Detection of pelagic habitats and abundance of skipjack tuna in relation to the environment in the Indian Ocean around Sri Lanka

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Using remote sensing data of sea surface temperature (SST), chlorophyll-a (Chl-a) together with catch data, the pelagic hotspots of Skipjack tuna (SKPJ) were identified. MODIS/Aqua satellite data and the fish catch data were obtained during 2002-2016 period. Empirical cumulative distribution frequency (ECDF) model of satellite-based oceanographic data in relation to skipjack fishing was used for the initial statistical analysis and the results showed that key pelagic habitat corresponded mainly with the 0.4 – 0.7 mg m^{-3} Chl-a concentration. Chl-a represents the phytoplankton that attracts the food items of SKPJ like zooplankton and nekton The favorable SST range for SKPJ is 26 - 27 ^{0}C which provides suitable thermocline and an optimum level of upwelling to circulate nutrients needed for the primary production. The high total catches and CPUEs were found within the months of September to December and the optimum levels of Chl-a, SST also were observed in similar months. Hence, the South-West monsoon season was identified as the best and peak season of SKPJ fisheries. SST and Chl-a are important indicators to detect the habitats of SKPJ and the maps prepared can be used in the future to cost-effectively and efficiently identify and demarcate the biological conservation regions or fisheries zones of SKPJ. According to GAM the 0.3 - 0.6 mg m^{-3} Chl-a, 28 - 28.5 ^{0}C SST in Western and 0.25 - 0.3 mg m^{-3} Chl-a and 28.5 - 28.8 ^{0}C SST in Eastern were found as highly correlated predictor variables value ranges with SKPJ abundance. The deviances explained in above areas in GAM were 90.8% and 61.4% respectively. The GAM was considered as a robustly dealing method with nonlinear relationships and it can be used to model the fish catch abundance with influencing variables significantly since it could predict the CPUE values greater than 90% similarly to nominal CPUEs in both subregions of the study area.

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ABSTRACT

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Keywords: Chlorophyll-a, Sea Surface Temperature, Indian Ocean, Bay of Bengal, Phytoplankton, Catch per unit effort, Fisheries, Generalized Additive Model

Introduction

Sri Lanka is one of the oldest and one of the most famous tuna producing islands in the Indian Ocean. Yellowfin tuna, Skipjack tuna, Marlin, Sailfish, Swordfish, rays, and sharks are some commercially valuable fish species live around Sri Lanka (Ariyawansa, Wijendra, and Senadheera 2003; Elepathage and Tang 2018; Indian ocean tuna commission 2019). Among these species Skipjack tuna (*Katsuwonus pelamis*) is an important migratory fish that significantly contributes to the economy and the global fishery industry. Skipjack tuna (SKPJ) plays an important role in tropics in balancing the ecosystems (Yen et al. 2016). SKPJ may relocate searching for the environment satisfy their physiological and phenological needs since they are sensitive to the environment change (Yen et al. 2012).

Some studies have recognized heat exchange as a factor that regulates the spatial range and depth of the habitats of tuna species and thus the catchability of fishing operations (Brill et al. 2005). Temperature variations in oceanic surface waters specially near coastal boundaries and near the equator are corelated to heat exchange at the ocean-atmosphere interface and to heat transported by ocean currents (Alexander et al. 2002; Luis and Kawamura 2004). The steep temperature gradient in the water column comprised with two layers with different temperatures is called thermocline (Qian, Hu, and Zhu 2003; Schott, Dengler, and Schoenefeldt 2002). When the wind blows, it mixes the surface waters but only down to the thermocline. The density difference is sufficiently strong to resist further mixing, and so the heat accumulates mostly near the surface (Jana et al. 2018). As the major indicator of the heat exchange, thermocline and stratification, sea surface temperature (SST) is used for investigating the distribution of migratory fish species (Abdellaoui B 2017; Brill et al. 2005; Lan, Evans, and Lee 2013; Yen et al. 2016).

Ocean temperatures and other physical and chemical variables change seasonally and they regulate the ocean climate (Badjeck et al. 2010; Fernandes et al. 2013). These changes in ocean affect several biotic components such as phytoplankton distribution and abundance (Elepathage and Tang 2018; Elepathage, Tang, and Wang 2018; Kong et al. 2019; MacNeil et al. 2010).

Phytoplankton is the primary biological component in the ocean that responsible for nutrient and energy transformations within both coastal and open ocean waters. The ability to produce energy from carbon dioxide and solar energy makes these organisms' key players in the global carbon cycle too (Kong et al. 2019). Conversely, blooms of toxic or noxious species of phytoplankton can disrupt energy transfer in planktonic food webs and result in illness or death of mammals, birds, and commercially important fish and shellfish (Hallegraeff 2010). SKPJ also depends on zooplankton and nekton (Zainuddin et al. 2017).

However, climate change has lead to several differences in ocean temperature and ecosystem stability (Chan et al. 2019; Pörtner and Peck 2010). Since the rate of climate change and the impacts differ in different oceanic environment regions (Pörtner and Peck 2010), and since there are some genetic variations and the adaptation differences among different communities of SKPJ (Dammannagoda, Hurwood, and Mather 2011) the favorable conditions for these communities also may be different in each region. However, the optimum environmental conditions for these species in the Indian Ocean region around Sri Lanka have not been studied sufficiently.

At present, the physical, chemical and biological components of the ocean can be detected using satellite remote sensing (SRS) data and geographic information system (GIS) methods (Kong et al. 2019; Nehorai et al. 2009; D. L. Tang, Kawamura, and Luis 2002; D. Tang and Pan 2011) and they provide powerful tools to detect potential fishing grounds, particularly for highly migratory fish species (Elepathage, Tang, and Wang 2018). Hence, in this paper, using SRS and GIS we studied the extent of the effect of Sea Surface Temperature (SST) and phytoplankton density (through Chl-a) to skipjack in the Indian Ocean region around Sri Lanka. The major objectives of the study were to identify the pattern of temperature, Chl-a, and SKPJ variations in Sri Lankan ocean region, to identify the optimum levels of SST and Chl-a favorable for SKPJ, to map the potential hot spot habitats of SKPJ according to the results and to model the SKPJ abundance according to the influencing factors.

Materials and methods

Study area

The area within latitudes 2^0N – 13.5^0N and longitudes 76.5^0E - 88^0E was the target area of this study and indicated in Figure 1. The study area was studied as four regions in initial analysis (NorthWest: NW, North East:NE, South West:SW, South East:SE) and as 2 region in modeling study (Western and eastern).

Satellite data

Aqua/MODIS satellite remote sensing data of SST and Chl-a were used to derive environmental variables. The data from 2002-2016 were used for initial analysis. Gillnet fishery data of SKPJ were obtained from the Indian Ocean Tuna Commission (IOTC) and The National Aquatic Resources Research and Development Agency (NARA)- Sri Lanka. Fishing frequency data can be used as an index of fish occurrence and CPUE data is a good proxy of fish abundance (Lehodey et al. 1998).

Fish catch per unit effort was calculated in

CPUE Skipjack tuna = Number of fish caught/ Number of trips of gill net fishing

Method

The SST and Chl-a data were extracted under the fish catch points and the monthly spatial distribution maps of the environment variables were prepared. Aqua/MODIS images were processed by SeaDAS, ILWIS 3.3 and Arc GIS 10.5 software. The point maps with fish catch data were interpolated using ArcGIS 10.5 to allege the potential fishing grounds.

To describe the relationship between oceanographic conditions of SST, Chl-a and fish CPUE, empirical cumulative distribution function (ECDF) analysis was used. The ECDF functions (Sukresno et al. 2015) can be mathematically represent as follows:

$$\mathrm{f(t)} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{l(x_i)} \qquad (1)$$

With the indicator function

$$l(xi) = \begin{cases} 1, & xi \leq 1 \\ 0, & xi > 1 \end{cases}$$

$$\mathrm{g(t)} = \frac{1}{n}\sum_{i=1}^{n} \frac{\mathrm{yi}}{\mathrm{y}} \mathrm{l(x_i)} \qquad (2)$$

$$D(t) = \max |f(t) - g(t)| \qquad (3)$$

Where,

f(t): empirical cumulative frequency distribution function,

g(t): catch-weighted cumulative distribution function,

l(xi): indication function

D(t): the absolute value of the difference between two curves f(t) and g(t) at any point t, and assessed by standard Kolmogorov- Smirnov test,

n: the number of fishing trips

xi : the measurement for satellite-derived oceanographic variables in a fishing trip i, t: an index, ranging the ordered observations from lowest to the highest value of the oceanographic variables,

yi: the CPUE obtained in a fishing trip i,

$\overline{y}$: the estimated mean of CPUE for all fishing trips. The coordinate labeled "max" represents the specific value of the variables at which the difference between the two curves (|g(t)-f(t)|) was maximum.

The graphs were drawn for the f(t), g(t) and D(t) values to analyze the pattern of distribution and to find out D(t) =max |f(t) – g(t)| graphically. Possible fishing grounds were demarcated in each map according to the time using the results of ECDF analysis.

Then to improve the nonlinear-correlation Generalized Additive Model (GAM) was tested approaching by means of smoothing functions fn(x) (Hastie and Tibshirani 1990). For GAM analysis, the data during 2014-2016 were used as the train data set ant it was conducted in Ri386 3.4.2. The aim of this investigation was to identify the nonlinear relationship between the abundance of SKPJ and environmental conditions. The year and the month were used as the seasonal factors and the cubic spline function used in GAM can be written as

$$SKPJ\ CPUE = Year + Month + s(SST) + s(Chl - a) + \varepsilon$$

Where ε = interactions.

GAM was applied to Western and eastern subregions separately. Using the model results the CPUE values for both regions were predicted. The similarity of the predicted values and the nominal values were tested using paired T-test in SPSS 16.

Results

Chl-a and SST change within the study area

In this study, we analyzed the variations of the SST and Chl-a during 2002-2015 initially. The ocean region around Sri Lanka experiences two major monsoons which are called South West monsoon (Summer monsoon) which prevails from June - September with heavy rains and the North East monsoon (Winter monsoon) occur from December - April (De Vos, Pattiaratchi, and Wijeratne 2014). These monsoonal events have half year cycles with reversing winds and currents. They make several changes in SST and the upwelling scenario (Rath et al. 2017).

Previous studies have found that the potential habitat for SKPJ lies within the warm surface layers of tropical and subtropical oceans (Akaomi et al. 2005; Lehodey et al. 1998) and their migration, distribution, and abundance are closely linked with oceanic fronts and eddies (Andrade 2003). During the summer monsoon, heavy rainfalls and enormous river discharge into the study area form a barrier layer between low-salinity surface waters and highly saline deep-ocean waters (Girishkumar et al. 2011). The stratification occurs with the barrier layer formation makes small-scale mixing across this layer which leads to heat mass momentum and biogeochemical fluxes (Vinayachandran, Murty, and Ramesh Babu 2002). Large-scale currents and eddies transport the low saline water towards the center of the Bay of Bengal which is located at the Eastern side of the study area. These eddies degenerate into submesoscale and create sharp salinity fronts and filaments (Sengupta et al. 2016). Lateral mixing is linked with these submesoscale dynamics and they regulate the SST (Jinadasa et al. 2016). During the SW monsoon with the high precipitation and lateral mixing SST gradually decreases while Chl-a increase, providing high biological productivity (Sarangi and Devi 2017). Hence it provides the clue to understand the SKPJ is linked with eddies due to the low SST and high primary productivity. The monthly plots in Figure 2 show the reducing SST and the increasing Chl-a within the study region from July to December in 2006 as an example.

SKPJ catch distribution in the study region

Several studies have found that SKPJ distribution is affected by the SST and the Chl-a (Andrade 2003; Lehodey et al. 1998; Zainuddin et al. 2017). The catch distribution of SKPJ from July - December in 2006 is mapped in Figure 3. Figure 2 and Figure 3 demonstrate a visible correlation of SKPJ with SST and Chl-a. The SKPJ catches are comparatively high during September - December and the cold SST and comparatively high Chl-a also can be observed in similar months within the study period. The graphs in Figure 4 demonstrate the fish catch frequency variation with the studied influencing factors.

Favorable conditions for SKPJ according to ECDF analysis and GAM

The ECDF plots of the relationship between studied fish CPUE and the influencing environmental variables are indicated in Figure 5. The variation SKPJ CPUE with Chl-a and SST monthly averages during 2014-2016 in Western and Eastern areas are indicated in Figure 7. The graphs show a seasonal biphasic cycle in the study area in all variables. The nonlinear relationships (GAM) between the SKPJ CPUE, SST, and Chl-a concentration are indicated in Figure 8. The ash area shows the 95% confidence level and the area it highly coincides with the fitted line can be considered as the highly correlated value range. The plots of the smoothing parameter selection done with the Generalized Cross Validation (GCV) method are indicated in Figure 9. Q-Q plots in both areas (Figure 9:A and E) coincides with straight line closely, indicate reasonable distributional assumption. The plots in B and F suggest that variance is not varying significantly as the mean increases. The C and G are the plots of response against fitted values. They demonstrate a positive linear relation with a good deal of scatter. The histograms of residuals (D and H) are consistent with normality. In the Eastern area, the basic dimension (k) was comparatively high in SST with the values of 8.00, 1.23, and 0.88 for edf, k-index, and p-value respectively. For Chl-a they were 2.65, 0.94, 0.26 respectively. In Eastern area in both SST and Chl-a basic dimensions were high and the above values were 1.00, 1.17, 0.82 for Chl-a and 3.47, 1.25 and 0.88 for SST respectively. k' value was 9 for all the influencing variables. Usually Low p-value with k-index<1 may show that k is too low, especially if edf is close to k'.

Discussion

Preliminary analysis and ECDF analysis

During the study period, the highest total catch of SKPJ was found in September. When NW, NE, SW, SE areas were considered separately in Economic Exclusive Zone (EEZ) of Sri Lanka the highest total catches and the CPUEs of the SKPJ were found in December in NE and NW regions and in September in SE and SW regions. The SST and Chl-a values extracted from the satellite images of the points which the positive fish catches had been obtained, showed a particular range which we can assume as the approximately suitable ranges of SST and Chl-a concentration for SKPJ. In the points that SKPJ were caught the SST and Chl-a were found in the ranges of 24-27 ^{0}C and 0-1.24 mg m^{-3} respectively. The SST and Chl-a values found under the highest catches were ~25 ^{0}C and ~0.23 mg m^{-3} respectively.

According to the graphs in Figure 4 with fish catch frequency variation with the influencing factor the SST and Chl-a range that SKPJ frequent catches were observed in 26-29 ^{0}C and 0 – 0.50 mg m^{-3}. According to the ECDF analysis, a strong correlation of SKPJ was identified with the 26-27 ^{0}C SST and 0.4 – 0.7 mg m^{-3} Chl- a. The ECDF analysis shows that favorable Chl-a for SKPJ has more specific range than the previous preliminary study. In the peak season of SKPJ fishery in the study region, a fairly well distribution of phytoplankton can be observed.

The maps in Figure 6 were prepared according to the optimum SST and Chl-a values identified from the ECDF analysis. They can be used to demarcate the biological hotspot habitats of SKPJ since there is a high probability of the SKPJs recruitment and feeding occurrence in the demarcated area since the favorable conditions for them are abundant in that area.

Generalized additive model

The monthly averages of the variables show a hot season with high SST from February to April and a comparatively cold season from May to December. In between that SST become a bit higher from August to October. The inter-annual variability of SST was not significantly large. Chl-a is low in the months with high SST and has come to a peak between June and September in both areas. The interannual variability of Chl-a is also not comparatively high. However in 2016 September in the Western area an unexpected Chl-a of (5.1mg m^{-3}) could be observed. In the Western area, the highest mean CPUEs were found in February- March, and August-September months. In Eastern area, they were found during January- March, and July-September months.

Relationship analysis with GAM

Generalized additive model (GAM) was used to highlight the relationship between predictor variables (SST and Chl-a), seasonal factor and fluctuations of CPUE. In the Western area the R^2.(adj), deviance explained and GCV values of the GAM were 0.854, 90.8% and 0.3274 respectively. In Eastern area they were 0.54, 61.4% and 0.12743 were respectively. That shows the smoothed values in Western area more significantly explain the variations of SKPJ CPUE variations than it is accomplished by GAM in Eastern area. According to GAM s(Chl-a) and s(SST), both were statistically significant variables that effect to the SKPJ CPUE abundance and their p-values were 0.00378 and 2.14e-09 respectively. In Eastern area s(SST) was significant (p-value= 0.032) and Chl-a had a p-value of 0.141. In Western area 0.3-0.6 mg m^{-3} Chl-a and SST from 28-28.5 ^{0}C seemed highly correlated with SKPJ CPUE variations. In Eastern area

0.25-0.3 mg m^{-3} Chl-a and 5 28.5- 28.8 ^{0}C were correlated more. In both areas, the residuals showed a normal distribution and the fitted values were smoothly fitted on the response. According to the GAM, the predicted values were calculated to both areas and in the Western area, the predicted values showed a 93% similarity while in Eastern area 90% similarity according to the t-test.

Conclusion

Habitat hotspots for skipjack tuna in the ocean region around Sri Lanka are influenced by the optimum combination of SST and Chl-a. The key pelagic habitat corresponded mainly with the 0.4 – 0.7 mg m^{-3} Chl-a concentration which could stimulate enhanced forage abundance for SKPJ. The favorable SST range for SKPJ is 26-27 ^{0}C which provides suitable thermocline and an optimum level of upwelling to circulate nutrients needed for the primary production. The optimum levels of Chl-a, SST and the high total catches and CPUEs of the train data set were found during the months of September to December. Hence, the South-West monsoon season can be précised as the best and peak season of SKPJ fisheries. SST and Chl-a act as important indicators to detect the habitat hotspots for SKPJ and the maps prepared can be used to demarcate the biological conservation zones or fisheries zones to identify the SKPJ abundant areas cost-effectively and efficiently. According to GAM the 0.3-0.6 mg m^{-3} Chl-a and SST from 28-28.5 ^{0}C in Western area and 0.25-0.3 mg m^{-3} Chl-a and SST between 28.5-28.8 ^{0}C in Eastern area are highly correlated with SKPJ abundance and Western sub-region was explained better by GAM than Eastern area. GAM was found to be a suitable model that can be used to model the fish catch abundance with influencing parameters since it could predict the values greater than 90% similarly in both subregions of the study area.

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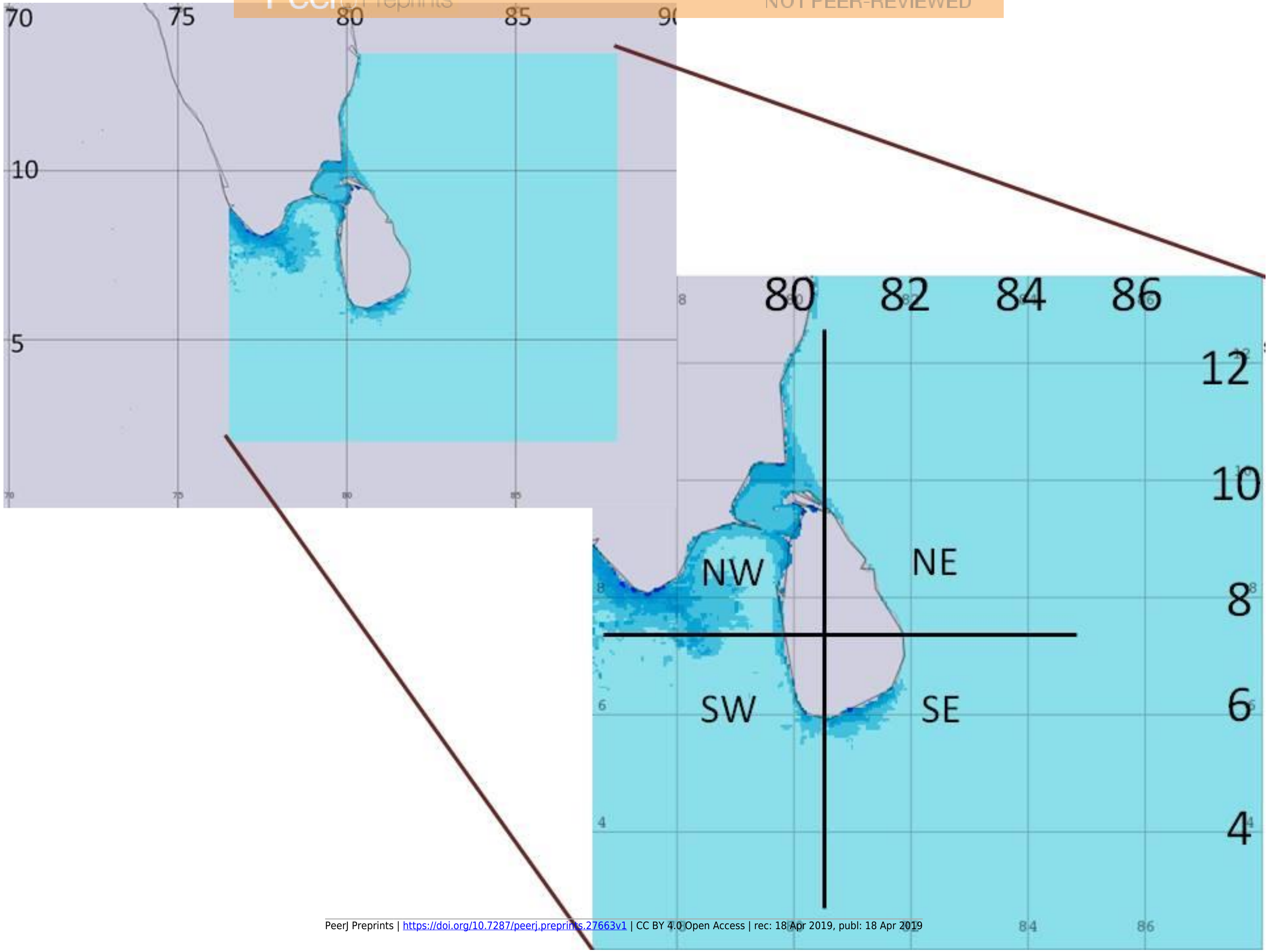
Figure 1 (on next page)

The study area was divided into 4 sub-areas of Northwest (NW: 8.14N -8.93N, 78.74E -79.71E), Northeast (NE:8.69°N -9.48°N, 81.38°E -82.35°E), Southwest (SW:6.19N -6.98N, 78.75E -79.72E), and Southeast (SE: 6.78°N -7.57°N, 82.02°E -82.99°E)

Study area is in blue color

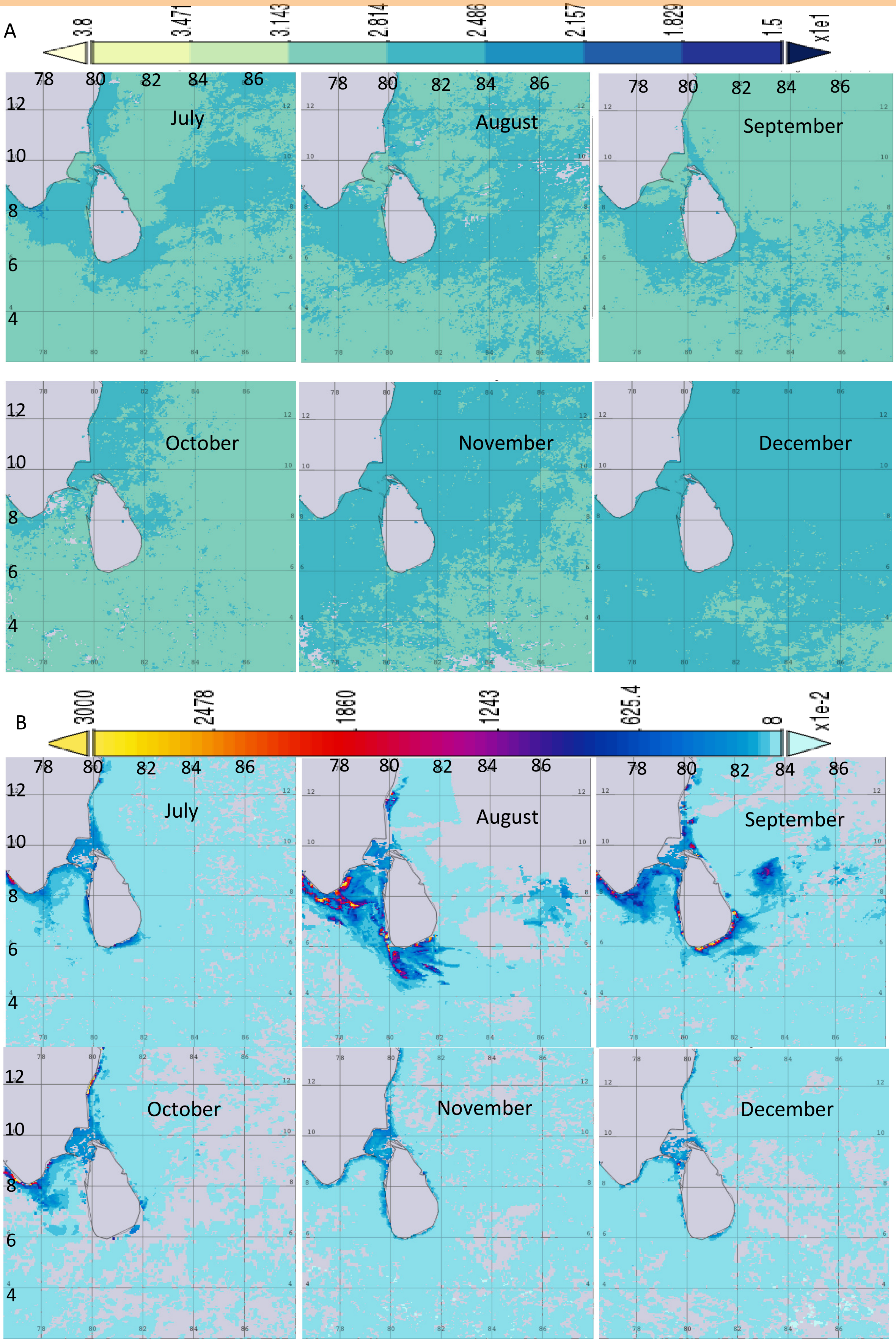
Land masks and outer space in ash color



70
75
80
85
90
10
5
80
82
84
86
12
10
8
6
4
NW
NE
SW
SE

Figure 2(on next page)

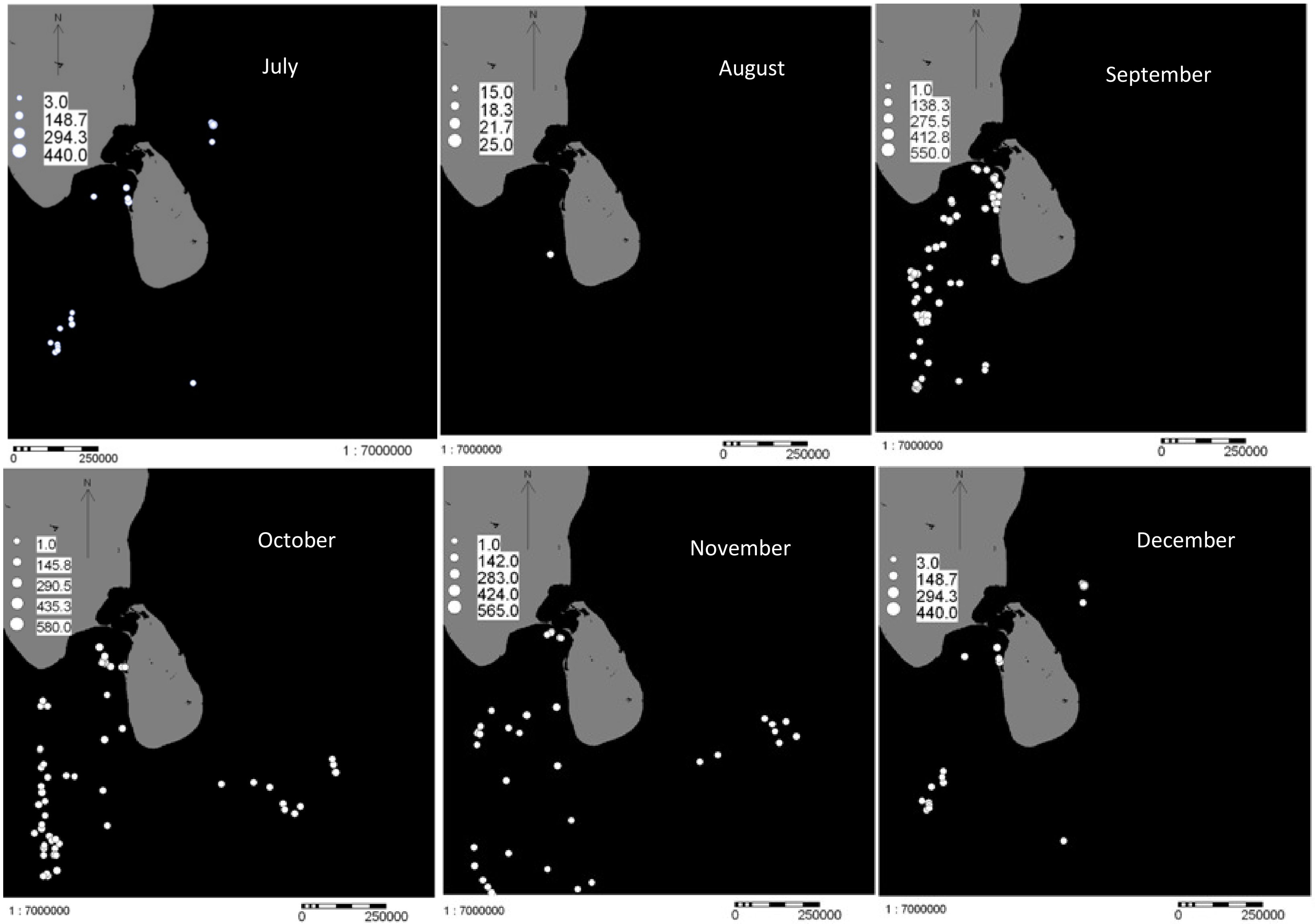
Monthly changes of A: SST and B: Chl-a from July- December 2006



A
3.8
3.471
3.143
2.814
2.486
2.157
1.829
1.5
x1e1
July
August
September
October
November
December
B
3000
2478
1860
1243
625.4
8
x1e-2
July
August
September
October
November
December

Figure 3 (on next page)

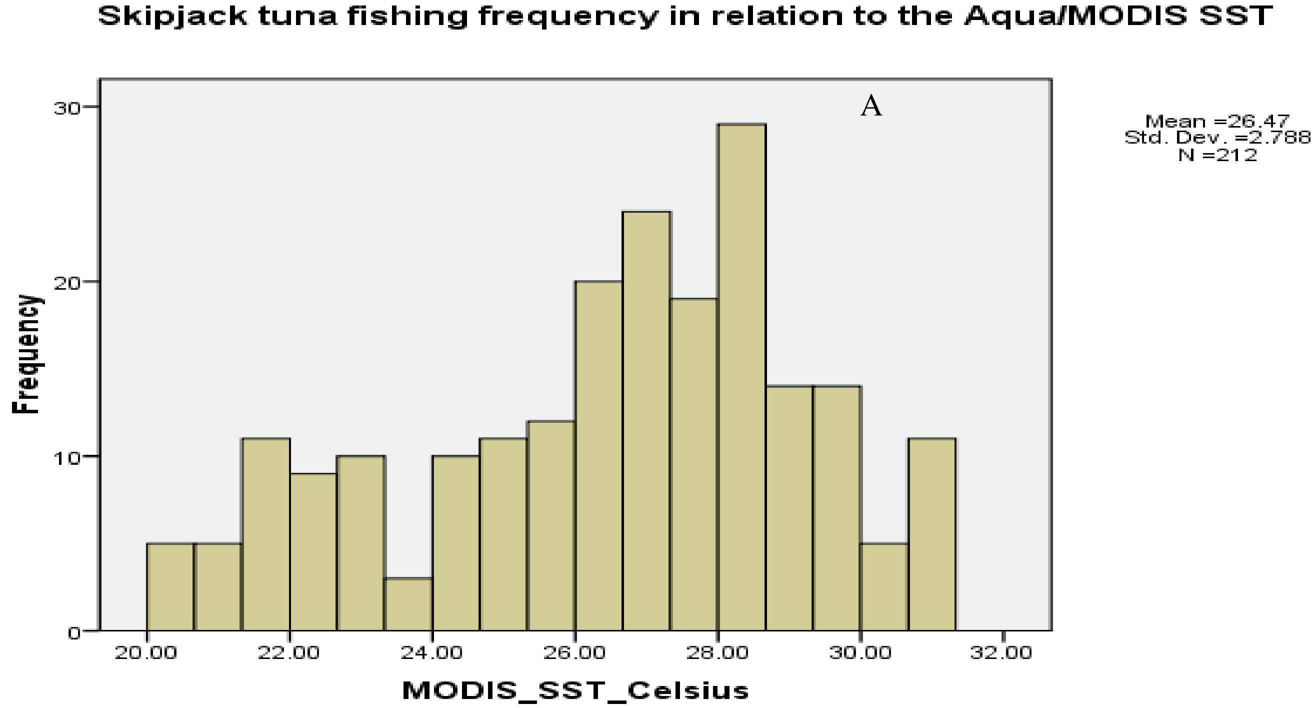
SKPJ distribution around Sri Lanka from July - December 2006. The ocean is marked in black color while the land masks are demarcated in ash color. The fishing points are marked in white color the amount of fish catch is represented by the symbol size



July
3.0
148.7
294.3
440.0
0 250000
1 : 7000000
August
15.0
18.3
21.7
25.0
1 : 7000000
0 250000
September
1.0
138.3
275.5
412.8
550.0
1 : 7000000
0 250000
October
1.0
145.8
290.5
435.3
580.0
1 : 7000000
0 250000
November
1.0
142.0
283.0
424.0
565.0
1 : 7000000
0 250000
December
3.0
148.7
294.3
440.0
1 : 7000000
0 250000

Figure 4(on next page)

Fish catch frequency vs influencing variables variation (A: SST, B:Chl-a)


Skipjack tuna fishing frequency in relation to the Aqua/MODIS SST
A
Mean =26.47
Std. Dev. =2.788
N =212
Frequency
0
10
20
30
20.00
22.00
24.00
26.00
28.00
30.00
32.00
MODIS_SST_Celsius

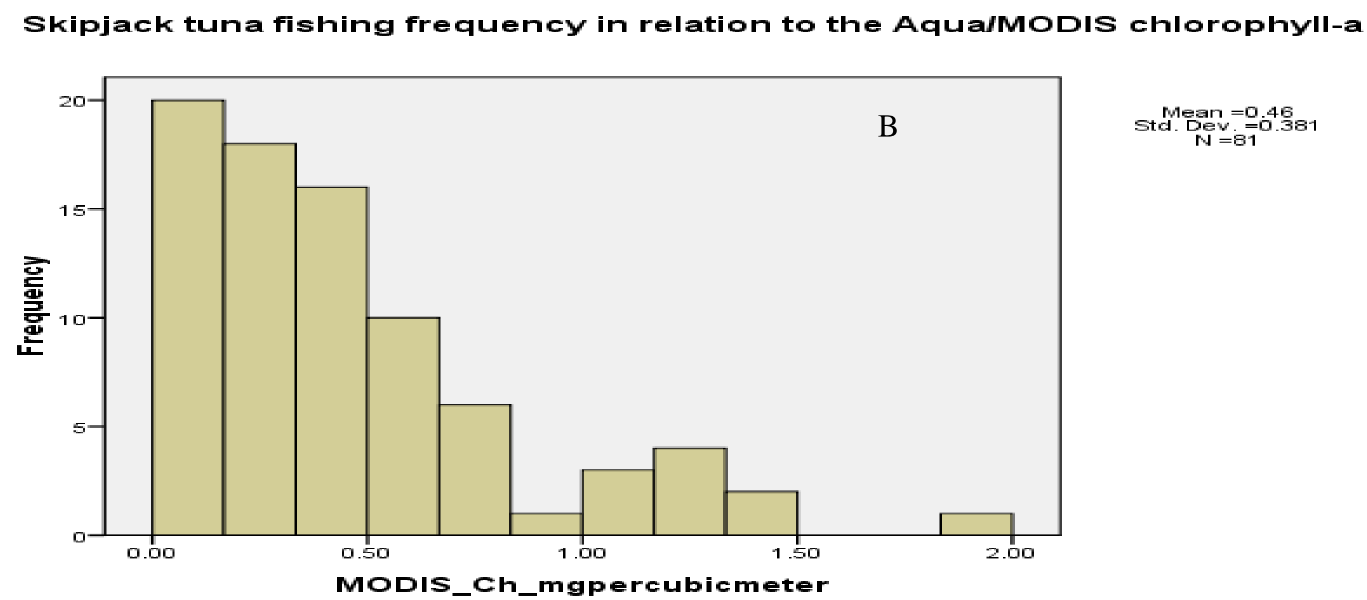
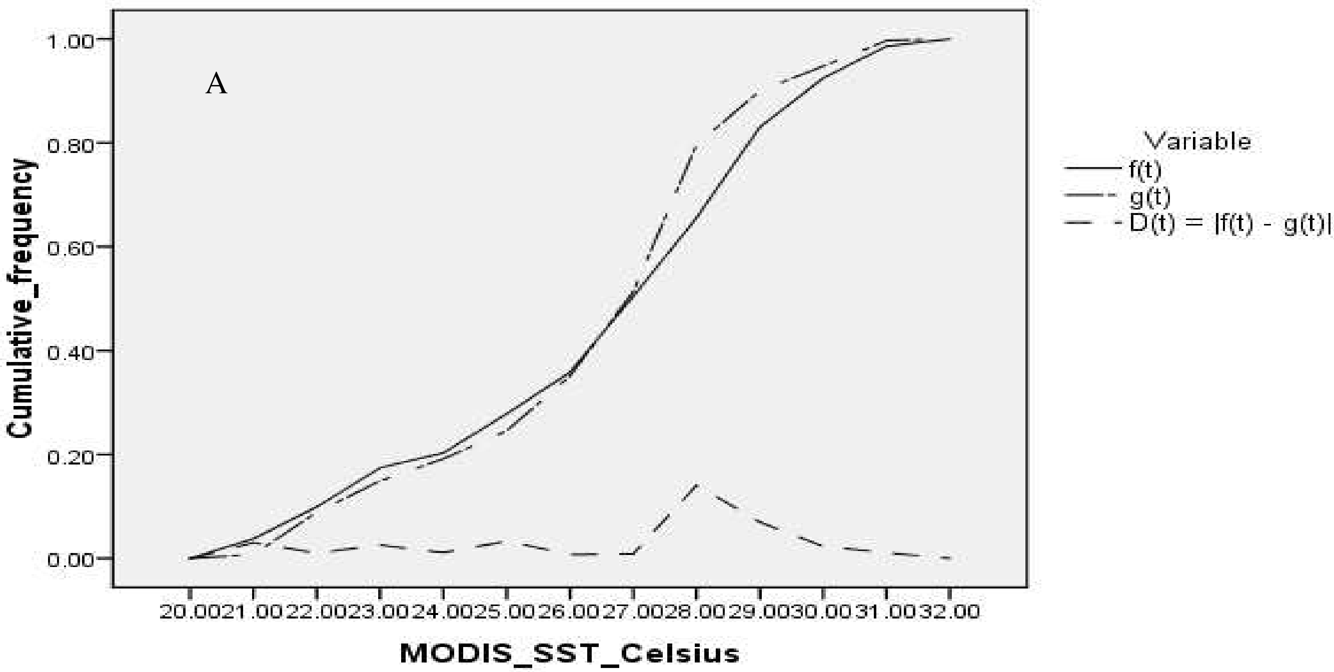

Skipjack tuna fishing frequency in relation to the Aqua/MODIS chlorophyll-a
B
Mean =0.46
Std. Dev. =0.381
N =81
Frequency
0
5
10
15
20
0.00
0.50
1.00
1.50
2.00
MODIS_Ch_mgpercubicmeter

Figure 5 (on next page)

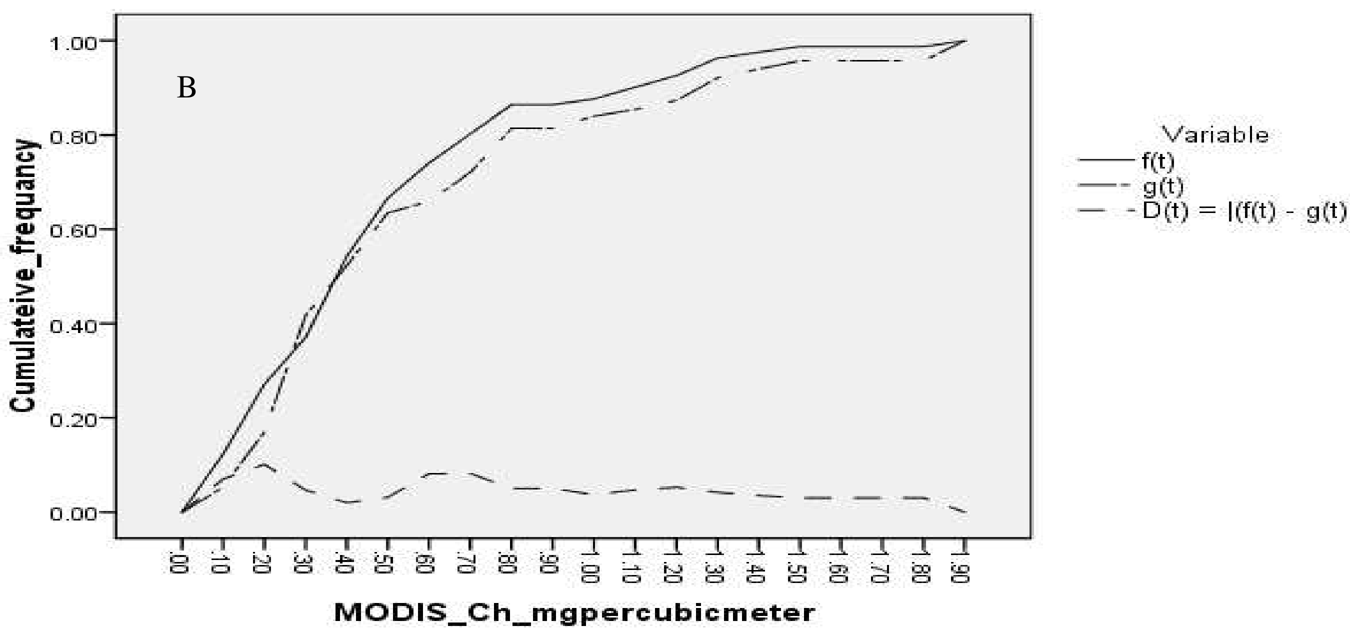
Graphs of Empirical Cumulative Distribution Frequency related to A: SST and B: Chl-a concentration

Empirical Cumulative Distribution Frequancy of Skipjack tuna for SST



Error bars: +/- 2 SE

Emperical Cumulative Distribution Frequencies of Skipjack tuna for Chlorophyll-a concentration



Error bars: +/- 2 SE

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Figure 6(on next page)

Potential fishing grounds of SKPJ spatiotemporal distribution according to the favorable SST and Chl-a identified from ECDF. Land masks are shown in ash color.

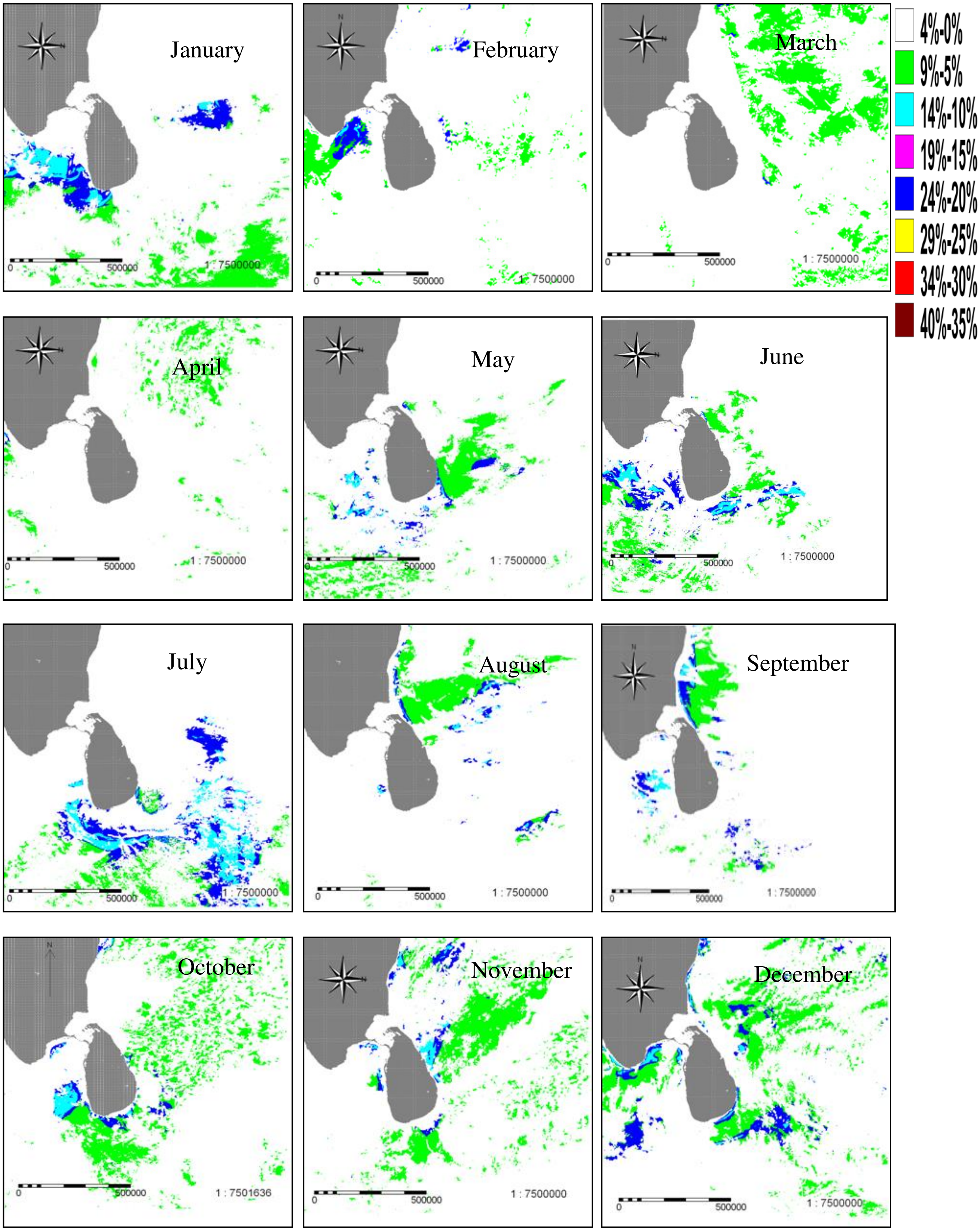
January
February
March
April
May
June
July
August
September
October
November
December
4%-0%
9%-5%
14%-10%
19%-15%
24%-20%
29%-25%
34%-30%
40%-35%
0
500000
1 : 7500000
1 : 7501636

Figure 7 (on next page)

Monthly variations of the SKPJ mean CPUE, mean SST and mean Chl-a during 2014-2016 within Western and Eastern areas

W= Western

E= Eastern

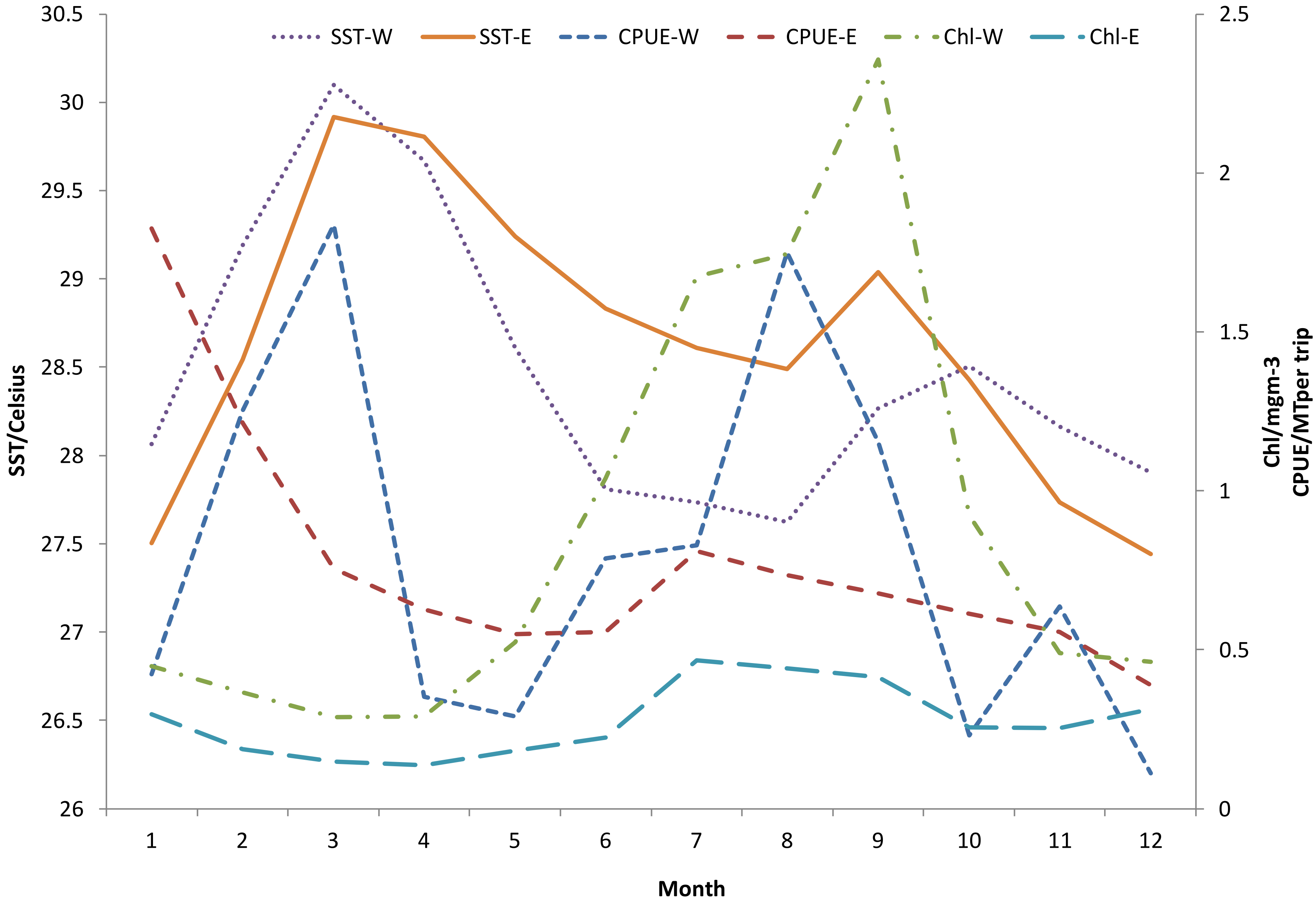

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Figure 8(on next page)

The nonlinear relationships (GAM) between the SKPJ CPUE, SST, and Chl-a concentration

A= Fit of SKPJ CPUE with Chl-a in Western area

B= Fit of SKPJ CPUE with SST in Western area

C= Fit of SKPJ CPUE with month in Western area

D= Fit of SKPJ CPUE with year in Western area

E= Fit of SKPJ CPUE with Chl-a in Eastern area

F= Fit of SKPJ CPUE with SST in Eastern area

G= Fit of SKPJ CPUE with month in Eastern area

H= Fit of SKPJ CPUE with year in Eastern area

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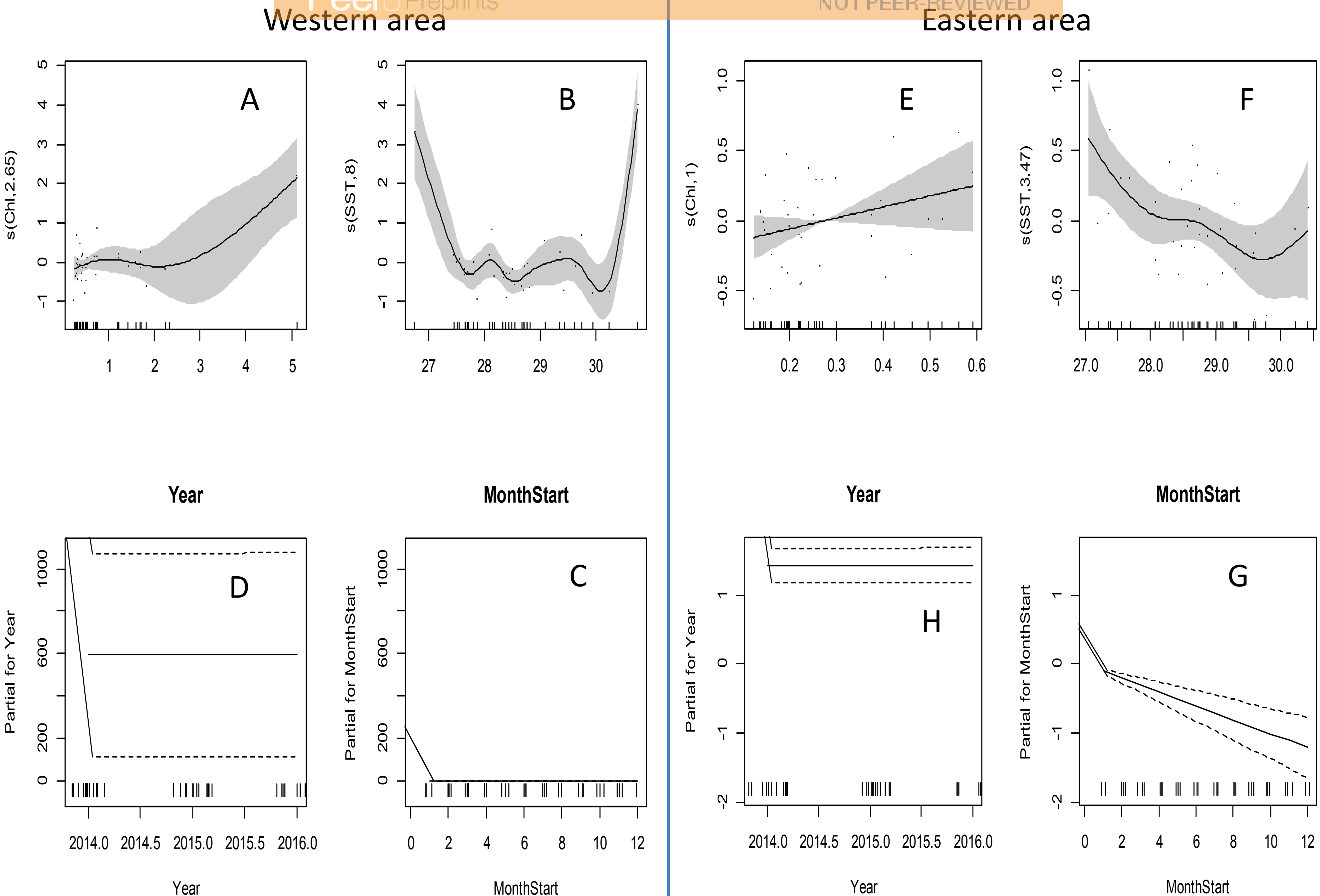

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Figure 9(on next page)

Basic residual plots for checking the GAM model fitting processin Western and Eastern areas

A= (Q-Q) plot for Western area

B= Residuals vs. linear predictors for Western area

C= Responce vs. fitted values for Western area

D= Histogram of residuals in Western area

E= (Q-Q) plot for Eastern area

F= Residuals vs. linear predictors for Eastern area

G= Responce vs. fitted values for Eastern area

H= Histogram of residuals in Eastern area

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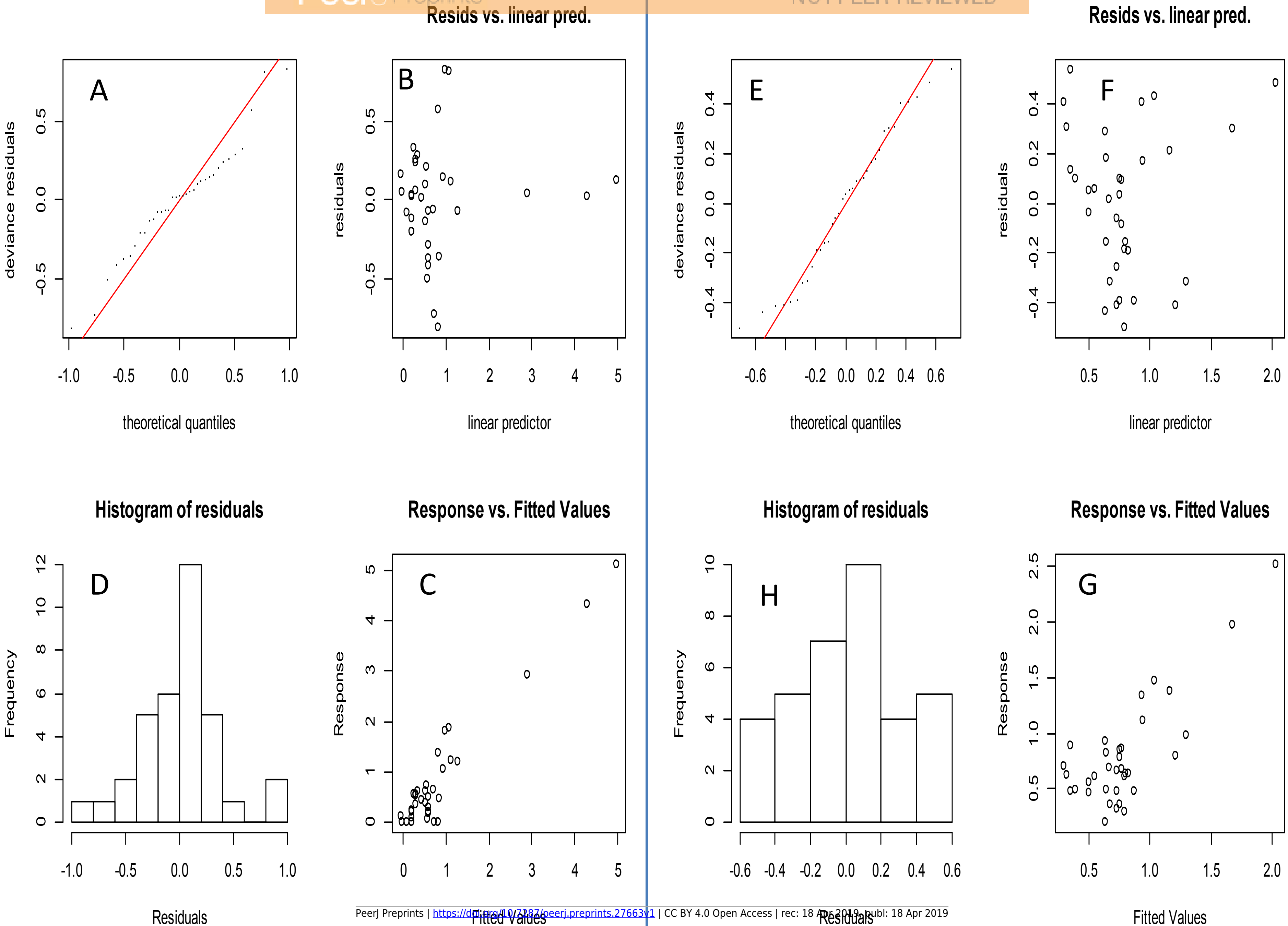
A
B
Resids vs. linear pred.
E
F
Resids vs. linear pred.
deviance residuals
theoretical quantiles
residuals
linear predictor
deviance residuals
theoretical quantiles
residuals
linear predictor
Histogram of residuals
Response vs. Fitted Values
Histogram of residuals
Response vs. Fitted Values
D
C
H
G
Frequency
Residuals
Response
Fitted Values
Frequency
Residuals
Response
Fitted Values

Figure 10(on next page)

SKPJ CPUE nominal and predicted values monthly changes in Western and Eastern areas

W= Western area

E= Eastern area

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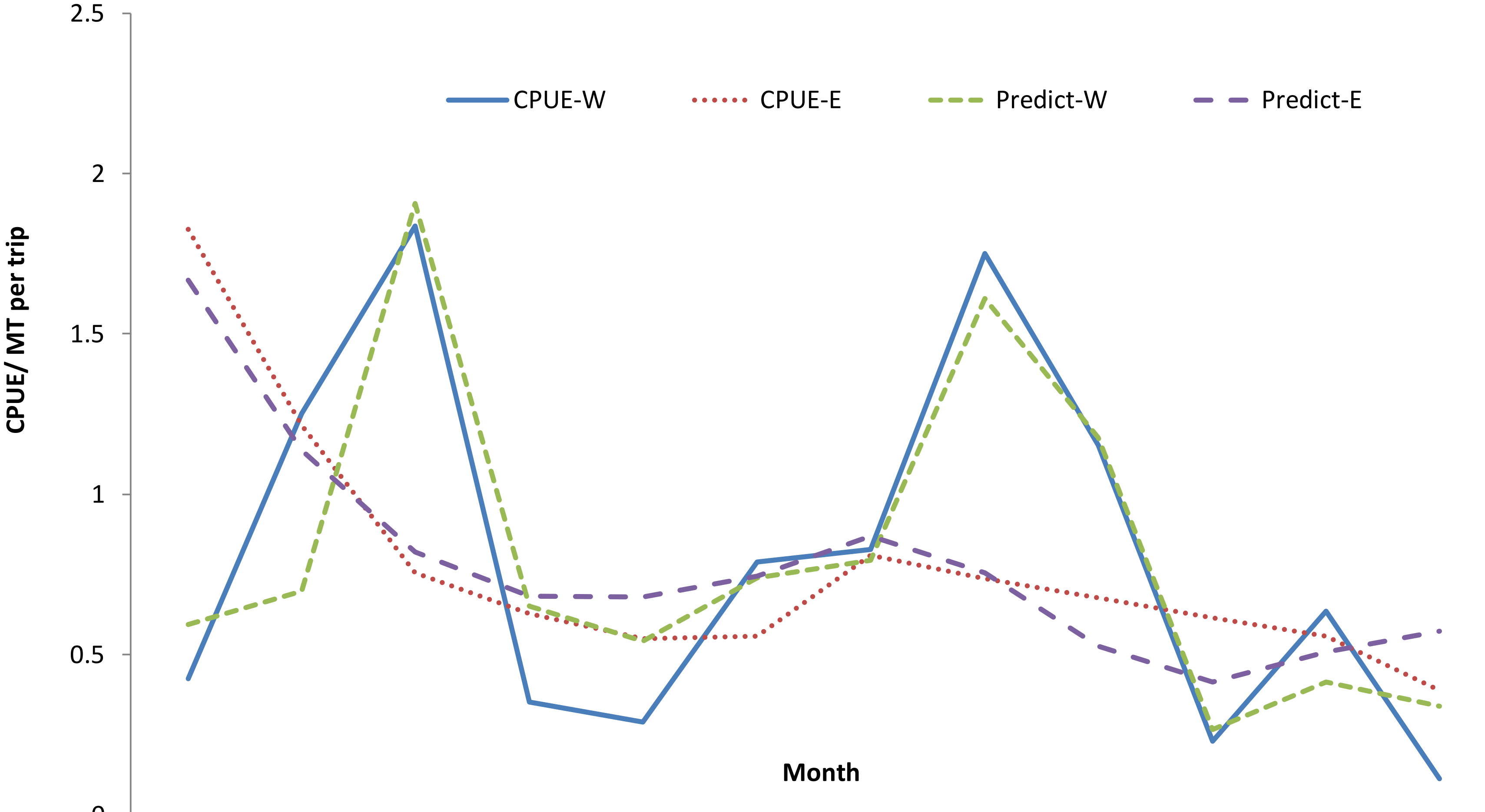

	1	2	3	4	5	6	7	8	9	10	11	12
CPUE-W	0.42353	1.252379	1.836766	0.351424	0.290122	0.787326	0.827943	1.750532	1.153403	0.229961	0.635718	0.112154
CPUE-E	1.824836	1.214087	0.754375	0.626926	0.548111	0.556942	0.809572	0.735292	0.677151	0.613826	0.556165	0.388087
Predict-W	0.59322	0.697562	1.907475	0.650657	0.539973	0.739373	0.79441	1.611417	1.175989	0.264175	0.413768	0.338785
Predict-E	1.667714	1.135912	0.818651	0.68132	0.679494	0.742993	0.867926	0.754858	0.524416	0.41438	0.506765	0.572752

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