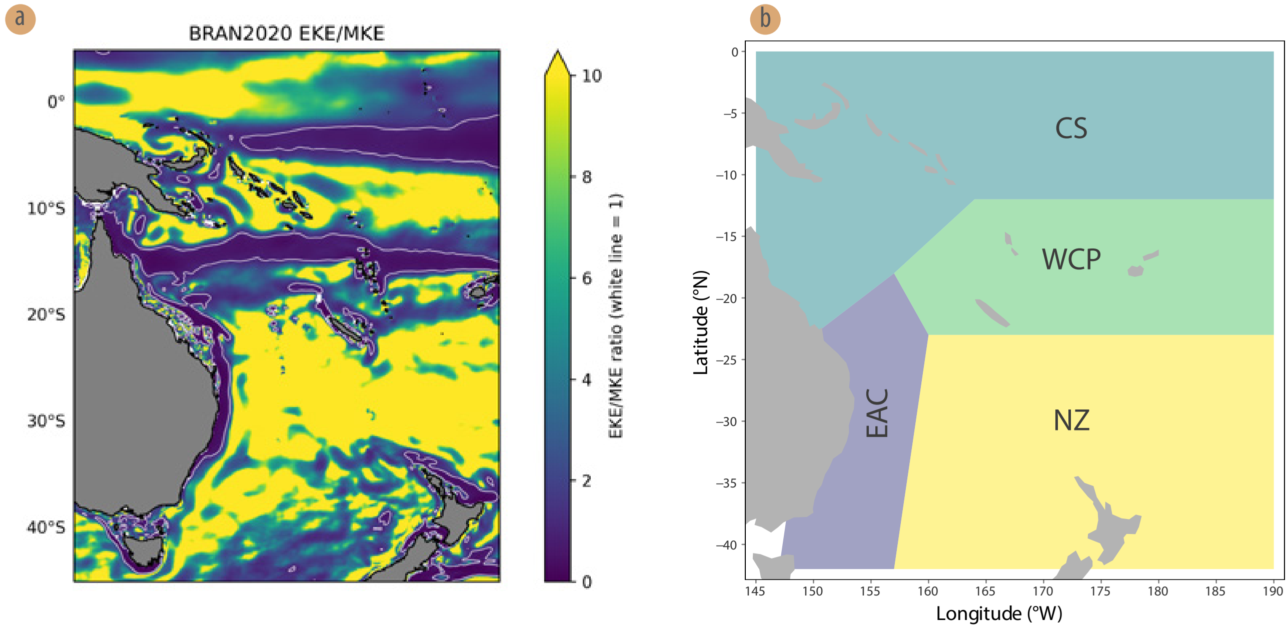

Figure 1 – a) Ratio of EKE to MKE and b) Four key regions defined for analysis. EAC = East Australian Current-dominated; CS = Coral Sea and Equatorial; WCP = Western-Central Pacific; and NZ = New Zealand.

By combining the EKE/MKE analysis with a geographical breakdown of Western and Central Pacific Fisheries Commission (WCPFC) nations, four key regions were identified. These are referred to here as East Australian Current-dominated (EAC), Coral Sea and Equatorial (CS), Western-Central Pacific (WCP) and New Zealand (NZ), and are shown in Figure 1b.

Results

Full results of this modelling approach will be in the soon-to-be released FRDC report, but to illustrate the approach, we consider yellowfin tuna for the whole domain and the four sub-regions. Although predictive power of the models is often generally low (maximum R-squared values of 0.45), it is still of interest to consider which ocean variables are contributing the most to explaining the deviance in the CPUE (catch per unit effort) for each species and region. The variables that are most influential vary significantly between the four regions (Figure 2). For yellowfin tuna (YFT), sea surface salinity (sss), eddy kinetic energy integrated over 0-300m depth (eke300) and temperature at 500-m depth (t500) were most influential in the whole domain model. Conversely in the EAC sub-region, mixed layer depth (mld), t500 and sea surface temperature (sst) came out as the best predictors, showing the importance of considering both the region and the sub surface variables describing ocean structure.

Table 1. List of oceanographic variables available from the ACCESS-S2 reanalysis data (direct and derived products) used in BRTs. Bathymetry data taken from TerrainBase (https://www.ngdc.noaa.gov/mgg/gravity/1999/document/html/tbase.html).

Variable name	Description
eke300	Eddy kinetic energy – weighted sum of 0-300 m
hc300	Heat content – upper 300 m
mld	Mixed layer depth
ssh	Sea surface height (corrected)
sss	Sea surface salinity
sst	Sea surface temperature
td	Thermocline depth
t500	Temperature at 500 m
u100	East/west velocity at 100 m
v100	North/south velocity at 100 m
bathy	Bathymetry

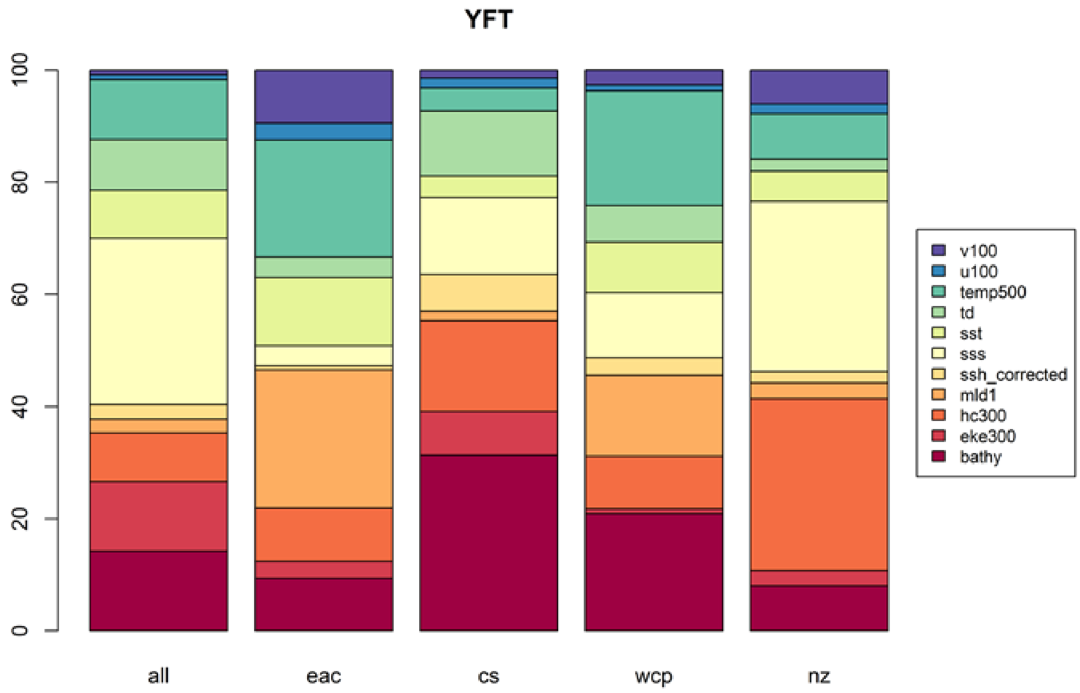

Figure 2. Relative contributions of each of the oceanographic variables included in the BRTs for yellowfin tuna (YFT) and region (all = whole region; eac = EAC-dominated region; cs = Coral Sea; wcp = Western-Central Pacific; nz = New Zealand) (see Figure 1b). See Table 1 for definitions of oceanographic variables.

Forecasts of future ocean state and catch distribution

One of the goals of the project was to investigate the feasibility of providing forecasts of fish distribution for the five key species for Australia and regional partners, using the habitat models developed in this work. Although the BRTs model catch rather than fish abundance, they can still be used to provide forecasts of catch distribution rather than fish distribution directly. Unfortunately, not all the ocean variables that were included in developing the ACCESS-S2 BRT models are available as real time forecasts at this time. Currently, four variables are available: sea surface temperature (sst), sea surface height (ssh), heat content in the upper 300 m (hc300), and mixed layer depth (mld). Thus, to use the BRTs to provide forecasts, the models were re-trained using only these four variables and bathymetry. An example of a forecast of yellowfin tuna CPUE for the whole region model is shown in Figure 3.

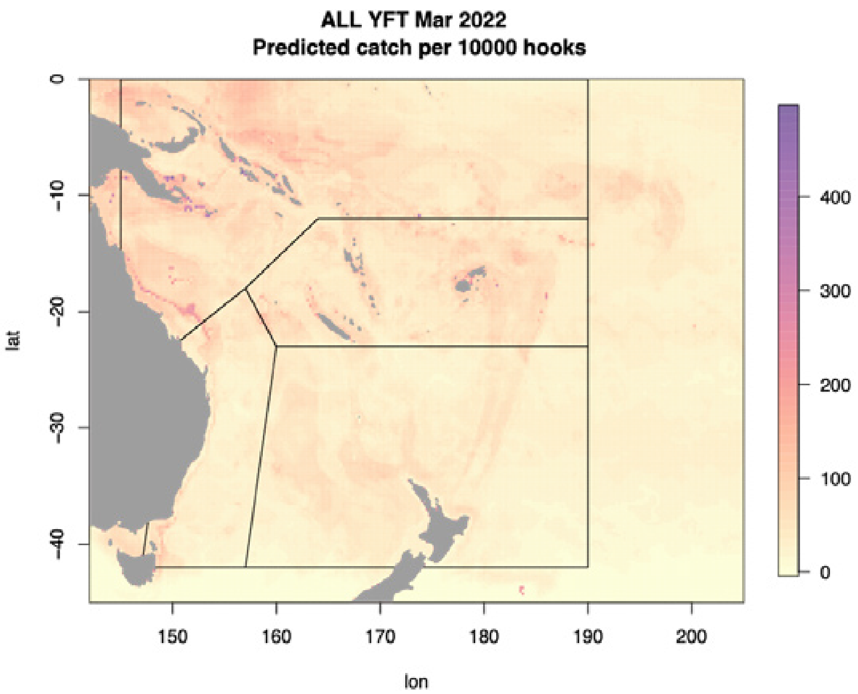

Figure 3. Example map of predicted CPUE for yellowfin tuna (YFT) for the whole domain model in March 2022, for an ACCESS-S2 forecast issued in January 2022.

Operational ACCESS-S ocean forecasts, available to the public, can be viewed on the web portals listed in Table 2. In addition, we have an experimental project page with real-time ocean seasonal forecasts for trialling with project partners and customers (examples shown in Figure 4).

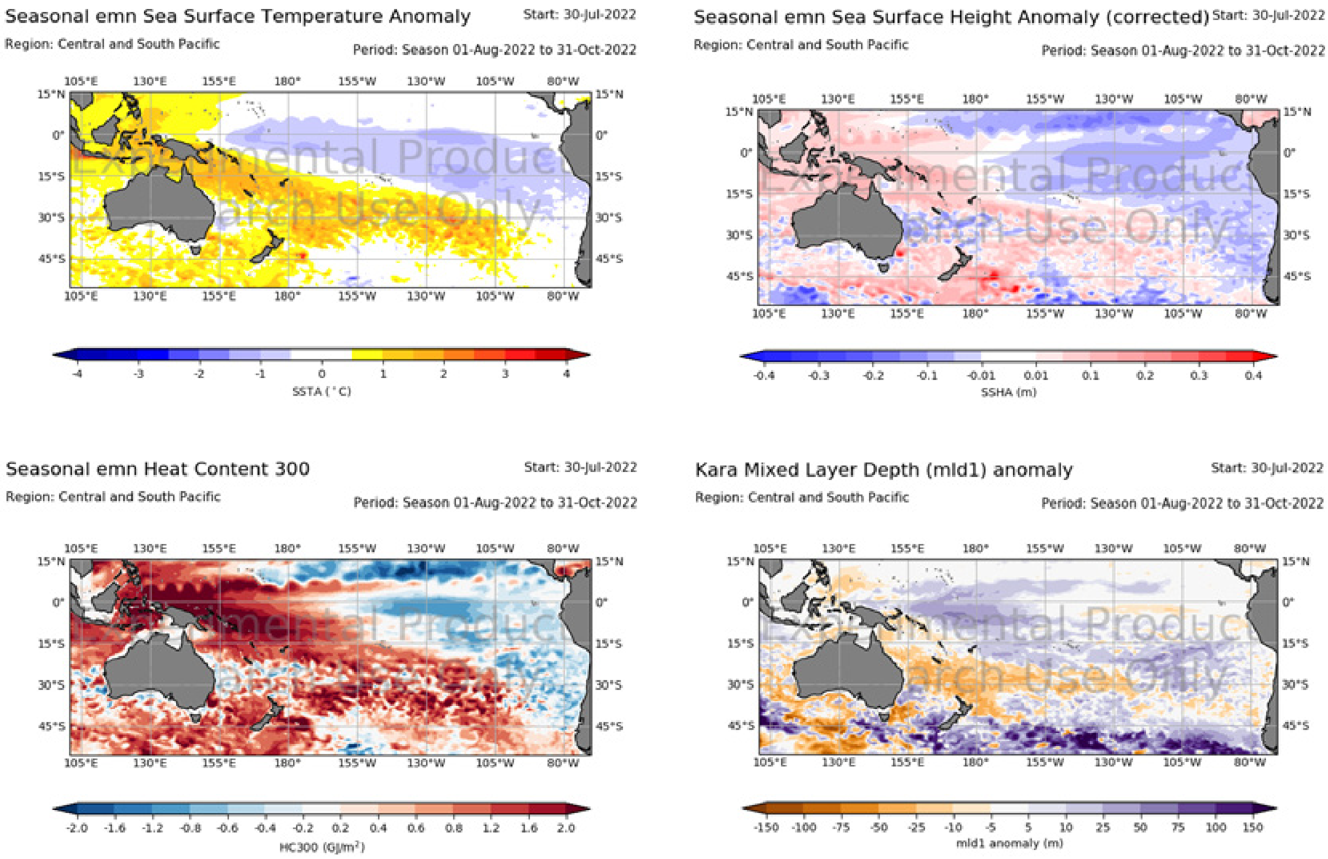

Figure 4. Example of trial ACCESS-S forecasts of surface and sub-surface ocean state for the August-October 2022 season. Each forecast is shown as an anomaly (deviation for the long-term mean) for the variable presented and shows the ensemble mean (emn) of the 99 individual model runs.

Table 2. Locations of portals and websites for investigating ACCESS-S forecasts.

Name	URL
Climate and Oceans Support Program in the Pacific (COSPPac)	http://oceanportal.spc.int/portal/app.html#climate
Global and Pacific ACCESS-S outlooks and Pacific climate monitoring	http://access-s.clide.cloud/
Seasonal ocean temperature outlook for Australia	http://www.bom.gov.au/oceanography/oceantemp/sst-outlook-map.shtml
Marine heatwave forecasting	https://research.csiro.au/cor/climate-impacts-adaptation/marine-heatwaves/dynamical-forecasting-of-marine-heatwaves/

Other applications

Along with the work presented in this article, we have also applied seasonal forecasts to other tuna fisheries (Hobday et al. 2011; Eveson et al. 2015; http://www.cmar.csiro.au/gab-forecasts/index.html), as well as prawn and salmon aquaculture (Hobday et al. 2014; Spillman et al. 2015). Typically, we found that forecasts were generally skilful out to three months into the future, depending on location and time of year. These applications have demonstrated that dynamic model forecasts provide a viable option for managing environmental risk for marine industries in a changing climate (Hobday et al. 2018).

Acknowledgements

We acknowledge provision of western and central Pacific fisheries data from the Pacific Community (SPC), and the Eastern Tuna and Billfish fisheries data from the Australian Fisheries Management Authority (AFMA). We are thankful for insights into the fisheries provided by members of the Tropical Tuna Resource Assessment Group, and Simon Nicol, John Hampton and Patrick Lehodey from SPC.

References

Chamberlain M.A., Oke P.R., Fiedler R.A.S., Beggs H.M., Brassington G.B. and Divakaran P. 2021. Next generation of Bluelink ocean reanalysis with multiscale data assimilation: BRAN2020, Earth System Science Data 13:5663–5688. https://doi.org/10.5194/essd-13-5663-2021

Eveson J.P., Hobday A.J., Hartog J.R., Spillman C.M. and Rough K.M. 2015. Seasonal forecasting of tuna habitat in the Great Australian Bight. Fisheries Research 170:39–49. http://www.sciencedirect.com/science/article/pii/S0165783615001496

Hobday A.J., Hartog J.R., Spillman C.M. and Alves O. 2011. Seasonal forecasting of tuna habitat for dynamic spatial management. Canadian Journal of Fisheries and Aquatic Sciences 68:898–911.

Hobday A.J., Spillman C.M., Eveson J.P. and Hartog J.R. 2014. Seasonal forecasting for decision support in marine fisheries and aquaculture. Fisheries Oceanography. https://doi:10.1111/fog.12083

Hobday A.J., Spillman C.M., Eveson J.P., Hartog J.R., Zhang X., Brodie S. 2018. A framework for combining seasonal forecasts and climate projections to aid risk management for fisheries and aquaculture. Frontiers in Marine Science 5(137).

Hudson D., Alves O., Hendon H.H., Lim E., Liu, G., Luo J.-J., MacLachlan C., Marshall A.G., Shi L., Wang G., Wedd R., Young G., Zhao M. and Zhou X. 2017. ACCESS-S1: The new Bureau of Meteorology multi-week to seasonal prediction system. Journal of Southern Hemisphere Earth Systems Science 67:3(132–159). https://doi: 10.22499/3.6703.001

O'Kane T.J., Sandery P.A., Kitsios V., Sakov P., Chamberlain M.A., Collier M.A., Fiedler R., Moore T.S., Chapman C.C., Sloyan B.M., and Matear R.J. 2021. CAFE60v1: A 60-year large ensemble climate reanalysis. Part I: System design, model configuration, and data assimilation. Journal of Climate, 34(13):5153–5169.

O'Kane T.J., Sandery P.A., Kitsios V., Sakov P., Chamberlain M.A., Squire D.T., Collier M.A., Chapman C.C., Fiedler R., Harries D., Moore T.S., Richardson D., Risbey J.S., Schroeter B.J.E., Schroeter S., Sloyan B.M., Tozer C., Watterson I.G., Black A., Quinn C. and Matear R.J. 2021. CAFE60v1: A 60-year large ensemble climate reanalysis. Part II: Evaluation. Journal of Climate 34(13):5171–5194.

Scales, K.L., Moore, T.S., Sloyan, B., Spillman, C.M., Eveson, J.P., Patterson, T.A., Williams, A.J., Hobday, A.J., Hartog, J.R. (in prep.). Forecast-ready models of tuna and billfish catches to support fisheries adaptation to global variability and change.

Spillman C. M., Hartog J.R., Hobday A.J. and Hudson D. 2015. Predicting environmental drivers for prawn aquaculture production to aid improved farm management. Aquaculture 447:56–65.

Wedd R., Alves O., de Burgh-Day C., Down C., Griffiths M., Hendon H.H., Hudson D., Li S., Lim E., Marshall A.G., Shi L., Smith P., Smith G., Spillman C.M., Wang G., Wheeler M.C., Yan H., Yin Y., Young G., Zhao M., Yi X. and Zhou X. In Review. ACCESS-S2: The upgraded Bureau of Meteorology multi-week to seasonal prediction system. Journal of Southern Hemisphere Earth System Science.