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THE IMPACT OF ENVIRONMENTAL CHANGES ON THE ABUNDANCE OF BLACK MARLIN, *Makaira indica* (Cuvier, 1832) IN THE EASTERN INDIAN OCEAN

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ABSTRACT

Black marlin (*Makaira indica*) is commonly caught as frozen by-catch from Indonesian tuna longline fleets. Its contribution was estimated around 18% (~2,500 tons) from total catch in the Indian Ocean. Catch-per-unit-of-effort (CPUE), as calculated based on commercial catch records, is one of the essential components for running stock assessment. Despite it always being associated with abundance index (number or biomass), little is known on how environmental factors might contribute to it. The objective of the study is to investigate the impact of physical attributes of the ocean on the distribution of black marlin. Data were collected from August 2005 to December 2017 through a scientific observer program (2005-2017) and a national observer program (2016-2017). Most of the monitored vessels were based in Benoa Port, Bali. In general, time trends of abundance fluctuated, although there had been an increasing trend since 2010, then dropped significantly into a relatively similar figure in 2005. Even though Sea Surface Temperature (SST) and Sea Surface Height (SSH) were statistically significant when incorporated into the models, it allegedly wasn't the main driver in determining the abundance of black marlin. Instead, it was more likely driven by spatio-temporal factors (year and area) rather than environmental changes.

Keywords: Impact; environmental factors; marlins; abundance; GLM

INTRODUCTION

Black marlin (*Makaira indica*) is an apex predator, highly migratory species (Hill *et al.*, 2016; Williams *et al*., 2012), and considered as a non-target species of industrial and artisanal fisheries in Indonesian tuna longline fishery (Setyadji & Nugraha, 2012; Widodo *et al*., 2016). It ranked second after swordfish in terms of catch composition (Setyadji *et al*., 2012). It is also known to have high commercial value in the tropical and subtropical Indian and Pacific Ocean (Nakamura, 1985). In the Indian Ocean, it was caught in the area between 20°N and 45°S, but more often off the western coast of India and the Mozambique Channel (IOTC-WPB16, 2018).

In the Indian Ocean, black marlin were largely caught by gillnets (~59%), followed by longlines (~19%), with remaining catches recorded under troll and hand lines (IOTC-WPB16, 2018). Landing Contribution of black marlin from Indonesian fleet (e.g. longline, handline, and gillnet fishery) between 2013-2017 was around 18% (IOTC-WPB16, 2018) of total catch in the Indian Ocean, ranked fourth after Iran, Sri Lanka, and India. The latest stock assessment result, as calculated using Just Another Bayesian Biomass Assessment (JABBA), suggested that black marlin stock of the Indian Ocean is not overfished but subject to overfishing (IOTC-WPB16, 2018). However, the result came with a high degree of uncertainty, which was driven by the increasing catch of offshore gillnet fisheries from I.R. Iran, the combination of gillnet and longline fishery from Sri Lanka, and the presence of deep-freezing longline from Japan and Taiwan off the western coast of India and the Mozambique Channel (IOTC-WPB17, 2019).

Estimations of relative abundance indices enable the use of more detailed models, which could be pivotal in determining the black marlin stock status and its trend. However It is often delivered with some uncertainties, probably due to its over-reliance on spatial (i.e. fishing location), temporal (i.e. year, month, and/or quarter), and operational factors (i.e. length of branchlines, number of hooks between floats), since most of the CPUE analyses are based on the fishery-dependent data, such as logbook. On the other hand, environmental factors are rarely

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involved in the analyses, probably due to poor understanding on the biology of related species, especially on their distribution.

Nevertheless, incorporating environmental factors into the analyses have been attempted by several authors. Sajeevan (2013) investigated the effect of monsoon and lunar cycle toward catch rates of billfish around Andaman and Nicobar Islands. In addition, Rathnasuriya, Gunasekara, Haputhanthri, and Rajapaksha (2016) put sea surface temperature (SST), sea surface chlorophyll (SSC), and dynamic height of the sea surface (SSH) as possible covariates affecting the abundance of billfishes in Sri Lankan waters. Moreover, Wang and Nishida (2013) found that various environmental factors, i.e. Oscillation Index, Dipole Mode Index, Southern Oscillation Index, sheer currents, amplitude of the shear current, thermocline depth, and temperature gradient only contributed around 15-20% to the nominal CPUE of blue marlin (*Makaira mazara*) and striped marlin (*Tetrapturus audax*) in the Indian Ocean. Despite the recent investigations, no attempt has been made on black marlin (*M. indica*), Indonesian tuna longline fishery in particular.

In this paper, we attempt to investigate the impact of limited environmental variables on the abundance of black marlin, especially from the north eastern Indian Ocean area which are the core fishing ground for Indonesian tuna longline fishery. Results are useful to indicate the relative abundance of black marlin, which is an important fishery resource in the Indian Ocean.

MATERIALS AND METHODS

Fishery and Environmental Data

A total of 2,887 set-by-set data span in detail 1x1 degree latitude and longitude grid from August 2005 to December 2017 were obtained from Indonesian scientific observer and national observer programs that cover commercial tuna longline vessels, mostly based in Port of Benoa, Bali. Fishing trips usually last from three weeks to three months. Main fishing grounds cover from west to southern part of Indonesian waters, stretching from 75˚E to 35 ˚S (Figure 1). It also informed concerning the number of fish caught by species, total number of hooks, number of hooks between floats (HBF), start time of the set, start time of haul, soak time, and geographic position where the longlines were deployed into the water. The response variable in the models was the catch of black marlin(number of fish). Year and quarter were used as categorical (factor) explanatory variables. Additional information was used as explanatory variables as follows:

a. Area stratification

Area stratification method was applied using GLM-tree approach proposed by Ichinokawa & Brodziak (2010); The algorithm showed that the area divided into four categories (Figure 1).

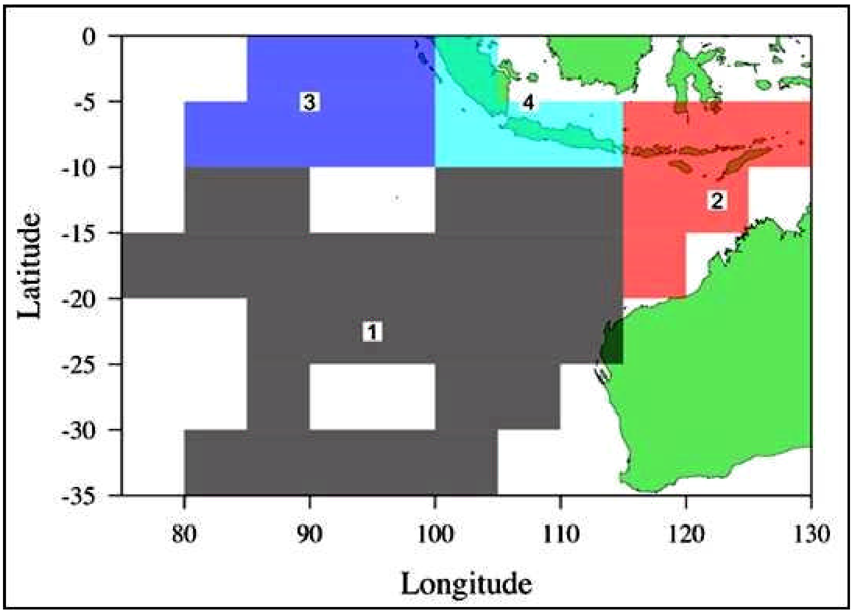

Figure 1. Area stratification used in the analysis based on GLM-tree algorithm.

b. Number of hooks between floats (HBF)

Number of hooks between floats was set as a categorical variable in the model. It was assigned as 1 if HBF <10 hooks (surface longline) and 2 if HBF $\geq$10 hooks (deep longline) following (Sadiyah *et al.*, 2012);

c. Soak time

Soak time was calculated as the time elapsed between the start of the fishing setting and the start of hauling of the longline. Soak time in the model was treated as continuous variable, thus the values were rounded to the nearest integer;

d. Moon phases (29.5 days) were simply categorized into two periods, light and dark, based on Akyol (2013). The light periods consist of the first/last quarters, waxing and waning gibbous, and full moon, while new moon and waning crescent are included into the dark periods.

e. Daily Mean Sea Surface Temperature (SST) was provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at https://www.esrl.noaa.gov/psd/. The spatial resolution was a quarter-degree global grid. To address any possibilities of non-linear (quadratic) relationship between CPUE and SST, it was assigned as a quadratic variable (expressed in R as poly (SST, 2)) (Sadiyah *et al*., 2012) and incorporated as a continuous variable.

f. Daily Mean Sea Surface Height (SSH) was extracted from Copernicus Marine Service Products, namely GLOBAL_REANALYSIS_PHY_001_025 for 2005-2015 datasets and GLOBAL_ANALYSIS_FORECAST_PHYS_001_015 for 2016-2017 datasets. The spatial resolution was a quarter-degree global grid. To address any possibilities of non-linear (quadratic) relationship between CPUE and SSH, it was assigned as a quadratic variable (expressed in R as poly (SSH, 2)) and incorporated as a continuous variable.

Modeling Approach

We considered four GLM models for investigating the abundance of black marlin in terms of its relation to environmental variables. These models were Poisson without environmental (P1), Poisson with environmental (P2), Negative Binomial without environmental (NB1), and Negative Binomial with environmental (NB2). The configuration of the base model is presented as follows:

$$Catch = \mu + Year + Quarter + Cat_{HBF} + Moon + Soak\ Time + AreaTree + offset(\log(Hooks)) + \varepsilon \quad \text{......................} (1)$$

Catch was defined in the number of black marlin caught, effort was the offset from the natural logarithm of the total number of hooks per set and error distribution followed either Poisson or negative binomial. We used a forward approach to select the explanatory variables and the order they were included in the full model. The first step was to fit simple models with one variable at a time. The variable included in the model with lowest residual deviance was first selected. As the second step, the model with the selected variable then received other variables one at a time, and the model with lowest residual deviance was again selected. This procedure continued until residual deviance did not decrease as new variables were added to the previous selected model. Finally, all main effects and the first order interactions were considered and a backward procedure based on Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978) were used to select the final models for the six approaches. We also rely on AIC and BIC to compare these models.

The qualities of the fittings were assessed by comparing the observed frequency distributions of the number of fishes caught to the predicted frequency distribution, as calculated using the selected models. Kolmogorov-Smirnov test was used to assess if the differences of the two distributions (observed and predicted) were significant. Maps were produced using QGIS version 2.14 (QGIS Developer Team, 2018) and the statistical analyses were carried out using R software version 3.3.3 (R Core Team, 2018), particularly the package *pscl* (Zeileis *et al*., 2008), *lsmeans* (Lenth, 2018), *MASS* (Venables & Ripley, 2002), *Hmisc* (Harrell Jr. *et al*., 2018), and *statmod* (Giner & Smyth, 2016).

RESULTS AND DISCUSSION

Results

Descriptive Catch Statistic

Scientific observers and national observers recorded catch and operational data at sea following Indonesian tuna longline commercial vessels from 2005-2017 and 2016-2017, respectively. The combined dataset contained 115 trips, 2887 sets, 3499 days-at-sea, and more than 3.5 million hooks deployed, respectively (Table 1). The spatial data were distributed mainly in the eastern Indian Ocean with most of the observation conducted in the area of southern Indonesian waters, between 0°-35° S and 75°-125° E.

Table 1. Summary of observed fishing effort from Indonesian tuna longline fishery during 2005–2017. Results are pooled and also presented by year of observation. Operational parameters are means (upper entries) and standard deviations (lower parenthetical entries).

Year	Trips	Sets	Days at Sea	Total Hooks	Hooks per Set		Hooks per Float	
2005	9	108	117	157,065	1,454.31	(151.8)	18.6	(1.5)
2006	13	401	401	577,243	1,439.51	(214.9)	11.2	(3.9)
2007	13	265	258	406,135	1,532.58	(326.5)	14.0	(4.4)
2008	15	370	404	483,662	1,307.19	(385.9)	13.0	(4.5)
2009	13	283	288	323,042	1,141.49	(234.7)	12.1	(4.9)
2010	6	165	152	220,394	1,335.72	(457.5)	13.6	(5.2)
2011	3	105	111	110,384	1,051.28	(173.9)	12.0	(0.0)
2012	8	198	192	290,265	1,465.98	(559.1)	14.1	(2.3)
2013	7	225	198	252,919	1,124.08	(210.4)	12.7	(2.1)
2014	5	167	265	193,740	1,160.12	(176.9)	15.0	(2.0)
2015	5	148	241	172,463	1,165.29	(145.2)	14.1	(3.2)
2016	8	244	383	324,068	1,314.89	(146.4)	15.2	(6.4)
2017	10	218	489	279,204	1.214.04	(395.3)	17.2	(4.8)

CPUE Data Characteristics

Black Marlin (BLM) nominal CPUE (fish/1000 hooks) series is presented in Figure 2. In general, the catches of BLM during the last decade were highly variable, but showing an increasing trend. The lowest CPUE recorded was in 2005 (0.05±0.19), as the highest one was in 2009 (0.22±0.59). On the other hand, the proportion of zero catch for BLM was also very high, varying annually between a minimum of 0.82±0.38 in 2011 and a maximum of 0.95±0.23 in 2017 with an average value of 0.89±0.30.

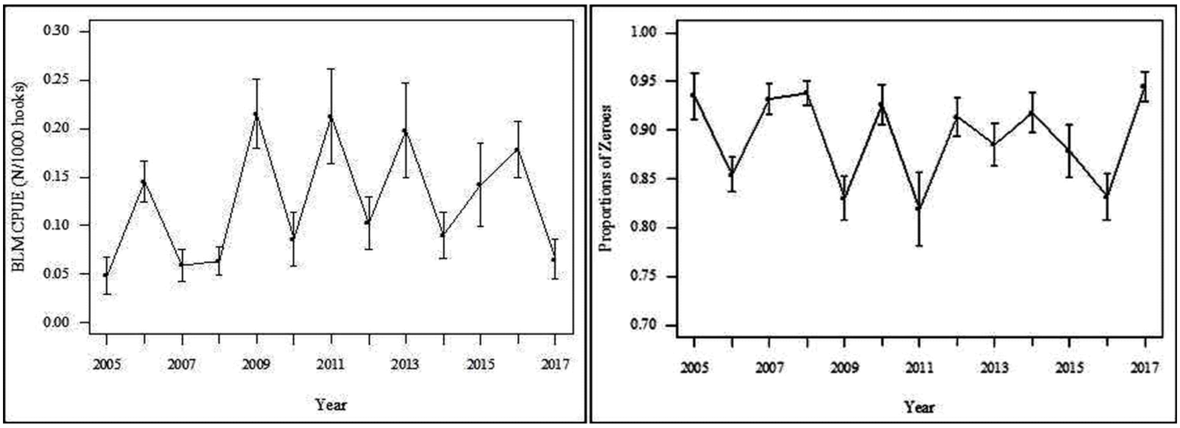

Figure 2. The proportion of zero BLM catches (left panel) and nominal CPUE series (N/1000 hooks) for BLM from 2005 to 2017 (right panel). Remarks: Vertical bars refer to the standard errors.

Influence of SST and SSH

The number of parameters (k), AIC, BIC, logarithm of the likelihood (logLik), number of predicted zero catches, and *p* values of Kolmogorov-Smirnov test were calculated using two model structures (Poisson and Negative Binomial) with two different conditions (with or without incorporating environmental factors). The summary is shown in Table 2. The interactions among variables were excluded to avoid overfitting on the models. A difference of 2 units in the AIC values is not a strong evidence that one model is better than the others (Burnham & Anderson, 2002). Hence, a simple negative binomial (NB) with incorporating SST and SSH into the model was preferred as it had the lowest AIC (2343.95) and BIC (2499.11) values (Table 2).

The number of zero catches in the database is 2,575, however, both Poisson and NB models were inaccurate in terms of predicting it, as shown by the differences between the observed and the predicted number of zero catches. Bias of all the models, including the simple ones, were insignificant as indicated by the *p* values (>0.05).

The negative binomial model with environmental factors was selected as the best profile to describe the effect of environmental changes to the abundance of black marlin. In addition, adding environmental factors only contributed around 2.5%-3% of deviance explained and insufficient to lower the AIC value in all models, although it was considered as influential contributors among variables (Table 3).

Table 2. Summary of indicators as calculated using six model structures: Poisson without environmental (P1), Poisson with environmental (P2), Negative Binomial without environmental (NB1) and Negative Binomial with environmental (NB2). The terms in the column at left indicate: number of parameters (k), Akaike (AIC) and Bayesian (BIC) Information Criteria, logarithm of the likelihood (logLik), number of predicted zero catches (zero), *p* values as calculated using a Kolmogorov-Smirnov test and deviance explained.

Parameters	Model Structures			
	P1	**P2**	**NB1**	**NB2**
k	21	26	21	25
AIC	2492.75	2454.96	2369.46	2343.95
BIC	2618.08	2610.12	2500.76	2499.11
logLik	-1225.38	-1201.48	-1162.73	-1145.97
zero	2523	2520	2538	2573
p.value	0.7371	0.6713	0.9717	1.0000
Deviance explained	14.51%	17.03%	13.67%	16.00%

Table 3. List of deviance table from all models (P1, P2, NB1 and NB2).

1. Model P1

	Df	Deviance	Residual Df	Residual Deviance	Pr(>Chi)	
NULL			2886	2050.3		
AreaTree	3	184.495	2883	1865.8	2.20E-16	***
Year	12	52.501	2871	1813.3	5.05E-07	***
Moon2	1	12.672	2870	1800.7	0.0003712	***
Cat_HBF	1	12.607	2869	1788.1	0.0003843	***
Quarter	3	17.989	2866	1770.1	0.0004422	***

2. Model P2

	Df	Deviance	Residual Df	Residual Deviance	Pr(>Chi)	
NULL			2886	2050.3		
AreaTree	3	184.495	2883	1865.8	2.20E-16	***
Year	12	52.501	2871	1813.3	5.05E-07	***
poly(SSH,2)	2	33.395	2869	1779.9	5.60E-08	***
Moon2	1	13.125	2868	1766.8	0.0002913	***
Cat_HBF	1	14.507	2867	1752.3	0.0001397	***
Quarter	3	16.732	2864	1735.6	0.0008023	***
Soak_Time	1	2.405	2863	1733.2	0.1209584	
poly(SST,2)	2	10.902	2861	1722.3	0.0042915	**

3. Model NB1

	Df	Deviance	Residual Df	Residual Deviance	Pr(>Chi)	
NULL			2886	1310.0		
AreaTree	3	127.445	2883	1182.6	2.20E-16	***
Year	12	38.775	2871	1143.8	0.0001146	***
Moon2	1	7.648	2870	1136.2	0.0056837	**
Cat_HBF	1	7.792	2869	1128.4	0.0052485	**
Quarter	3	8.366	2866	1120.0	0.0390269	*

4. Model NB2

	Df	Deviance	Residual Df	Residual Deviance	Pr(>Chi)	
NULL			2886	1344.7		
AreaTree	3	130.971	2883	1213.8	2.20E-16	***
Year	12	39.559	2871	1174.2	8.51E-05	***
poly(SSH,2)	2	28.12	2869	1146.1	7.83E-07	***
Moon2	1	6.647	2868	1139.4	0.00993	**
Cat_HBF	1	8.224	2867	1131.2	0.004134	**
Quarter	3	7.599	2864	1123.6	0.055065	.
poly(SST,2)	2	7.925	2862	1115.7	0.019017	*

Remarks: Asterisk sign (*) means the significance level, i.e. 0 '***' 0,001 '**' 0,01 '*'

The estimation of standardized catch rates is shown in Figure 3. Overall, the time trends of standardized CPUE were highly fluctuated although there was an indication of increasing trend since 2010, but then dropped significantly in 2017 into relatively similar level as in 2005.

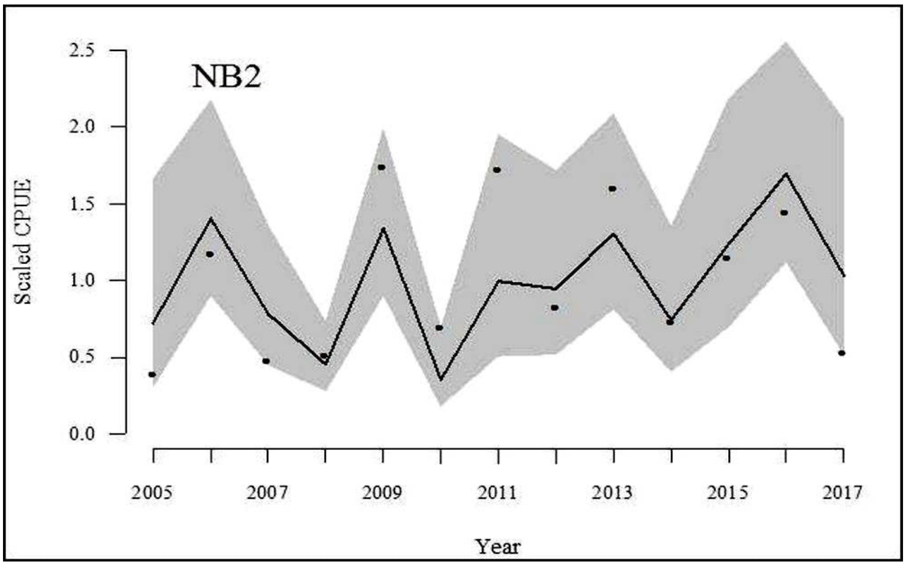

Figure 3. Standardized catch per unit effort (CPUE) calculated using Negative Binomial with environmental factors (NB2). Values were scaled by dividing them by their means.

In addition, the level of uncertainty (showed by the large range of confidence intervals) must be closely put into consideration, even though SST and SSH were significantly contributedIt looked like the abundances of black marlin were driven by other factors, such as the presence of large sum zero-catch-per-set in the data, rather than environmental factors. The lack of spatial coverage also hampered the calculation and perhaps inflicted some biases.

Discussions

Based on the previous study, the model was allegedly influenced more by the number of zero-catch-per-set instead of spatio-temporal factors (Setyadji *et al*., 2018). Moreover, lack of spatial coverage and the fact that black marlin is not a target species hamper the calculation. A few workarounds can be done in order to reduce unwanted zero catches, i.e., using core area (Yokoi *et al*., 2016). This area, which is a 1x1 degree-based catch block with a minimum constant catch for at least 6 years (doesn't need to be consecutive), could reduce the proportion of zero catch from 93% to 58%. Other solutions, such as incorporating random effect into General Linear Mixed Model (GLMM) (Ijima, 2017), using more complex model, i.e., delta-lognormal (Wang, 2017), or applying to smooth in the zero-inflated negative binomial model (Minami *et al*., 2007), could be considered.

However, unlike tunas, which are usually forming school, billfishes (i.e. marlins and swordfish) prefer to get together within specific oceanographic features such as temperature fronts (Brill & Lutcavage, 2001). It is likely due to their life characteristics, where they usually live scarcely and solitary, despite being at the larval or adult stage (Au, 1998; West, 2004). Therefore, it is difficult to estimate their abundance just by merely limited catch and effort data from just a single gear (i.e. longline). In order to get a better understanding amid the "true abundance" of billfishes, we put some environmental factors as additional covariates into the model.

Both sea surface temperature (SST) and sea surface height (SSH) are closely related to the abundance of tuna and billfish species (Lan *et al*., 2017; Lumban-Gaol *et al*., 2015; Su *et al*., 2011, 2015). In this study, high CPUE occurred between 29-31^{o}C, wherein CPUE propensity linearly rose with SSH. Overall, SST was considered as the best predictor for determining the spatial distribution for most marlin species (Su et al., 2011, 2015), although there was a weak relationship between SST and SSH. Even though SST played an important role in this study, it actually did not explain the model a lot. In fact, it only explained merely just 3.4% of total residual deviance in model NB2. Instead, AreaTree, Year, and SSH were the main predictors, contributing 57.2%, 17.3%, and 12.3%, respectively.

CONCLUSION

Despite some constraints related to the data quality (spatial coverage), in general Sea Surface Temperature (SST) and Sea Surface Height (SSH) were statistically significant when incorporated into the models, but it allegedly wasn't the main driver in determining the abundance of black marlin. Instead, it was more likely driven by the effects of spatio-temporal factors (year and area).

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