The use of CMEMS and Argo Float Data for Bigeye Tuna Fishing Ground Prediction

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Abstract. Performance test of bigeye tuna (Thunnus obesus) potential fishing ground (PFG) in South of Java Indian Ocean (SJIO) has been conducted. The input data of this study were sub-surface temperature of Copernicus Marine Environment Monitoring Service (CMEMS) at a depth of 180 m and Argo Float at a depth of 200 m. PFG of bigeye tuna was developed by applying empirical cumulative distribution function (ECDF) analysis. Validation of PFG was done by applying quantitative method. A total number of 1,311 sample location of fish catchment during 2013 were overlayed with PFG map. The results show that the regions with high density of PFG were distributed around the latitudes of about 10°S to 17°S, with preferred temperature between 14.5°C and 17.5°C. Accuracy of CMEMS PFG and Argo Float PFG were 87.2% and 83.7% respectively. Based on the result of the analysis, it can be concluded that both of CMEMS and Argo Float sub-surface temperature shows a high performance.

1. Introduction

Based on the report of the Indian Ocean Tuna Commission (IOTC) in 2016, the annual catch of bigeye tuna (Thunnus obesus) in Indonesia has a considerable amount. Bigeye tuna catchment was amounted to 26,020 tons in 2011 and increased to 35,505 tons in 2013. By 2015 bigeye tuna catchment was recorded at 22,433 tons. Bigeye tuna fishing ground is distributed from west of Sumatra to the south of East Nusa Tenggara [1].

Tuna became mature at 1.47 year for a female with fork length (FL) 88.08 cm and age 1.41 year for a male with FL 86.85 cm [2]. The spatial distribution of bigeye tuna in the East Tropical Indian Ocean (ETIO) is spread over several areas including the area south of Java Island [3]. Bigeye tuna distribution is correlated with oceanographic parameters such as temperature, salinity, and chlorophyll-a [4] and [5]. Thus, the oceanographic factor changes will affect the Potential Fishing Ground (PFG) of bigeye tuna. The dynamics of oceanography in SJIO are influenced by upwelling phenomena. Upwelling will cause the decrease of sea surface temperature (SST) [6].

SJIO has unique oceanographic characteristics where the waters are affected by Indonesian Through Flow (ITF) and El Nino Southern Oscillation (ENSO) [7]. The flow of ITF bring the water mass of the Pacific Ocean to the Indian Ocean reduced SST along the coast of Java and Sumatra [8]. ITF is also causing the rise of thermocline [9]. Water mass of ITF mainly flows in sub-surface below thermocline through three exit passages of Lombok Strait, Ombai Strait and Timor Passage [10]. On the other hand SJIO is also influenced by South Java Current (SJC) [11] and [12], South Equatorial Current (SEC) [13], Kelvin wave [14] and Rosby wave [15].
The habitat of bigeye tuna is strongly influenced by environmental variables, especially SST [16]. Vertical and horizontal distribution of bigeye tuna is also influenced by monsoon, as changes in monsoon cause changes in water temperature [17]. Spatial distribution of tuna is also affected by Indian Ocean Dipole mode (IOD) [18]. This condition is due to the influence of IOD and ENSO to the variability of SST in Indonesian waters [19].

To improve the effectiveness and efficiency of fishing effort, it is necessary to do further analysis on the prediction of high density of fishing ground. PFG was specified based on analysis of SST and chlorophyll-a data through spatio-temporal clustering method [20] and partial correlation method [21], while [22], used the same data to determine the PFG through the suitable index method.

On the other side, various methods of determining bigeye tuna potential fishing ground have been implemented to get the best approach. The 5-degree square cells method was applied to determine the distribution of bigeye tuna. The data used in the analysis are fishing location data, total fish catch, actual deep of fish hooks, in situ measurement of water temperature and dissolved oxygen. The analysis results show the horizontal distribution of bigeye tuna in the 5-degree square cell area and the vertical distribution of fishing rate [3].

Hierarchical cluster analysis was applied to find out the environmental preference of bigeye tuna. The data used are water temperature, salinity, dissolved oxygen, vertical profiles of chlorophyll-a, deployment position of fishing hooks, and number of fish catch [5]. Fishery catch data including fishing position, fish weight, number of fish caught and number of hooks was correlated with satellite remotely data. The spatial distribution of fishing location was then divided into a grid of 1° latitude and 1° longitude. Finally, monthly prediction maps of bigeye tuna catch probability were generated through analysis of the distribution of tuna fishing areas and their correlations with satellite data using Generalized Additive Model (GAM) method [4]. The GAM method was also used to determine the environmental preference of bigeye tuna in southern water of Java-Bali using SST, chlorophyll-a and sea surface height deviation (SSH) data [23].

Bigeye tuna swim in horizontal and vertical movement, recorded in the depth around 100 m during night, and at deeper layers during the day [24]. Swimming layer of bigeye tuna was estimated to be at a depth where its temperature is about 12°C - 13.9°C [5]. Bigeye tuna fishing layer is at the depth around 161 m - 280 m with temperature around 10°C - 16°C [3].

Another method to predict PFG of bigeye tuna is by considering sub-surface temperature. [25], use the data of sub-surface temperature obtained from Argo Float to determine spatial distribution of bigeye tuna. Analysis of spatial distribution of bigeye tuna was done by applying empirical cumulative distribution function (ECDF), the algorithm was analyzed by polynomial regression. Comparison of each PFG studies can be seen in Table 1.

To apply ECDF method into PFG map, accurate sub-surface temperature data are required, therefore need to do performance test to the data. In this study, we are using sub-surface temperature data from Copernicus Marine Environment Monitoring Service (CMEMS) and sub-surface temperature data from Argo Float. This study focuses on performance test of sub-surface temperature data from Argo Float and CMEMS to develop PFG of bigeye tuna.
Table 1. Comparison of PFG studies

| No | Approach                        | Data                                                   | Method                      | Result                                   |
|----|---------------------------------|--------------------------------------------------------|-----------------------------|------------------------------------------|
| 1  | Data mining approach [20]       | SST, Chlorophyll-a, Time and location of fish catches | Spatio-temporal clustering method | Potential Fishing Zone (PFZ)            |
| 2  | Fishing productivity [21]       | SST, Chlorophyll-a, Fish production                    | Partial corelation method   | Fish productivity                        |
| 3  | Mapping of PFG [22]             | SST, Chlorophyll-a, Fish location                      | Suitable Index              | Potential Fishing Ground (PFG)           |
| 4  | Spatial Distribution [3]         | fishing location, total fish catch, actual deep of fish hooks, temperature, DO | 5-degree square cells method | Horizontal and vertical distribution of bigeye tuna |
| 5  | Environmental preference (Song et al, 2009) | temperature, salinity, DO, Chlorophyll-a, vertical profiles, fishing position and number of fish catch | Hierarchical cluster analysis | Catch rate                               |
| 6  | Catch rate (Syamsuddin et al, 2013) | fishing position,fish weight, number of fish caught and number of hooks, SST, Chlorophyll-a, SSHA | Generalized additive model (GAM) | Prediction map                           |
| 7  | Scatterplot Smoothers [23]      | SST, Chlorophyll-a, sea surface height deviation (SSDH) | Generalized additive model (GAM) | potential habitat map                    |
| 8  | Subsurface tuna distribution [25] | Time and location of fish catches, number of fish catch, Multilayer sub-surface temperature | Empirical Cumulative Distribution Function (ECDF) | Spatial distribution map                 |

2. Material and Method

2.1. CMEMS Sub-surface temperature

The sub-surface temperature data of CMEMS is the data of global ocean physics analysis and forecast. This data is part of the global ocean mercator analysis and forecast system. With a horizontal resolution of 1/12 degree, CMEMS data is available at several depth levels between 0 m – 5,500 m [26]. Sub-surface temperature data was generated through a process of combining satellite data with in situ data. The SST of the satellite data was analyzed using multiple linear regression with synthetic temperature profile data from the altimeter to obtain sub-surface temperature [27].

In situ data input of sub-surface temperatures development consist of Argo Profiling Float, expendable bathythermograph (XBT), conductivity—temperature—depth (CTD) and mooring data while satellite data input consist of SST data from Advanced Very High Resolution Radiometer (AVHRR)
and Advanced Microwave Scanning Radiometer (AMSR). RMS error at sea surface is around 0.4°C, reaching its peak at mix layer depth at 0.65°C, and then decreasing with the depth. Temperature data at 0 m - 1,500 m depth is arranged based on satellite data and synthetic temperature profile of altimeter [28].

The CMEMS data used in this study was A Global_Analysis_Forecast_Phy_001_024. The data is a netCDF 4 format on a daily basis – near real-time with 1/12 degree. This high resolution global analysis and forecasting system uses NEMO Version 3.1 ocean model. The NetCDF4 data is a unique data. It can store a 4-dimensional spatial data, latitude, longitude, temperature data and time. To simplify the processing, we extract a netCDF data to GeoTIFF data for each time series. Spatial distribution of sub-surface temperature at 180 m depth is used in this study as presented in Figure 1.

![Figure 1. CMEMS Sub-surface temperature of 180 m depth in January 1, 2016.](image)

2.2. Argo Float sub-surface temperature

The sub-surface temperature data of Argo Float is obtained from the devices that work autonomously with the battery power supply. This equipment collects temperature data from sea level to a depth of 2,000 m. Started in 1999 Argo Float is increasing rapidly with international cooperation programs of many countries, so the global temperature can be observed. Global array of Argo Float provides data through open access database for use in various interests. The data available through the open access database is daily near real-time data, which is processed less than 24 hours since the data is transmitted from each single device of Argo Float. Argo Float devices drift at 2,000 m depth. Every 10 days, these devices float to the surface. In the process of floating to the surface, the device is recording temperature and salinity. When it comes to the surface, satellite gets positions of latitude and longitude [29]. Current condition of Argo Float global array can be seen in Figure 2. Currently Argo Float has involved into an important part of the ocean observation system involving many countries for various interests and issues [30]. The use of Argo Float data includes national security, economic development, quality of life, science education, climate change, observation of temperature, salinity and global ocean circulation [31]. Quality control of Argo Float has been performed [32].
Figure 2. Global ARGO Float Array in June 13, 2017.
Source: http://www.argo.ucsd.edu/

Monthly temperature at 200 m depth of Argo data in 1 degree spatial resolution are downloaded using the Global Argo Marine Atlas application in NetCDF data format (*.nc). The Global Argo Marine Atlas application is available from open source. The data are then converted into tiff raster format (*.tif) in order to be able to use in GIS application, such as QGIS and ArcGIS as presented in Figure 3 (a). Re-interpolation technique by using Kriging method is applied to resample the data from 1 degree (approx. 111 km) to 2 km spatial resolution. Argo Float sub-surface temperature at 200 m depth can be seen in Figure 3 (b).

Figure 3. Argo Float sub-surface temperature in January 2016.tif (a) and kriging interpolation (b).
Source: Global Argo Marine Atlas

2.3 Bigeye tuna PFG
Bigeye tuna fishing layer is at the depth around 161 m - 280 m with temperature around 10°C - 16°C [3]. Spatial distribution of bigeye tuna based on sub-surface temperature divided into two seasons consisting of northwest monsoon (October - March) and southeast monsoon (April - September) [25]. Environmental preference of bigeye tuna was analyzed by empirical cumulative distribution function (ECDF), while algorithm of bigeye tuna spatial distribution is determined by polynomial regression. Then equation to develop PFG is as follow:

Bigeye tuna spatial distribution of southeast monsoon:

\[ P = -0.0005t^2 + 0.016t + 0.016 \]  

(1)
Bigeye tuna spatial distribution of northwest monsoon:

\[ P : -0.012t^2 + 0.411t - 3.229 \]  

(2)

Where \( P \) is Probability of fish catchment and \( t \) is sub-surface temperature (\(^\circ\)C)

Temperature range and \( R^2 \) of equation 1 and equation 2 are provided in table 2.

Table 2. Equation of bigeye tuna spatial distribution \[25\]

| Season   | Layer depth (m) | Equation         | \( R^2 \) | Temperature range °C |
|----------|-----------------|------------------|------------|----------------------|
| Southeast| 200             | \( P = -0.0005t^2 - 0.001t + 0.016 \) | 0.005      | 15 - 19              |
| Northwest| 200             | \( P = -0.012t^2 + 0.411t - 3.229 \) | 0.794      | 15 - 17              |

The equation 2 shows better accuracy than equation 1, where \( R^2 \) of equation 2 is 0.794 while \( R^2 \) of equation 1 is 0.005. Therefore PFG of bigeye tuna in this study will be determined by using equation 2. According to equation (2), when the value of \( P \) is scaled into range value of 0 – 1 (percent), then the equation (2) become as follows:

\[ P : -0.1311t^2 + 4.222t - 32.991 \]  

(3)

2.4 Validation of bigeye tuna PFG

PFG of bigeye tuna was obtained by conducting image analysis of ARGO Float and CMEMS sub-surface temperature using equation 3. Accuracy of PFG for each different type of sub-surface data are performed by applying quantitative method. A total of 1.311 sample of fish catchment during 2013 were employed. The sample were obtained from the annual report of longliner fisherman in Benoa and Cilacap fishing port of Indonesia. Location of sample was overlayed with PFG map. The corresponding data is then calculated and analyzed to determine the percentage of its accuracy. Detail of fish catchment data consist of fishing vessel location (latitude, longitude), fishing date, number of fish and species of fish caught.

3. Result and Discussion

3.1 Sub-surface temperature variability

Monthly sub-surface temperature in the study area are varied. The average temperature during northwest monsoon is relatively cooler than that of the south east monsoon as presented in table 3 which shows the variability of lowest and highest sub-surface temperature of CMEMS and Argo Float during 2016. Also variability of sub-surface temperature average and standard deviation.

Mean differences of CMEMS and Argo Float sub-surface temperature is 1.21°C, this bias can be interpreted that sub-surface temperature of CMEMS is higher than Argo Float. The difference of sub-surface temperature of CMEMS and Argo Float is probably due to difference of measurement depth. Sub-surface data of CMEMS that used in this analysis is at a depth of 180 m, while the Float Argo data is at a depth of 200 m.
Table 3. Cell statistic of CMEMS and Argo Float subsurface temperature in 2016

| No | Date   | CMEMS Min (°C) | CMEMS Max (°C) | CMEMS Mean (°C) | CMEMS Std Dev | ARG0 Min °C | ARG0 Max °C | ARG0 Mean °C | ARG0 Std dev | Mean Diff (°C) | Std dev Diff (°C) |
|----|--------|----------------|----------------|-----------------|---------------|-------------|-------------|--------------|--------------|----------------|------------------|
| 1  | January| 11.22          | 20.18          | 15.21           | 1.42          | 10.04       | 18.17       | 14.04        | 1.72         | 1.17           | -0.30            |
| 2  | February| 10.71         | 20.35          | 14.95           | 1.59          | 10.31       | 17.67       | 13.84        | 1.76         | 1.11           | -0.17            |
| 3  | March  | 11.00          | 20.45          | 14.95           | 1.70          | 10.56       | 17.48       | 13.85        | 1.61         | 1.10           | 0.09             |
| 4  | April  | 11.04          | 20.51          | 15.12           | 1.75          | 11.18       | 17.49       | 14.12        | 1.56         | 1.00           | 0.19             |
| 5  | May    | 12.59          | 20.50          | 15.58           | 1.58          | 12.58       | 17.83       | 14.97        | 1.29         | 0.61           | 0.29             |
| 6  | June   | 13.45          | 20.92          | 15.96           | 1.25          | 13.11       | 17.54       | 15.14        | 1.09         | 0.82           | 0.16             |
| 7  | July   | 12.45          | 21.49          | 15.84           | 1.23          | 12.33       | 17.81       | 14.86        | 1.35         | 0.98           | -0.12            |
| 8  | August | 11.93          | 21.78          | 15.92           | 1.44          | 10.86       | 18.34       | 14.75        | 1.72         | 1.17           | -0.28            |
| 9  | September | 11.64      | 21.08          | 16.15           | 1.48          | 10.83       | 18.69       | 14.72        | 1.87         | 1.43           | -0.39            |
| 10 | October| 11.14          | 22.36          | 16.09           | 1.51          | 10.65       | 18.86       | 14.74        | 2.04         | 1.35           | -0.53            |
| 11 | November | 10.95        | 22.22          | 16.31           | 1.47          | 10.19       | 19.13       | 14.66        | 1.96         | 1.65           | -0.49            |
| 12 | December | 11.67         | 22.25          | 16.19           | 1.44          | 10.22       | 19.23       | 14.04        | 1.98         | 2.15           | -0.54            |
| Average: | | 1.49 | 1.66 | 1.21 | 0.17 |

The standard deviation average of CMEMS and Argo Float sub-surface temperature is about 1.49°C and 1.66°C respectively as presented in table 3. The standard deviation of CMEMS sub-surface temperature is consistent with [28], who found that bias error of CMEMS sub-surface temperature is less than 2°C. [32], found that standard deviation of Argo Float sub-surface temperature reach its peak at mix layer depth about 1.5°C and then decrease with the depth. The differences of both sub-surface temperature standard deviation average is about 0.17°C. Spatial distribution of sub-surface temperature will affect the accuracy of PFG. Variability of sub-surface temperature based on Argo Float can be seen in Figure 4. Spatial distribution of sub-surface temperature in study area is characterized by cold temperatures in the northern region close to Java Island. Sub-surface temperature in the region close to Java Island ranges from 12.5°C to 14°C. While the region around latitude of 15°S has a higher sub-surface temperature ranges from 15°C to 17°C as presented in Figure 5.

Figure 4. time series of sub-surface temperature in 2016.
Source : Global ARGO Matine Atlas
Figure 5. Cross section of sub-surface temperature in 110°E from north to south in February 2016.
Source: Global ARGO Marine Atlas

The low temperature around Java Island may be due to the mechanism of upwelling. The changes of wind speed and direction as a response of the monsoon climate will change the upwelling feature propagation. The shoaling of the thermocline was intensified in June and lead to decrease sub-surface temperature [6]. Besides caused by upwelling, the cold temperatures in the northern region close to Java Island is also as compensation of ITF mechanism [8].

Sub-surface temperature differences of both depth level are confirmed in Figure 6, where the average of sub-surface temperature in 180 m is higher about 1°C to 1.5°C than that of 200 m.

Figure 6. Profile of temperature average in 2016.
Source: Global ARGO Marine Atlas

3.2 Spatial Distribution of PFG
By inserting sub-surface temperature data of CMEMS and Argo Float into equation 3 then we will get spatial distribution of bigeye PFG. Figure 7 and Figure 8 shows the PFG prediction of bigeye tuna in 2016 obtained from Argo Float and CMEMS respectively. As explained earlier, the standard deviation of CMEMS is higher than that of Argo Float, so sub-surface temperature of CMEMS is provides better spatial distribution detail of bigeye PFG than Argo Float.
Figure 7. PFG of bigeye tuna obtained from CMEMS sub-surface temperature in 2016.

Based on the analysis, preferred temperature of bigeye tuna swimming layer was between 14.5°C and 17.5°C. This result is different from those of [5], who find that the most preferable temperature of bigeye tuna swimming layer is in the range of 12.0°C to 13.9°C.

Argo Float PFG in January 2016 shows a high density of PFG (P). The region with high density of PFG was distributed in the latitude around 10°S to 17°S. Waters close to Java Island are marked in blue color, defined as low density of PFG. This condition lasted until March 2016. In April 2016 areas with high density of PFG shifted southward around latitude 12°S, this condition continues even in June 2016 shifts to latitude 15°S. But this condition changed in August 2016 where the high density of PFG shifted back northward to the island of Java around the 9°S latitude and lasted until November 2016.

The spatial distribution of bigeye tuna is in accordance with [1], who states that bigeye tuna fishing ground were observed in the area around 15°S spread from west of Sumatra to the south of East Nusa Tenggara while the fishing effort of longline fleets are recorded around latitude 15°S and longitude between 115°E to 120°E. [31], also states that high-density of fishing ground near Java island reached its peak in July, and decreased in March-June, especially in areas between 5°S-10°S. The decrease of fishing ground in March – June is in accordance with the soutward sifting of high density of PFG around 12°S to 15°S.
Figure 8. PFG of bigeye tuna obtained from ARGO float sub-surface temperature in 2016.

3.3 Validation of PFG

By using bigeye tuna fishing data in 2013 collected from Benoa and Cilacap fishing port of Indonesia, the accuracy of PFG can be obtained. Validation process is done by overlay between data fishing location with PFG of Argo Float and CMEMS as presented in Figure 9 and Figure 10 respectively.

Figure 9 and figure 10 shows the overlay between the fishing location data and the spatial distribution of PFG from the Argo Float and CMEMS sub-surface temperature respectively. High density of PFG is indicated in red, low density is indicated by blue while the medium density is indicated with yellow. Low density is ranges from 0 to 0.33, the medium density is ranges from 0.34 to 0.66 while the high density is ranges from 0.67 to 1. Based on Figure 9 and Figure 10, it can be said that generally most of the fishing location are matched up with the high density of PFG.

Table 4 confirms the accuracy of PFG of Argo Float data. The accuracy of Argo Float PFG is varies between 64% to 92%. Average accuracy of Argo Float PFG is about 83.7%. Overlay between the fishing location data and the spatial distribution of PFG from CMEMS sub-surface temperature is presented in Figure 10. The accuracy of CMEMS PFG is better than that of Argo Float. This is confirmed in Table 5 where the average accuracy of CMEMS PFG is about 87.2%. In general the accuracy of CMEMS are varies between 74% and 95%.
Figure 9. Spatial distribution of actual catch of bigeye tuna and ARGO Float sub-surface temperature PFG in 2013.

Figure 10. Spatial distribution of actual catch of bigeye tuna and CMEMS sub-surface temperature PFG in 2013.
Table 4. Validation data of fishing location and ARGO Float sub-surface PFG in 2013.

| No | Month    | Number of Match up sample | Percentage |
|----|----------|---------------------------|------------|
| 1  | January  | 51 of 67                  | 76         |
| 2  | February | 112 of 123                | 91         |
| 3  | March    | 207 of 225                | 92         |
| 4  | April    | 240 of 283                | 84         |
| 5  | May      | 110 of 122                | 90         |
| 6  | June     | 132 of 142                | 92         |
| 7  | July     | 112 of 128                | 87         |
| 8  | August   | 49 of 53                  | 92         |
| 9  | September| 14 of 22                  | 64         |
| 10 | October  | 31 of 38                  | 81         |
| 11 | November | 38 of 51                  | 74         |
| 12 | December | 47 of 57                  | 82         |

Average: 83.7

Table 5. Validation data of fishing location and CMEMS sub-surface PFG in 2013.

| No | Month    | Number of Match up sample | Percentage |
|----|----------|---------------------------|------------|
| 1  | January  | 63 of 67                  | 94         |
| 2  | February | 118 of 123                | 95         |
| 3  | March    | 206 of 225                | 91         |
| 4  | April    | 269 of 283                | 95         |
| 5  | May      | 115 of 122                | 94         |
| 6  | June     | 130 of 142                | 90         |
| 7  | July     | 116 of 128                | 90         |
| 8  | August   | 48 of 53                  | 90         |
| 9  | September| 17 of 22                  | 77         |
| 10 | October  | 31 of 38                  | 81         |
| 11 | November | 38 of 51                  | 74         |
| 12 | December | 43 of 57                  | 75         |

Average: 87.2

The use of sub-surface temperature data from both CMEMS and Argo Float has a higher accuracy than data usage of SST. [23], use the data of SST, chlorophyll-a and sea surface height deviation to determine the environmental preference of bigeye tuna by applying scatterplot smoother and get the accuracy about 80.5%. [20], use the data of SST and chlorophyll-a by applying spatio-temporal clustering method and get the accuracy about 87.11%.

4. Conclusions
Based on the result of the analysis, it can be concluded that the regions with high probability value of PFG were distributed around the latitudes of about 10°S to 17°S. Based on the analysis, preferred temperature of bigeye tuna swimming layer was between 14.5°C and 17.5°C. In general CMEMS accuracy is higher than that of Argo Float. The standard deviation of CMEMS is better than that of Argo Float. Match up data of bigeye tuna fishing location with CMEMS PFG also higher than that of Argo Float. Generaly it can be said that both of CMEMS and Argo Float sub-surface temperature shows a high performance.
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Author Contributions: Bambang Sukresno designed the study, conducted data analysis, and wrote papers. Ari Murdimanto collected data from ARGO Float, performed pre-process data and image analysis. Rizky Hanintyo collected data from CMEMS, performed pre-process data and image analysis. Denny Wijaya Kusuma collected and analyzed fish catch data. Dinarika Jatisworo performed data interpolation and overlay.

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