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Predicting thermal structure of the ocean using satellite data to locate hooking depths of tuna longlines in the north east Indian Ocean

Jagath Rajapaksha,
National Aquatic Resources Research and Development Agency (NARA),
Crow Island, Colombo 15, Sri Lanka

Tel: +94 112520367 Fax: +94 112520367
Email: Jagath_r@hotmail.com

Satsuki Matsumura
Fisheries Research Agency
15F Queen's Tower B, 2-3-3 Minato Mirai, Nishi-ku, Yokohama, Kanagawa, JAPAN 220-6115
Tel: +81-45-227-2600 FAX : +81-45-227-2700
Email: smatsu@affrc.go.jp

Lal Samarakoon
Geoinformatics Center, Asian Institute of Technology, PO. Box4, Klong Luang,
Pathum Thani 12120, Thailand
Tel: +66 25246487 Fax: +66 25246147
Email: lal@ait.ac.th

Abstract

Ocean environmental parameters such as sea surface temperature, chlorophyll and sea surface height derived from remote sensing satellites were analyzed with yellowfin (*T.albacores)* catches. Fishery data from Sri Lankan long-liners in the northeast part of the Indian Ocean were used. The results have shown that the relationship between yellowfin catch rates and oceanographic parameters are significant. These relationships have been used to predict fishable aggregations of yellowfin tuna using near-real time satellite derived oceanographic parameters. Predicted fishing grounds were validated and shown encouraging results. However, the spatial variability of fishable aggregations is influenced by the thermal structure of the ocean influencing the swimming depths of yellowfin tuna. The accuracy of the tuna forecast can be enhanced by providing hooking depths by predicting vertical temperature profiles in space and time. Hence a predictive model for the vertical temperature of the ocean is developed incorporating temperature vertical profiles from Argo profiling floats, sea surface heights and sea surface temperature obtained from earth observing satellites.

Temperature vertical profiles during the period from 2007-2009 were fitted to a simple 5-parameter model combining a sigmoid curve which represent the mixed layer, thermocline and a linear term to account for deep water cooling with depth. Thermocline depths determined form the model and Sea surface heights were matched on latitudinal basis and found linear relationships. Therefore the sea surface height obtained from satellite data enables to predict thermocline depths which can be used to determine the model parameters for the vertical temperature profiles. Hence, the depths of any temperature considered to be favorable for yellowfin tuna can be predicted.

To predict the swimming depth of yellowfin tuna using the model, swimming temperatures are to be known. Therefore, temperature depth recorders (TDRs) have been distributed among five longline fleets operating in various fishing depths.

Key words: yellowfin tuna, sea surface height, thermocline, fish forecast, Indian Ocean

1 Introduction

Although Sri Lanka has a long history of tuna fishing activities, the technology to increase the fishing efficiency has not been developed compared to the other fishing nations in the Indian Ocean. Length of Sri Lanka's longline fleets falls below 20 m and the fishing capacity is limited in terms of storage, equipments fishing gears and onboard technology. The annual fish production is approximately 385,000 tons from marine coastal fishery (52%), offshore/high-seas fishery (34%), and inland/aquaculture fishery (14%). Offshore/high-seas production is 130,000 tons and out of 32% is total tuna while 20% is yelowfin tuna as at 2010 statistics. Yellowfin tuna is a commercially important species and the economic regain in this fishery is low due to inefficient catch rates and high operational cost. Long search time leads to an increased fuel cost as well as low quality fish landings thereby less export and low revenue. Therefore increasing the fishing efficiency will helpful to reduce the operational cost and quality fish landed.

Satellite based fish forecasting system was developed in 2008 analyzing the available fishery data with satellite derived oceanographic parameters such as sea surface temperature, chlorophyll and sea surface heights (Rajapaksha et al 2010). However, the forecast system needs to be improved in several aspects such as increase the precision of forecasting parameters by long term fishery data collection, incorporate higher resolution near real-time satellite information and providing hooking depths for longlines settings. Existing tuna forecasts accompany potential areas for fishing however accurate fishable depths are missing to ensure the catch efficiency of longlines. Therefore, this study reveals an approach to predict vertical temperature in space and time.

Indian Ocean is greatly influenced by two monsoon winds; southwest and northeast causing characteristic seasonality of temperature, phytoplankton concentration, circulation and mixed layer properties. Previous studies have indicated that the distribution of tuna species is greatly affected by oceanographic conditions such as sea surface temperature (Sund et al., 1981; Ramos et al., 1996), hydographic fronts (Laurs and Lynn, 1977; Laurs et al., 1984; Stretta, 1991; Kimura et al., 1997), and depth of the thermocline (Ueyanagi, 1969).

Remote sensing techniques show a great potential to support global fisheries management and the successful exploitation of pelagic fishery resources (Santos, 2000; Yamanaka et al., 1988). Further, the satellite remote sensing has proved to be a useful tool to study thermal fronts, eddies and other oceanographic features where tunas are reported to be aggregated. There are several studies have shown associate movements of tuna and catch rates with environmental conditions (Ramos, 1992; Podesta et al 1993; de Rosa & Maury 1998; Bigelow et al 1999). However, it is important to know the fishable depths for longlines to increase the fishing efficiency of the gear on species and to understand the vertical distribution of fish (Nakano 1997). Setting longline hooks deeper is generally accomplished by increasing number of branch line between floats, since the distance between branches remain unchanged, about 50 m.

It has been repeatedly claimed that sea level, isotherm depth, heat content and dynamic height of the upper layer of the ocean are related. Shoji (1972) related sea level and dynamic height in the Kuroshio and found an excellent linear relation over a wide range of 1m. Saur (1992) invested the sea level differences between Honolulu and San Francesco and obtained the correlation coefficients of 0.65 and 0.54 respectively between sea level and dynamic height at the two locations. Wunsch (1972) found that low-frequency variations of sea level at Bermuda are reflected in the density structure and dynamic height. Chaen and Wyrki (1981) related sea level and isotherm depth at Truk and found a correlation of 0.92 for monthly mean values.

This study reveals an approach made to find relationships of the dynamic SSH and thermal structure by modeling temperature profiles obtained from Argo floats in the North East Indian Ocean.

2 Objectives

The aim of this study is to develop a predictive model for thermal structure of the ocean using satellite derived oceanographic parameters such as sea surface temperature (SST) and sea surface height (SSH). The distribution and abundance of yellowfin tuna in the water column is vital to improve the existing fishery forecasting system. Therefore, knowing swimming temperature of fish, the depth of that temperature can be predicted by the model to support hooking depth for tuna longliners.

3 Materials and methods

3.1 Temperature and depth profiles

Argo is an array of approximately 3000 profiling floats that observe the upper 2000 m of the ocean in near real-time. The floats capture important oceanographic parameters such as salinity and temperature and upload data to ground stations via satellites in 10-day cycles. Argo temperature and depth profiles were obtained from the Global Ocean Data Assimilation Experiment (GODAE), a near real-time global ocean data support for climate forecasts and oceanographic research. In this study, the data were obtained between latitude from 00-20N and longitude between 070-095E during a 3-year period from 2007 to 2009. Figure 1 shows the distribution of data sets in the study area.

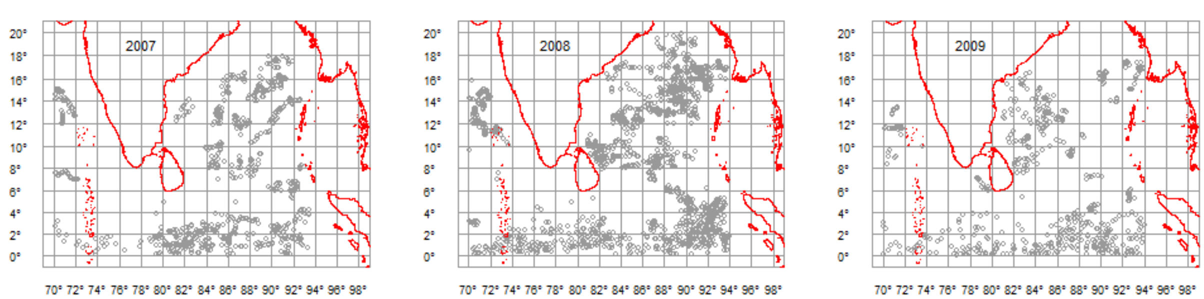

Figure 1: Maps showing the distribution of Argo temperature profiles used in the study during 3-year period (2007-2009).

3.2 Sea surface height

Sea surface height data were obtained from the information collected by TOPEX/Poseidon and ERS satellite altimeter data. The data were available at archiving, validation and interpolation of satellite oceanographic data (ftp://ftp.cls.fr/pub/oceano/AVISO/) in netCDF format. These data (gridded 1/3 latitude x longitude) were obtained in merged delayed time products of sea surface dynamic heights (SSH)

3.3 Sea surface temperature

Sea surface temperature (SST) merged data product from two satellite sensors AMSRE and AVHRR were obtained from the NOAA optimum interpolation 1/4 degree daily sea surface temperature analyses. The SST data are distributed by National Climate Data Center of NOAA (ftp://eclipse.ncdc.noaa.gov) in netCDF format.

4 Data treatments

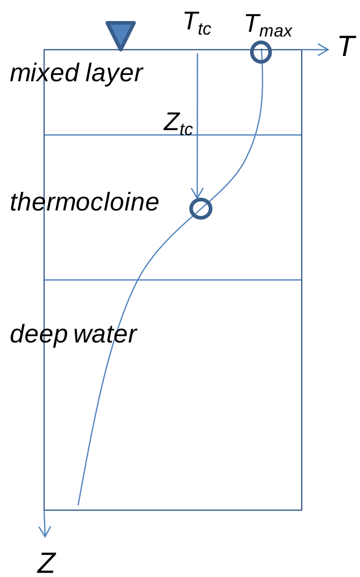

Figure 2 Sketch diagram showing temperature vertical profile of the ocean, illustrating upper mixed surface waters and non-mixed deep waters and in between the thermocline layer

A simple 5-parameter equation combining a sigmoid curve which represents the mixed layer and thermocline, and a linear term to account for deep water cooling with depth can be represented as,

$$T_a(z) = T_{max} + (\rho z - A)\left(\frac{z^\lambda}{z_{tc}^\lambda + z^\lambda}\right) \qquad \text{Equation 1}$$

where z being the depth, T_a the ambient temperature, z_{tc} the depth of thermoline (depth of maximum temperature gradient) and ρ, A and λ being parameters.

SSH datasets were gridded into 1 degree (lat x lon) grids during the 3-year period and matched with model parameters of corresponding profiles. Statistical analyses were performed on latitudinal basis to obtained relationships between model parameters and sea surface heights and sea surface temperatures measured from satellites.

5 Results and Discussion

Argo observation of temperature profiles are not an *in-situ* but measure temperature and pressure in the water column with self controlled buoyancy to move from surface down to 1000-2000 m. at the same time the floats are moving with the prevailing horizontal currents. The average equatorial surface current is around 0.5 m s^{-1} but it is low towards the mid latitudes. However, Argo floats spent their time below the very surface layer during its 10-day cycle. Therefore, we assumed that the average horizontal speeds of floats are around 0.125 ms^{-1}, so that the spatial extent of 10-day cycle can be taken as 1 degree. Hence data matching were performed in 1 degree grids of sea surface heights.

Figure 3 shows the temperature profiles in the study area during the 3-year period. Total of 1391 profiles were used in this analyses. Temperature of the upper 40 m varies from 24-31^{o}C while the temperature at 500 m fluctuate between 9-11^{o}C.

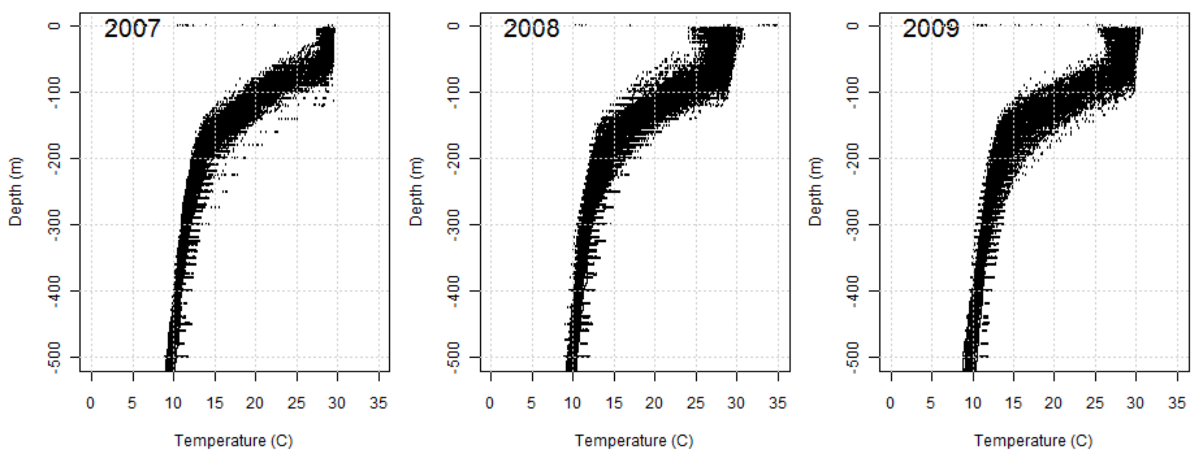

Figure 3: Temperature vertical profiles in the surface 500m obtained from Argo floats in the study area during the period from 2007-2009.

The 5-parameter model (Eq.1) is fitted to the observed temperature profiles and given that the R^2 over 0.9 implying the goodness of model fits. Figure 4 shows the measured argo temperature profile (dots) and model fit (solid line) to the profile on Jan. 25th 2008 at latitude 12.66N and longitude 70.33E. Similarly all the profiles were fited in to the model to obtain the series of parameters including temperature at thermocline. The dashed horizontal line indicates the thermocline depth (127.26 m) and dashed vertical line indicates the corresponding thermocline temperature (27.8^{o}C).

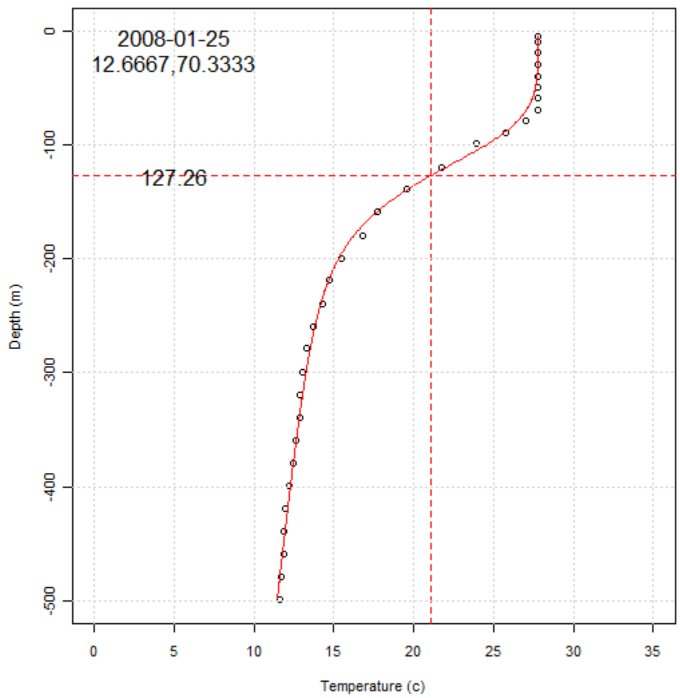

Figure 4: Model fit (solid line) to the temperature profile measured by Argo float (dots) on 25.01.2008 at location 12.66N and 70.33E.

Thermocline depth varied from about 75 m to 150 m occurring highest frequency around 110 m. Temperature at thermocline varied from 19.0-23.0^{o}C while its mean around 21^{o}C. Average temperature of the surface 40 m layer varied from 27-30^{o}C and the mean is around 29^{o}C (Figure 5).

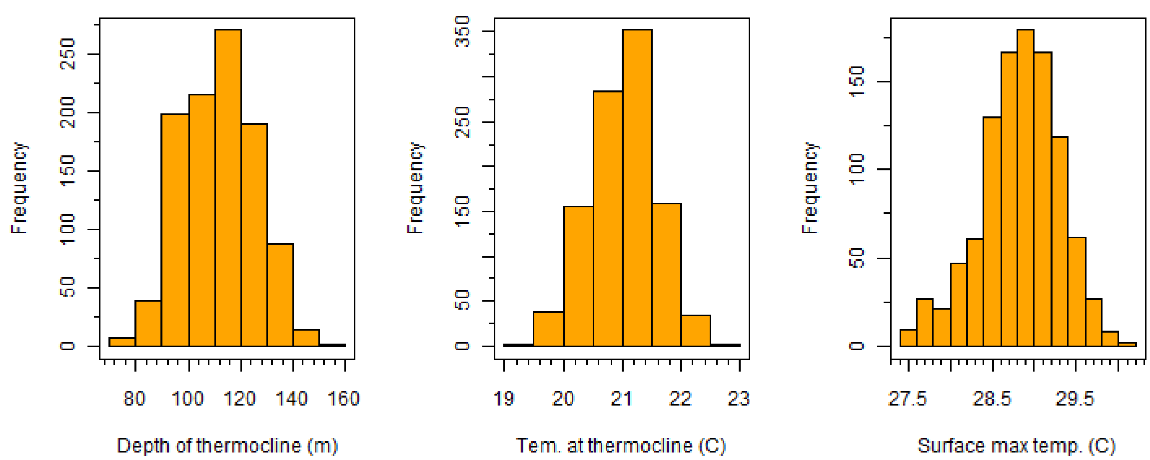

Figure 5: Histograms of thermocline depth, thermocline temperature and surface maximum temperature from model fits to the Argo data obtained during the 3-year period.

Matching the profile parameters to satellite sea surface heights, latitudinal depths of thermocline has shown linear relationships. Hence the sea surface heights measured by satellites can be used to predict themcline depth in space and time (Figure 6). The linearity of thermocline depth against sea surface height may influenced by the other oceanographic parameters such as tides, currents, local winds etc. This relation may also be influenced by the corresponding sea surface height variation over the float cycle (10-day). However, assuming float drift during the 10-day cycle is 1 degree, the SSH data in 1x1 degree grids have been used for data matching.

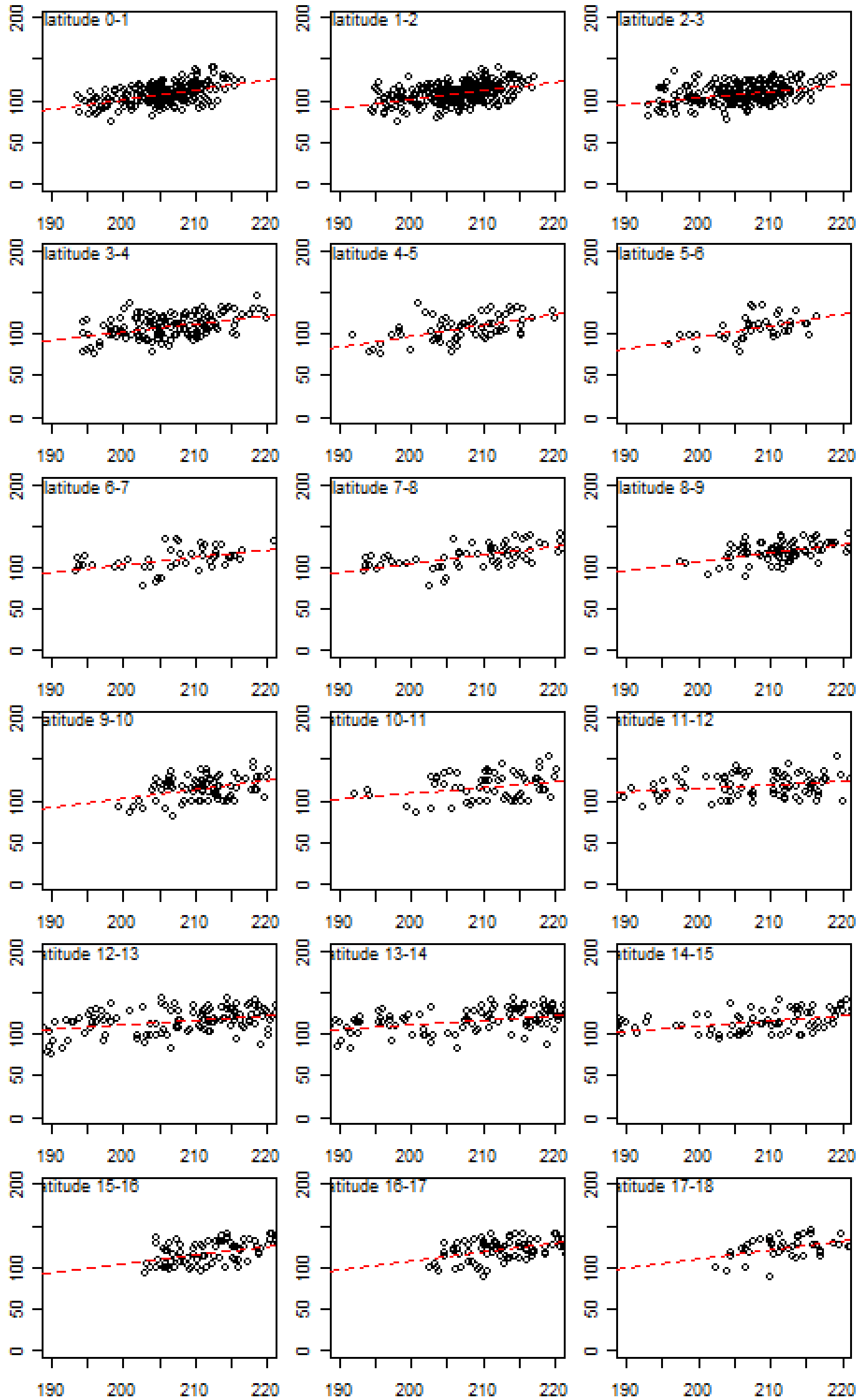

Figure 6: Latitudinal (00-18N) plots of thermocline depths against sea surface height obtained from TOPEX/Poseidon showing a linear relationship

Estimation of other model parameters for latitude between 12-13N can be obtained by fitting linear models as shown in the Figure 7. Similar relationships have been obtained for other latitudes from 00-18N for profile predictions using satellite SSH and SST.

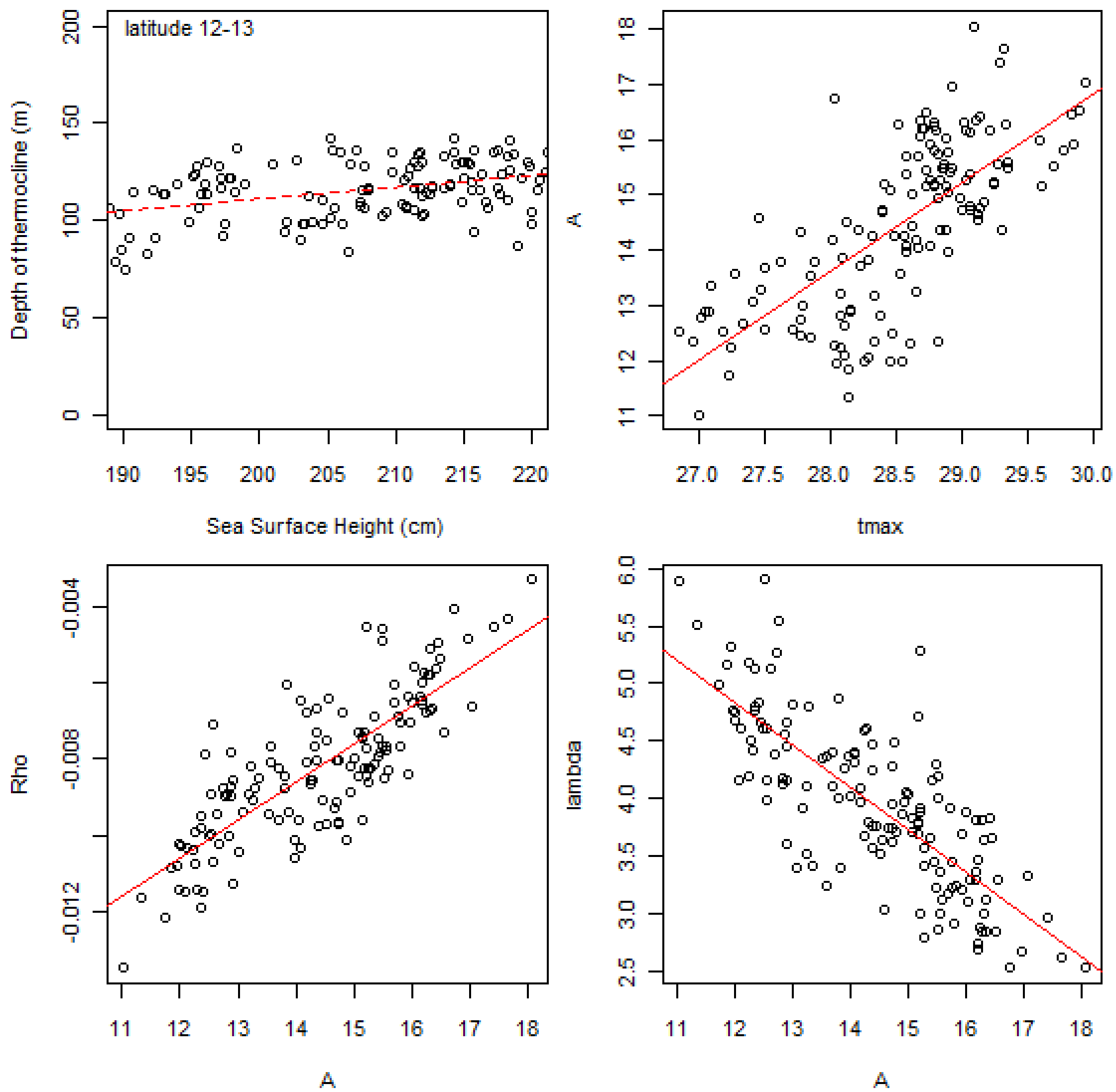

Figure 7: Linear model fits to the model coefficients, upper left Z_{tc}, vs SSH, upper right A vs T_{max}, lower left ρ vs A and lower right λ vs A

Test predictions have been made using SSH and SST data obtained from the two satellites and the Figure 8 shows the model predictions compared with Argo observations on 16th Sep. 2007. Predicted profiles are reasonably close to the observations and therefore, spatial prediction of temperature profiles can be made using TOPEX/Poseidon SSH and AMSRE-AVHRR SST data products.

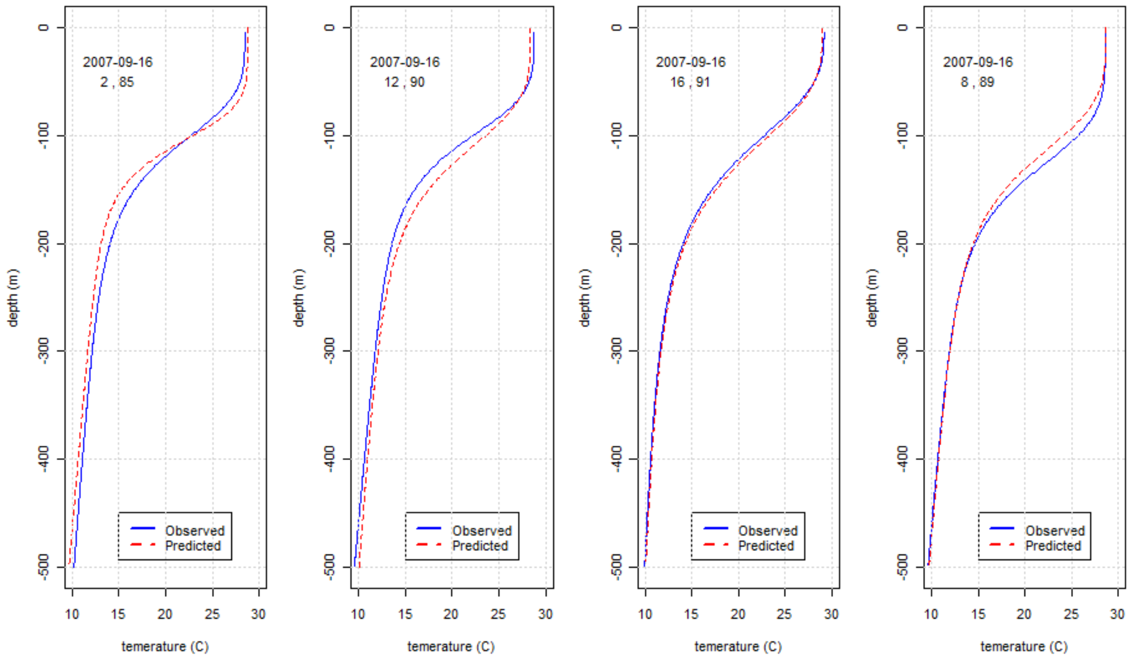

Figure 8: Comparison of model predicted temperature profiles (dashed line) and Argo profiles (solid line) in four locations (02N, 085E), (12N, 090E), (16N, 091E) and (08N, 089E) on 2007.09.16

6 Conclusion

Satellite derived surface information such as SSH and SST can be used to predict subsurface thermal structure of the ocean. However, the relationships between surface information and subsurface structure can be improved by incorporating oceanographic parameters that influence the model results. Sea level variability on top of dynamic sea surface height may have an influence for the relationships obtained in this study. As the Argo floats provide the profile data in 10-day cycles, SSH variability during this period may have influences on the results. Horizontal movements of float in 3-dimensional oceans are variable and depend on the prevailing ocean currents. Therefore, the averaging grid sizes for SSH to match with the temperature profiles is uncertain as the horizontal movements of floats have different speeds in time and space. On the other hand the Bay of Bengal has considerable salinity variation due to huge fresh water supplies from major rivers such as Ganges and Brahmaputra may also affecting the depth measurements by Argo floats.

Although satellites provide bulk surface information, this study is an approach to use satellite surface information to predict subsurface thermal structure of the ocean. The prediction methodology can also be incorporated with near real-time observation of Argo data.

This study reveals that the methodology developed can be used to predict any depth of interested temperature, for instant tuna aggregating temperature to locate tuna longlines in appropriate depths. However, tuna aggregating temperature in the North East Indian Ocean is not properly known. Therefore, temperature depth recorders (TDRs) have been distributed among five fishing fleets to collect necessary data to determine the swimming temperatures of yellowfin tuna.

7 Acknowledgements

The Argo data were obtained from Global Ocean Data Assimilation Experiment (GODAE) at ftp://usgodae.org/. Sea surface height obtained from TOPEX/Poseidon and blended sea surface temperature products obtained AMSRE and AVHRR distributed by NCDC, National Climate Data Center (ftp://eclipse.ncdc.noaa.gov/) of NOAA. This study was supported by the Space Application for Environment (SAFE) which is an initiative of Asia Pacific Space Agency Forum (APRSAF).

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