IOP Conference Series: Earth and Environmental Science

PAPER • **OPEN ACCESS**

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To cite this article: C K Tito *et al* 2023 *IOP Conf. Ser.: Earth Environ. Sci.* **1251** 012019

The response of tuna to ocean acidification in Indonesian waters (Case study: Gulf of Bone)

C K Tito[1,2,3*], E Susilo[1] and R D Sasongko[1]

[1] Institute for Marine Research and Observation, Ministry of Marine Affairs and Fisheries, Jl Seacorm KM. 2, Negara-Jembrana, Bali 82251, Indonesia
[2] National Research and Innovation Agency, Research Center for Oceanography, Jl. Pasir Putih I, Ancol Timur, Jakarta 14430, Indonesia
[3] Department of Marine Science and Technology, Faculty of Fisheries and Marine Sciences, IPB University, IPB Dramaga, Bogor 16680, Indonesia

*E-mail: came002@brin.go.id

Abstract. There is growing concern about ocean acidification (decrease in pH of the ocean as a result of increased atmospheric carbon dioxide absorption by ocean) as one threat of climate change that may have significant impacts on marine organisms, such as fish. Recent studies suggest that adult fish are not directly impaired by OA, however, for the earliest fish stages, a number of direct effects have been observed. Hence, we observed the response of OA on monthly larvae density of yellowfin tuna in the Indonesian water, especially in the Gulf of Bone. The pH on the total scale (pH) and surface aqueous partial pressure of CO_2 (pCO_2) data were derived from Copernicus Marine Environment Monitoring Service (CMEMS) model product; meanwhile, fish data from 2014-2016 were derived from daily Infrastructure Development for Space Oceanography (INDESO) tuna population model outputs. This study indicates that the variability of pCO_2 tends to increase while the pH tends to decline. During the northwest monsoon periods, pH in the Gulf of Bone tends to be lower. The larvae and juvenile of yellowfin tuna in the Gulf of Bone waters have various spatial correlations with pH and pCO_2. Both have the potential to decrease with the declined pH and elevated pCO_2.

Keywords: acidification, larvae, INDESO, juvenile, yellowfin tuna

1. Introduction

Ocean acidification (OA) is the global decrease in ocean pH due to the absorption of atmospheric carbon dioxide. These OA may be characterised by different risk levels and resilience or vulnerability in identified regions of the world's ocean, with regard to fisheries and aquatic species as well as economic impact and social adaptation. Previous research indicates that OA reveals a consistent decrease in calcification, growth and the development of numerous calcified marine organisms, while certain taxa are likely to be more resilient or able to benefit from OA (e.g. brachyuran crustaceans, fish, fleshy algae, and diatoms) [1]. Some direct effects from OA on early life stage of fish, which are considered most vulnerable due to their lack of maturity in their physiological systems and thus limit their adaptation capacity, have been observed [2]. Other research works of fish larvae have shown the negative effects of OA on a sensitive subset of early larvae, which are likely to be caused by large phenotypic variation in larval populations, whereas other species remained unaffected [3].

In terms of catch weight, tuna is the most important fishing species in the world. The economic contribution to many Pacific island countries and territories from tuna is very significant as a major component of the Pelagic ecosystem [4], [5]. In order to investigate the effects of lower pH on sperm vitality, egg fertilisation, egg and larval development, where the genotype affects the response of eggs and larvae to OA, previous research has been carried out to assess the effects of OA on the four main species of tuna, skipjack, yellowfin, big eye and South Pacific albacore. [6], [7]. Another research revealed that the effects of OA on the egg and larvae of yellowfin tuna have caused a few inconsistencies in results, though it is relatively apparent that they are not clearly influenced by OA until the partial pressure of carbon dioxide (pCO_2) levels exceeded 1500 µatm [8], [9]. pCO_2 is the gas phase pressure (i.e. in the air above a waterway) of carbon dioxide, which would be in equilibrium with the dissolved carbon dioxide. The dissolution of atmospheric CO_2 is affected by the pCO_2 differential between the atmosphere and coastal water body, wind speed and water temperature. An increase in the CO_2 concentration of the atmosphere directly leads to an increase in the amount of CO_2 absorbed by the oceans, it's known as OA [1].

Meanwhile, in a study conducted by yellowfin larvae revealed the negative effects of elevated pCO_2 by histological studies of organs at levels where major effects on survival were not yet evident [10]. A recent study provides an update on the earlier yellowfin tuna Spatial Ecosystem and Populations Dynamics Model (SEAPODYM); in order to investigate how climate change impacts on tuna populations, it is a useful modelling framework [11]. SEAPODYM is a numerical model initially developed to investigate physical-biological interaction between fish populations and the ocean pelagic ecosystem. It simulates functional groups at the Lower and Mid-Trophic Level (LMTL) and detailed age structure populations of top predators. Using predicted environment from ocean-biogeochemical models, SEAPODYM integrates spatio-temporal and multi-population dynamics and considers interactions among populations of different species and between populations and their physical and biological environment (including intermediate trophic levels).

Indonesia is a major tuna producer contributing almost 16% or 800,000 MT of tuna annually [12]. In Indonesia, most tuna fishing industries are located in the eastern regions and contribute about 46% of all tuna catches in the Western and Central Pacific Ocean [13], [14]. This is one of the most potentially productive tuna fishing zones in Indonesian seas, where several commercial tuna fisheries operate [15], [16]. This area is also well known as a tuna nursery and migratory path, especially yellow fine tuna. However, there is a critical lack of information concerning the impacts of OA on tuna (particularly in the Gulf of Bone, Indonesia).

For the foreseeable future, direct measurements of OA by ship surveys, long-term time series observation stations and increasing numbers of autonomous and operated moored platforms will provide the most accurate means [17]. However, in situ OA data in the Indonesia waters are restricted in space (time series, moored stations) and/or time (ship surveys). Therefore, we observe the response of OA on monthly larvae density of yellowfin tuna in the Gulf of Bone, Indonesia using CMEMS and INDESO tuna population model outputs.

2. Material and methods

2.1. Study site

The Gulf of Bone is located between the South and Southeast peninsulas of Sulawesi Island, Indonesia and it opens on the south into the Banda Sea, as shown in Figure 1. This area is well known as one of the yellowfin tuna fishing grounds in the eastern part of Indonesia. Fisheries activity centralized in six regencies, including Makassar City, Barru, Bulukumba, Sinjai, Bone, and Luwu. In general, fishing is carried out around Fish Aggregating Devices (FADs) by using a handline. In 2019, the volume of tuna production in South Sulawesi reached 66,385 tons, including skipjack tuna and mackerel tuna [18].

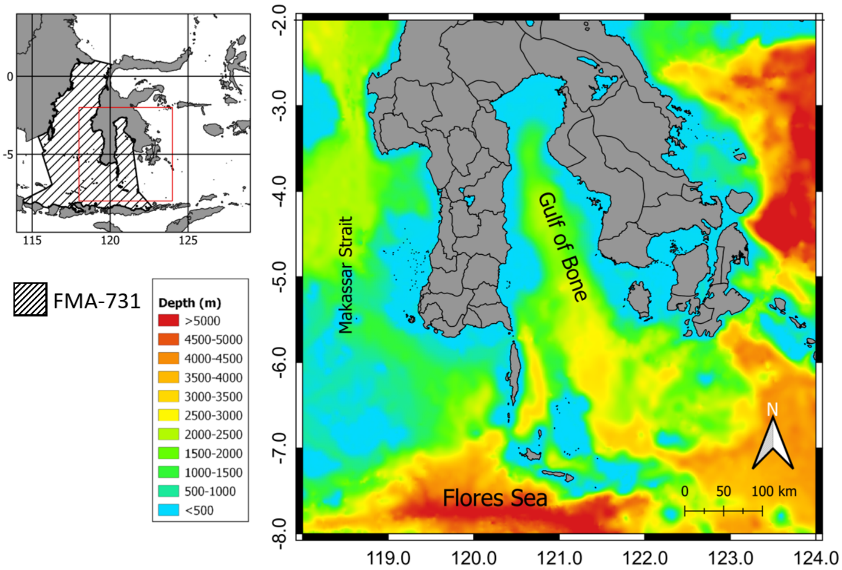

Figure 1. Gulf of bone in the Indonesian Fisheries Management area 713.

2.2. Dataset

The pH and pCO_2 datasets from 2010 to 2019 were derived from Copernicus Marine Environment Monitoring Service (CMEMS) model product (https://marine.copernicus.eu). The pH was calculated from pCO_2 and reconstructed surface ocean alkalinity using the CO2SYS speciation software. Meanwhile, pCO_2 was reconstructed by a Forward Feed Neural Network (FFNN) model. The product reconstructs global properties at a monthly resolution and 1°x1° spatial resolution [19].

Fish data from 2014-2016 were derived from daily INDESO tuna population model outputs (http://www.indeso.web.id/). The tuna dynamic model used for the INDESO project is a regionalized version of the SEAPODYM model, SEAPODYM model, which is designed to replicate spatial and temporal dynamics of age structured pelagic fish populations under the combined pressure of fisheries and oceanic variability. The catch is predicted in this model by using the measured fishing effort and its characteristics, catching capacity and selectivity of gear. The SEAPODYM adapted to the Indonesian archipelago includes a representation of three tuna species: skipjack (*Katsuwonus pelamis*), yellowfin (*Thunnus albacares*) and bigeye (*Thunnus obesus*) [20].

3. Results and discussion

3.1. OA trend analysis

In our research, we analyse pH and carbon dioxide concentrations data from 2010 to 2019 in the Indonesian fisheries management area 713 to observe its variability due to climate change. The analysis shows that during ten years of observation, the variability of pCO_2 tends to increase while the pH tends to decline (Figure 2). This indicates the pH is decreasing, due to ocean absorption of carbon dioxide. The increase of pCO_2 for about 57.870 µatm (347.970 – 405.841 µatm) was found during ten years of observation, with an average of 371.887 µatm. Coinciding with the elevation of pCO_2, the decline of pH (for about 0.048 units) was observed. The highest monthly pH data series was observed in July 2011 (8.064) while the lowest pH was in December 2019 (8.016), with an average of 8.041.

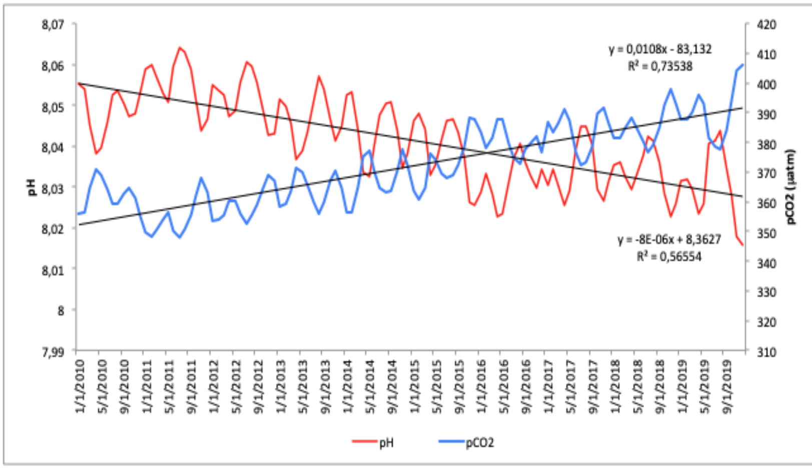

Figure 2. Relationship of pH with pCO_2 in surface seawater of the Indonesian Fisheries Management. area 713

The concentrations of carbon dioxide in the ocean are in approximate equilibrium with the atmosphere. The concentrations of atmospheric carbon dioxide were projected to reach 750 to more than 1300 μatm by 2100 (scenario IPCC without explicit additional efforts to reduce greenhouse gas (GHG) emissions [21]. Previous works suggest that the Pacific Ocean has significant seasonal and vertical/horizontal spatial variation in pH and pCO_2. Today, surface layer pH levels are lowest in higher latitudes and areas where upwelling may bring subsurface waters with lower pH to the surface. The rate of change is expected to be higher in high latitudes and lower in tropical or subtropical water than globally, although the average seawater pH is expected to decrease [22], [23]. By 2100 (under the high atmospheric carbon dioxide scenario of IPCC), the mean decline in pH of surface waters in the western Pacific Ocean is projected to be 0.40 pH units (with a maximum predicted decline of 0.46) [21]. In the coastal ocean, such as semi-enclosed gulf, acidification is a more complex process as carbonate chemistry is also expected to be strongly regulated by changes in biological activity related to the increase in anthropogenic delivery of nutrients by rivers, groundwater and eutrophication. This anthropogenic activity can have a greater influence on the level of acidity of coastal waters than on the high seas, resulting in regional acidification of the sea in coastal waters [1].

In comparing seasonal variability, generally pH in the Gulf of Bone was lower during northwest monsoon, except in certain years (2010, 2014, and 2015) (Figure 3a and 3b). This result coincided with carbon dioxide concentrations data, which showed higher concentrations in the northwest monsoon compared to the southeast monsoon (Figures 3c and 3d). According to previous research, this region is heavily impacted by a tropical monsoon climate, which is caused by the Asia-Australian monsoon wind systems, which shift wind direction with the seasons, i.e. southeast monsoon and northwest monsoon [15]. [24] reveals that the variation of pH in the Indonesia waters is strongly influenced by monsoon. Since climate change tends to potentially change monsoonal variation over the Indonesian region, it will also have implications for the ocean pH variation.

However, this result analysis is contrary to previous research that documented pH variability in Indonesian Waters. By estimating the monthly fluctuation of sea surface pH in the Banda Sea during the last 18 years (1992-2009) of data based on monthly average temperature and salinity, it found higher pH during the northwest monsoon compared to southeast monsoon [24]. Contrary results between our study and the previous one is likely to result from differing data sources used for analysis. Previous research estimated pH using the algorithm from OCMIP-3 (Ocean Carbon Model Intercomparison Project version 3), which requires certain input parameters for pH calculation, i.e., sea surface temperature and salinity data are derived from HAMburg Shelf Ocean Model (HAMSOM) baroclinic model simulation result, while dissolved inorganic carbon and total alkalinity are obtained from World Ocean Atlas (WOA) climatology [25].

IOP Conf. Series: Earth and Environmental Science 1251 (2023) 012019 doi:10.1088/1755-1315/1251/1/012019

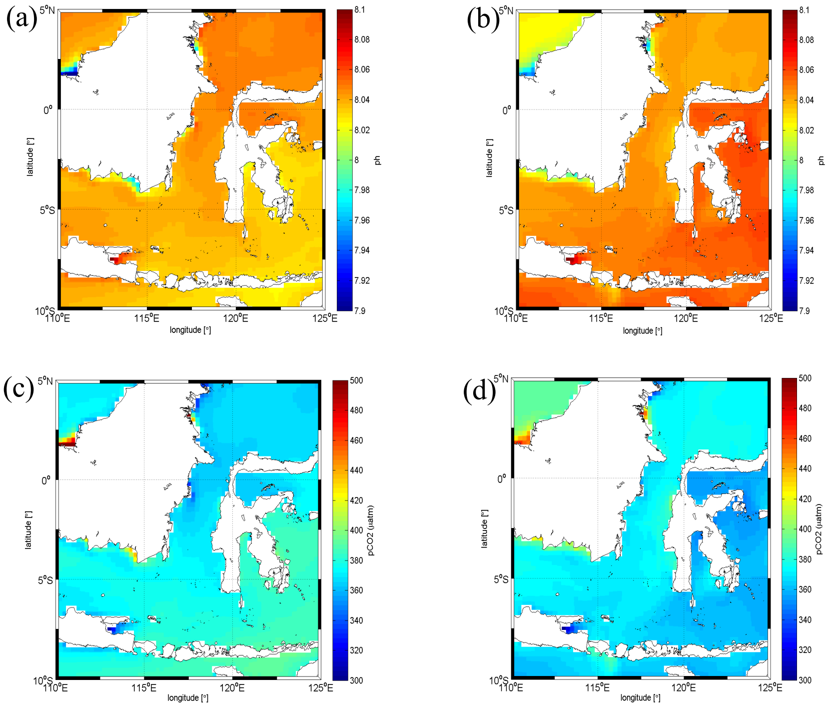

Figure 3. Seasonal variability of pH in Northwest monsoon (a), Southeast monsoon (b) and *p*CO_2 in Northwest monsoon (c), Southeast monsoon (d).

Meanwhile, our study derived pH from CMEMS model product, which was computed from the Surface Ocean Partial Pressure of Carbon dioxide ($SPCO_2$) and reconstructed surface ocean alkalinity using the CO2SYS speciation software. A multivariate linear regression with salinity, temperature, dissolved silica and nitrate as independent variables has resulted in time and space varying alkalinity fields [19]. In situ and satellite observations are integrated within CMEMS data [26]. Both HAMSOM and CMEMS model products were at a monthly resolution, however had differences in a spatial resolution that is 5°x5° and 1°x1° spatial resolution, respectively. This different spatial resolution was considered to contribute to the contrary result.

3.2. Response of Tuna Larvae and Juvenile

Exposure of early life stages of tuna to *p*CO_2 has been found to affect its growth [27], therefore larvae and juvenile be considered in this analysis. Due to the availability of fish data, we analyse the larvae and juvenile density of yellowfin tuna from July 2014 to April 2017. The analysis of fish data shows that the average of yellowfin potential larvae and juvenile density in the Gulf of Bone was 0.426 nb/km^2 and 0.729 nb/km^2, respectively. The highest abundance of larvae and juvenile was found in January and March 2015. Meanwhile, the lowest of it was observed in May 2014. During three years of observation (2014-2017), both yellowfin larvae and juvenile density data series in this area were slightly increasing (Figure 4).

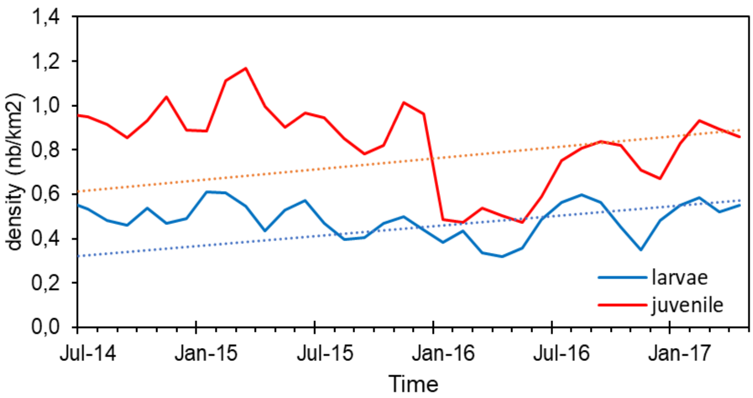

Figure 4. Monthly variability of the larvae and juvenile density of yellowfin tuna.

Yellowfin tuna larvae and juvenile in the Gulf of Bone waters have various spatial correlations with pH and pCO_2 (Figure 5). Generally, a strong relationship is found in the Gulf waters. In comparison, different effects are seen in the southern part of the Gulf of Bone. pH has a positive correlation with two stages of tuna development (larvae and juvenile). Otherwise, pCO_2 has a negative correlation with those two stages of tuna development. It means that OA has a potential impact on reducing skipjack larvae and juvenile in the Gulf of Bone.

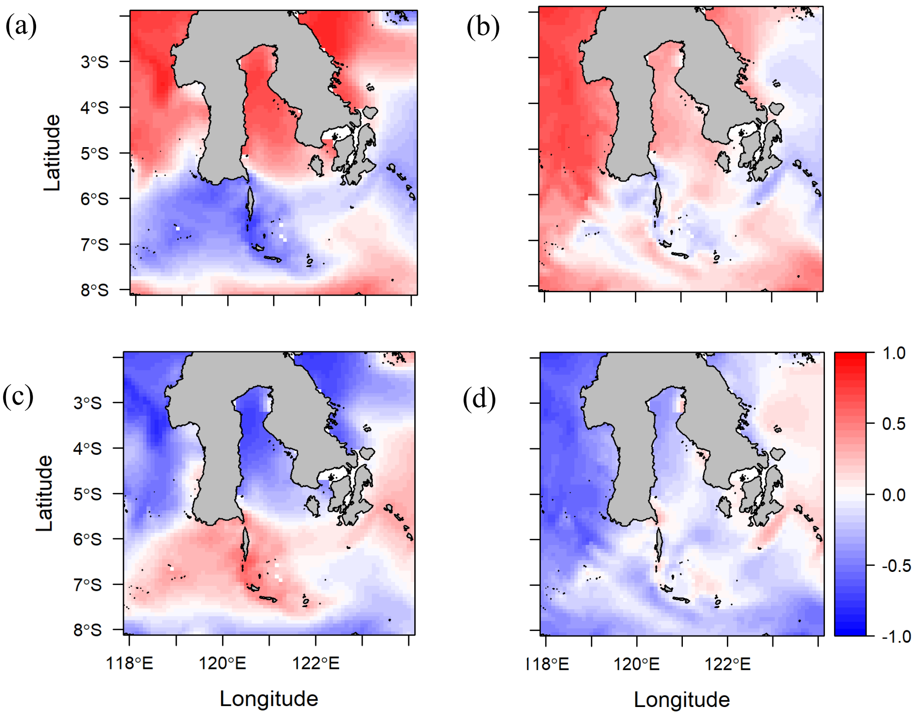

Figure 5. Correlation of yellowfin tuna larvae (a, c) and juvenile (b, d) with pH (upper) and pCO_2 (lower).

Few research works have been assessing the impact of OA on tuna with various findings [6], [7], [8], [9], [10], [11]. However, as a number of studies have failed to detect direct relationships between near future levels of OA and potential tuna vulnerability, it appears that these effects are species specific [3], [8], [9]. For yellowfin tuna, they could adapt more rapidly to near future OA levels because of the very high fecundity and relatively short period of production [8].

4. Conclusion

According to the findings of this study, the variability of pCO_2 tends to increase while the pH tends to decline. As a result, that pH declined in response to ocean absorption of carbon dioxide. The increase of pCO_2 for about 57.870 μatm (347.970 – 405.841 μatm) was found during ten years of observation. During the northwest monsoon periods, pH in the Gulf of Bone tends to be lower compared to other periods. The density of yellowfin larvae and juvenile in the Gulf of Bone was little bit increasing. Both have the potential to decrease with the declined pH and elevated pCO_2 with various spatial correlations. A strong relationship is found in the inner Gulf of Bone. pH has a positive correlation with two stages of tuna development (larvae and juvenile). Otherwise, pCO_2 has a negative correlation with those two stages of tuna development. In comparison, different effects are seen in the southern part of the Gulf of Bone.

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