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Development of a Web Portal to Forecast the Monthly Mean Chlorophyll Concentration of the Waters off Peninsular Malaysia's West Coast

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ABSTRACT

The principal photosynthetic pigment of chlorophyll (chl-a) in the water is produced by phytoplankton and its concentration (CC) is the biomass and abundance indicator of phytoplankton. The small pelagic fishes which feed on phytoplankton is one of the dominant groups caught in Malaysia. The typical challenge in fisheries is to identify a fruitful fishing ground at any given time. Based on the relationship amongst CC, phytoplankton and food chain of pelagic fishes, it can be suggested that waters with high levels of CC may indicate a more favourable fishing ground. Thus, using CC may help to narrow down the fishing ground search and would be useful to fishermen. This paper described the development of a web portal to forecast the monthly mean CC of the waters off Peninsular Malaysia's west coast. The portal's functionality was illustrated with time series modelling and forecasting of 3 fisheries sites using Holt-Winters seasonal additive model. The portal consists of forecast outputs as well as related information and is primarily intended for use as a tool for fishermen with the advantage of easy accessibility.

Keywords: chlorophyll concentration, phytoplankton, small pelagic fish, forecasting, web portal.

1. Introduction

Chlorophyll (chl) is a green pigment found in photosynthetic organisms such as green plants and algae. The principal photosynthetic pigment of chl is known as chl-a, which also contributes to the observed green colour of most plants (Schalles (2006)). Chl-a in the ocean water is generally produced by the tiny, floating plants called photosynthetic plankton or phytoplankton. These plants are an important part of the ocean's food chain because many marine animals for example small fish and whales feed on them. The concentration of chl-a (CC) measured in milligrams per cubic metre, mg/m^3 is a proxy for the amount of phytoplankton present in the ocean (O'Reilly et al. (1998)). Colour is proportional to the amount of chl-a pigments close to the surface and the amount of chl-a is proportional to the amount of phytoplankton in the water. Consequently, waters with great numbers of phytoplankton are green, while pure ocean water is deep navy blue (Schalles (2006)). Thus, scientists use measures of CC as biomass and abundance indicator of phytoplankton near the surface of the ocean.

Fisheries sector is a significant contributor to Malaysia's gross domestic product (GDP), source of employment and as well as major and cheap source of animal protein with per capita consumption of 50kg fish per year, see Samsudin et al. (2015). The small pelagic fishes including mackerel, scad, tuna, sardines and anchovies are common species found in warmer oceans and one of the dominant groups caught in marine capture fisheries sub-sector of Malaysia. The Indian mackerel (*Rastrelliger kanagurta*) is the most prominent group together with the king mackerel, short mackerel, Spanish mackerel, fringe scale sardine, smoothbelly sardine, rainbow sardine, longtail tuna and frigate tuna (Noraisyah and Raja Bidin (2009)). It is important to note that most pelagic fishes feed on phytoplankton (Shitan et al. (2008)).

The typical challenge in fisheries is to determine where and when to fish i.e. finding the most fruitful fishing ground at any given time. This eventually increases the cost of a fishing trip in terms of fuel and wages. As a matter of fact, fishing grounds are always dynamic in nature, therefore it is complicated to identify the rewarding fishing grounds at most of the time. Employment of fish movement detection technologies like Sound Navigation and Ranging (SONAR) helps to detect fish based on information of fish size, location, abundance and behavior but SONAR may not be affordable for everyone and it is also proven to have some effects on marine life, for instance creating temporary hearing loss in dolphins, as stated in Gordon et al. (2003).

Based on the underlying relationship amongst CC, phytoplankton and the food chain of fish in particular the small pelagic fishes, it can be suggested that waters with high levels of CC may indicate a more favourable fishing ground. This suggestion is supported by the logic that we can expect more fish to be in the area with higher amount of phytoplankton (food) in relative to areas with lower amount of phytoplankton. Therefore, employing CC could help to narrow down fishing grounds search and reduce the time spent in unfruitful areas. Mustapha et al. (2013) reported that the preferred range of CC for pelagic fishes in the Exclusive Economic Zone (EEZ) of East Coast waters of Peninsular Malaysia was found to be 0.21 - 0.31 mg/m^3. This range of CC values can be used as a reference for the west coast fisheries as well.

The role of CC in fisheries is currently applied through the employment of Fishing Site Identification (FSI) system which is actively used in the east coast of Peninsular Malaysian fisheries. FSI makes use of satellite remote sensing to extract levels of environmental variables in the waters namely CC and sea surface temperature (SST) (Razib and Mustapha (2013)). Over the recent years, the application of satellite image extraction has become immensely important because the data collection allows for large spatial coverage and frequent measurement over time, which is useful for assessing long-term changes in relative to data collection from field observations. Nevertheless, in tropical regions like Malaysia, the satellite's vision is distorted by unforeseen circumstances such as clouds blocking the satellite's view; glare of the sun blocking the satellite's ability to see the water and cloudy conditions further reducing the frequency caused by climatic factors, see Al-Wassai and Kalyankar (2013).

Taking into account the aforementioned issues on using satellite remote sensing, a cost-effective approach such as implementation of a web portal for the fisheries to forecast CC levels can be considered as an alternative to FSI. Moreover, acquiring CC levels consistently is essential for sustainable fishing. As CC levels are measured over time, it results in a time series data and hence, statistical time series modelling methods would be appropriate to forecast it. Besides that, CC levels naturally fluctuate over time, thus indicating the presence of temporal variation. Previous researches related to this study have been conducted to study various application of CC in fisheries. Nurdin et al. (2012) mapped the potential fishing grounds of *Rastrelliger kanagurta* in the archipelagic waters of Spermonde using satellite images, as well as studied the relationship between SST and CC in fisheries aggregation area in the same region in 2013, see Nurdin et al. (2013). Ismail et al. (2012) conducted studies on large offshore remote system for Malaysian deep sea fishing; Zainuddin (2011) described the relationship of Skipjack tuna with SST and CC in Bone Bay using satellite data; Lanz et al. (2009) studied the relationship between small pelagic fish catches in the Gulf of California with SST and CC; Tan et al. (2002)

studied the variations of SST and CC in east coast of Peninsular Malaysia and Mansor et al. (2001) developed a satellite fish forecasting framework for South China Sea.

Koutroumanidis et al. (2006) asserted that forecasting using historical time series data has become an important tool for fisheries management. Accordingly, many time series techniques were used to forecast fish catches such as in the studies by Bako et al. (2013) that forecasted the pelagic fish catch in Malaysia using seasonal ARIMA (SARIMA) model; Shitan et al. (2008) forecasted annual demersal and pelagic fish production in Malaysia by fitting the catch data to ARIMA and integrated ARFIMA models; Bako (2014) compared two model classes i.e. SARIMA and Error, Trend & Seasonal (ETS) state space exponential models for forecasting *Dussumiera acuta*, *Rastrelliger kanagurta* and *Thunnus tonggol* fishes in Malaysian waters; Tsitsika et al. (2007) used univariate and multivariate ARIMA models to model and forecast the monthly production of pelagic fish species in the Mediterranean Sea during 1990-2005; Park (1998) forecasted the monthly landings of *Theragra chalcogramma* fish species in Korean waters by employing SARIMA; Koutroumanidis et al. (2006) used ARIMA, Optimal Forecasting and Decision Support Systems to forecast anchovy fish catches landed in Thessaloniki, Greece during 1979-2000 and *Hake* and *Bonito* total fish catches during 1982-2000; Rodriguez et al. (2009) used functional autoregressive (FAR) model for one month ahead monthly sardine catches forecasting in northern waters of Chile; Potier and Drapeau (2000) forecasted the catch of the scads in the northern coast of the Java Island using SARIMA; Sathianandan (2007) employed vector autoregressive (VAR) models to model and discover the relationships between landings of eight commercially important marine fish species in Kerala, India; and Lloret et al. (2000) forecasted monthly catches of 53 commercial fish species in the northwestern Mediterranean Sea, up to one year in advance using SARIMA models.

In view of the above discussion, the objective of this paper is to develop a web portal to forecast the monthly mean CC of the waters off Peninsular Malaysia's west coast within the EEZ of Malaysia. The methodology and data set used in this study are described in Section 2 followed by the results and discussions in Section 3. The conclusions are contained in Section 4.

2. Materials and Methods

2.1 CC Data Description

The CC data used in this study were monthly observations obtained from global satellite measurements by the Moderate Resolution Imaging Spectroradiometer (MODIS)-Aqua projects of National Aeronautics and Space Administration (NASA) (1 Month – AQUA/MODIS: NASA Earth Observations (NEO) retrieved from *http://neo.sci.gsfc.nasa.gov/*). Satellite remote sensing can detect CC directly as chl-a absorbs most visible light but reflects some green and near-infrared light. By measuring what kind of light is absorbed and reflected, the MODIS sensor aboard NASA's Aqua satellite can measure CC in the ocean that is to measure how much phytoplankton are growing in the ocean by observing the color of the light reflected from the shallow depths of the water.

The original data set were in the form of monthly mean CC values beginning from July 2002 in 0.5° resolution for the global range of latitudes and longitudes. The first step in data compilation was extracting the CC values for data points within the latitudes of 1.15°N to 7.35°N and longitudes of 98.05°E to 105.85°E (EEZ of Peninsular Malaysia) (Malaysian EEZ: Marine Gazetteer Placedetails retrieved from *www.marineregions.org/gazetteer.php?p=details&id=8483*). The extracted values were further compiled as monthly data for each subsequent years. The following step involves compilation of the time series data accordingly into months and years overall. The final steps were filtering the data points of west coast waters and compiling the yearly data with months as time index starting from January 2002 for each of the fisheries sites.

Each data point (location in the sea) that lies within the EEZ of west coast waters represented by its Global Positioning System (GPS) coordinates was designated as a fisheries site close to a landing site assigned under each of the 22 fisheries districts of the west coast waters (DOF (2015)). In this paper, to illustrate the web portal's functionality, three fisheries sites near to landing sites representing the northern, central and southern region of Peninsular Malaysia's west coast fisheries were selected for time series modelling and forecasting. The selected fisheries sites were 6.45°N, 99.75°E near Teluk Yu in Langkawi Island (north), 3.25°N, 100.65°E near Jeram in Kuala Selangor (central) and 1.65°N, 102.75°E near Minyak Beku in Batu Pahat (south).

2.2 Shiny Web Framework

The R programming language is an important tool in statistical computing (R Development Core Team (2008)). R is a high level and interpreted programming language that is best to create reproducible, high quality analysis with flexibility and power when dealing with data (Beeley (2016)).

Previously, it was not a straight-forward process to create a web application with R. The R code has to be embedded into compiled programming languages like C++ or Java and finally converted into a web application that runs in the incorporated language. If using R code in a standalone manner was opted, then it requires the computer or device running the application to have an R software environment installed on it. It was until the creation of Shiny that transformed the ability of R code to be run as a standalone web application without requiring any extra efforts.

Shiny web framework is a free contributed package to R provided by RStudio (Chang et al. (2015), RStudio Team (2015)). It combines the computational power of R with the interactivity of the modern web and makes it simple for R users to turn analyses into interactive web applications that anyone can use, see Beeley (2016). Shiny comes with a variety of widgets for rapidly building user interfaces and does all of the heavy lifting in terms of setting up interactive user interfaces with applications that let users specify input parameters using friendly controls like sliders, drop-downs, and text fields; and they can easily incorporate any number of outputs like plots, tables, and summaries (Chang et al. (2015)). The primary advantage of Shiny is that it only requires some experience with R and no web development skills like HTML, CSS or JavaScript knowledge is necessary for building Shiny web applications.

A Shiny application is comprised of two programming components namely a user-interface definition script (**ui.R**) and a server script (**server.R**). The ui script acts as an HTML interpreter in which buttons, checkboxes, images, and other HTML widgets are created. The server script is where the functionality of Shiny can be seen as this is where the widgets that were created in the *ui* can be made to do something (Beeley (2016)). In other words, it is where any R users can turn their application into a dynamic visual masterpiece by using only R. In a nutshell, Shiny is a R package that enables users to run their R code as an interactive webpage, which was definitely not an easy task prior to the emergence of Shiny.

2.3 Time Series Modelling of Selected Fisheries Sites

In the real practice of this portal, forecasting of CC for a fisheries site $s_f, (f = 1, 2, \ldots, N)$ (N = number of fisheries sites) is performed using automated time series model selection from a variety of possible ETS and ARIMA models. The best fit model from the possible models for s_f is selected based on Akaike Information Criterion (AIC) (Hyndman and Khandakar (2008)). As the time series of each s_f is updated at time t, data will be refitted to the selected model for forecasting. This step ensures the models to be dynamic and not fixed to a specific model. This helps to produce more accurate forecasts in accordance with the latest values of monthly mean CC. The automated model selection is implemented by employing the `forecast`(Hyndman (2017)) package in R.

However, in order to illustrate how time series modelling and forecasting were performed in the portal and as well as to demonstrate the portal's output and functionality, a conventional method to fit time series with trend and seasonal pattern namely the Holt-Winters (HW) seasonal method (*one of the possible models from ETS*) was chosen to serve as an example in this paper. Let $X(s_f, t) = [x_{1(s_f)}, x_{2(s_f)}, \ldots, x_{n(s_f)}]$ $(f = 1, 2, 3)$ denote the time series of the monthly mean CC of s_f and n is the time index of the final month in the updated data set. The time series plots of the selected three fisheries sites indicated the presence of trend and seasonal pattern (refer to the solid black lines in Figures 7, 8 and 9). The existing data were fit to the two variants of the HW method i.e. the additive and multiplicative models. The HW seasonal additive model is given as below (Hyndman and Athanasopoulos (2013)):

$$\hat{x}_{t+h} = l_t + hb_t + s_{t-m+h_m^+} \tag{1}$$

$$l_t = \alpha(x_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{2}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)(b_{t-1}) \tag{3}$$

$$s_t = \gamma(x_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{4}$$

The HW seasonal multiplicative model is given as below (Hyndman and Athanasopoulos (2013)):

$$\hat{x}_{t+h} = (l_t + hb_t)s_{t-m+h_m^+} \tag{5}$$

$$l_t = \alpha(\frac{x_t}{s_{t-m}}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{6}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)(b_{t-1}) \tag{7}$$

$$s_t = \gamma(\frac{x_t}{l_{t-1} + b_{t-1}}) + (1-\gamma)s_{t-m} \tag{8}$$

The parameters are defined as follows:

- m : length of seasonality, ($m = 12$ in this case)
- h : number of forecast period (forecast horizon, e.g., $h = 1$ for one month ahead forecast)
- α, β, γ : smoothing parameters (constants estimated from the observed data); $\alpha, \beta, \gamma \in (0, 1)$
- $h_m^+ = \lfloor (h-1) \bmod m \rfloor + 1$ which ensures that the estimates of the seasonal indices used for forecasting come from the final year of the sample and for any $k \in \mathbb{R}$, $\lfloor k \rfloor = j$, where $j \leqslant k$ and $j \in \mathbb{Z}$

Equations (1) and (5) are the forecast equations; Equations (2) and (6) are the smoothing equations for level of the series at time $t\,(l_t)$; (3) and (7) are the smoothing equations for trend (slope) of the series at time $t\,(b_t)$; and (4) and (8) are the smooothing equations for seasonal component of the series at time $t\,(s_t)$ respectively. The initializations for each component are given as below:

$$\begin{aligned} l_0 &= \frac{1}{m}\sum_{i=1}^{m} x_i \\ b_0 &= \frac{1}{m^2}\sum_{i=1}^{m}(x_{m+i} - x_i) \\ s_{i-m} &= x_i - l_0, i \in [1, m](\text{for additive}) \\ s_{i-m} &= \frac{x_i}{l_0}, i \in [1, m](\text{for multiplicative}) \end{aligned}$$

where l_0 is the average of first year observed data and b_0 is the average of slopes for each period in the first two years. Additionally, there will be m seasonal components ranging from s_{1-m} up to $s_{m-m} = s_0$ (Maridakris et al. (2008)).

The smoothing parameters and initial estimates for the components were estimated by minimizing Root Mean Square Error (RMSE). Since equal number of parameters were estimated in both methods, the training RMSE from both models were compared. In this case, the additive model fitted the data for these fisheries site best with a lower RMSE value. Therefore, only the results for additive model were provided in Section 3.2.

3. Results and Discussions

3.1 Development of Web Portal

The web portal built using Shiny was compatible with common internet browsers and operating systems including on latest smartphones. The portal can be divided into five panels viz. main output panel, output & info tab panel, app tab panel, chl-a tab panel and contact us tab panel. The main output panel on the left-hand portion of the portal's layout comprised of the fisheries district, fisheries site and forecast period selection control boxes to allow end users to make the necessary selections; as well as the forecast plot generated for the selected fisheries site and forecast period. The forecast plot created using the `ggplot2` (Wickham (2009)) and `plotly` (Plotly (2015)) graphing libraries is equipped with a cursor to display the value at each point when hovered over. It also facilitates zooming ability and download as *png* image option. The plot not only displayed the observed and forecasted values graphically but also helps end user to visualise the variation in monthly mean CC over time from July 2002. This visualisation might assist them to identify the presence of special pattern(s) (such as peak CC level or around constant CC level) for a specific fisheries site or period of time, which may not be easily identified from numerical output. Figures 1 and 2 depict the default view of the portal and main output panel respectively.

The output & info tab panel (Figure 3) is the default view of the right-hand portion of the portal's layout and incorporated the forecast table, selection summary and general information. The forecast table displayed the point forecast and 80% prediction interval (PI). These numerical outputs served the same purpose of the visual output (forecast plot) but in a different aspect. Crucial details which may not be visible enough in the plot can be obtained by looking at the numerical outputs. The selection summary consisted of information on latest data update and the end user's selection of fisheries site, district and forecast period. Next, the general information portion detailed out useful insights about the data; along with a warning message about the leaving the portal idle state and finally, a disclaimer. The app tab panel in Figure 4 contained description of the portal while the chl-a tab panel (Figure 5) displayed detailed information on chl-a. Lastly, the contact us tab panel shown in Figure 6 contained the contact information of the developer and some useful related links.

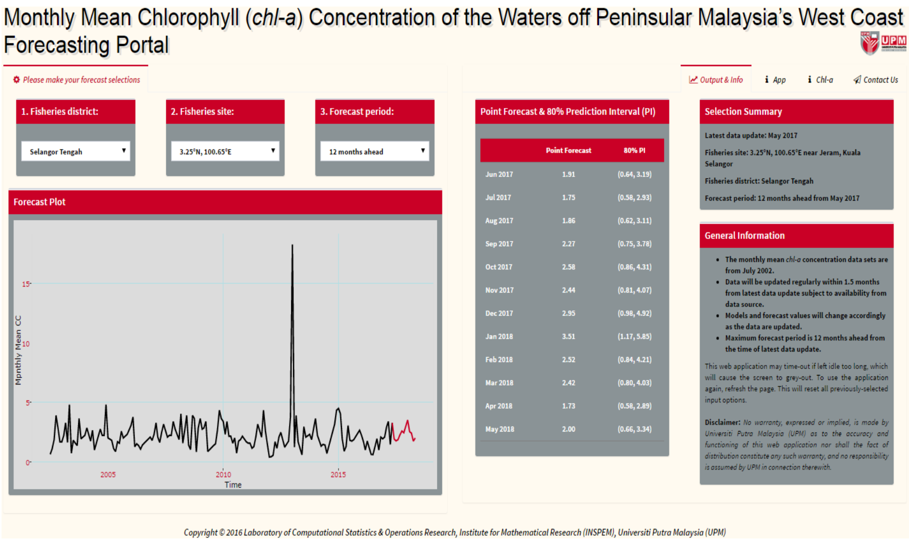

Figure 1: Default view.

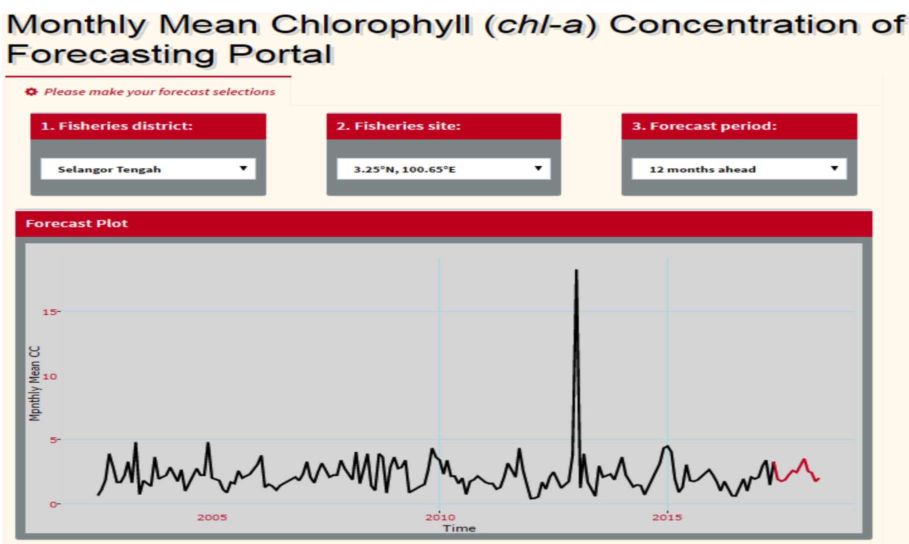

Figure 2: Main output panel.

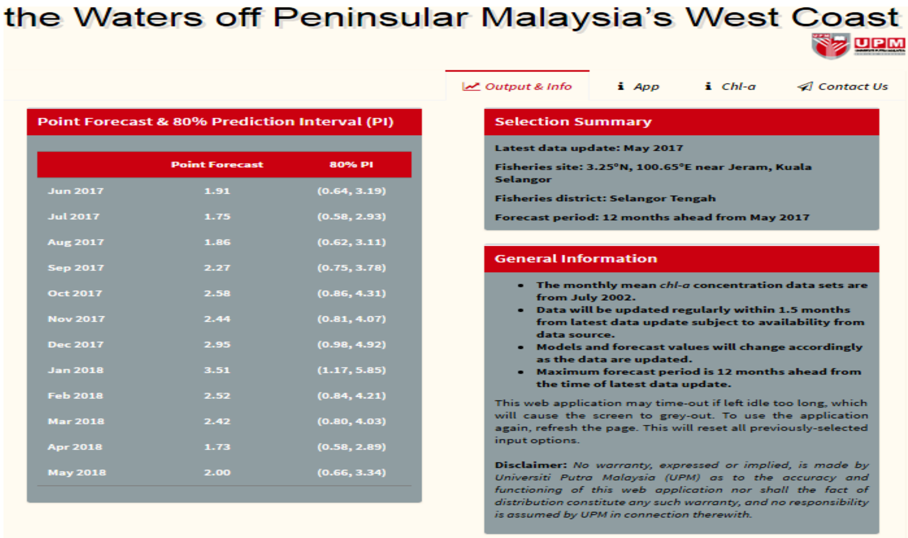

Figure 3: Output & info tab panel.

Figure 4: App tab panel.

Figure 5: Chl-a tab panel.

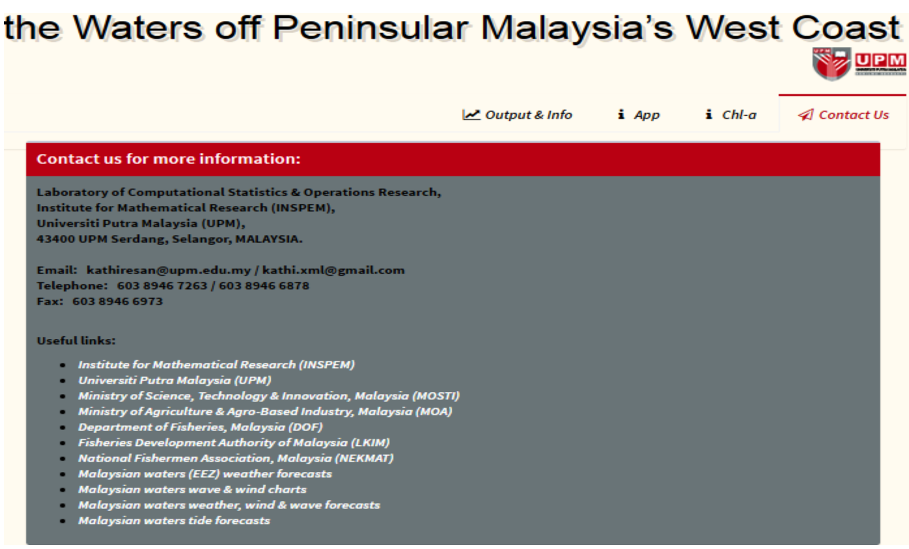

Figure 6: Contact us tab panel.

3.2 Model Summary

The estimated smoothing parameters of the HW seasonal additive model summary for the selected fisheries sites for the forecast period of $h = 12$ months ahead of May 2017 are given in Table 1.

Table 1: Smoothing parameters.

Fisheries site	Parameters		
	α	β	γ
6.45°N, 99.75°E	0.415	0.048	0.133
3.25°N, 100.65°E	0.587	0.141	0.211
1.65°N, 102.75°E	0.487	0.293	0.051

The initial states of the level, trend and seasonal components are provided in Table 2.

Table 2: Initial states.

	Fisheries site		
	6.45°N, 99.75°E	3.25°N, 100.65°E	1.65°N, 102.75°E
l_0	2.209	2.148	2.889
b_0	-0.012	0.080	0.022
s_{-11}	1.154	0.822	1.116
s_{-10}	1.113	0.858	0.881
s_{-9}	0.964	0.744	0.657
s_{-8}	1.188	1.037	0.664
s_{-7}	1.135	1.083	0.804
s_{-6}	1.219	1.507	0.808
s_{-5}	0.929	1.267	0.932
s_{-4}	0.643	1.048	1.004
s_{-3}	1.025	1.108	1.128
s_{-2}	0.874	0.974	1.301
s_{-1}	0.824	0.800	1.320
s_0	0.932	0.753	1.385

The point forecast and 80% PI are shown in Tables 3 and 4 respectively. The 80% PI is the range of monthly mean CC values (in mg/m^3) represented as (lower bound, upper bound). The PI provided a surety of 80% that the actual values of monthly mean CC would fall within the intervals whereas the point forecast may or may not be close to the actual values at the given time.

Table 3: Point forecasts.

	Fisheries site / Mean CC (mg/m^3)		
Time	6.45°N, 99.75°E	3.25°N, 100.65°E	1.65°N, 102.75°E
Jun 2017	2.22	1.91	6.14
Jul 2017	1.80	1.75	7.65
Aug 2017	1.59	1.86	7.33
Sept 2017	1.69	2.27	7.25
Oct 2017	1.98	2.58	6.32
Nov 2017	1.24	2.44	5.65
Dec 2017	1.80	2.95	5.27
Jan 2018	2.36	3.51	4.59
Feb 2018	2.20	2.52	4.58
Mar 2018	2.30	2.42	3.80
Apr 2018	1.87	1.73	3.78
May 2018	2.16	2.00	5.09

Table 4: 80% Prediction intervals.

	Fisheries site / Mean CC (mg/m^3)		
Time	6.45°N, 99.75°E	3.25°N, 100.65°E	1.65°N, 102.75°E
Jun 2017	(1.13, 2.92)	(1.64, 2.79)	(5.13, 7.15)
Jul 2017	(1.12, 2.77)	(1.38, 2.93)	(6.43, 8.88)
Aug 2017	(1.06, 2.52)	(1.42, 2.86)	(6.85, 8.11)
Sept 2017	(1.22, 2.75)	(1.95, 3.08)	(6.42, 8.08)
Oct 2017	(1.54, 2.32)	(2.06, 3.31)	(5.78, 7.16)
Nov 2017	(1.03, 2.14)	(1.81, 3.07)	(4.60, 6.02)
Dec 2017	(1.42, 2.97)	(1.98, 3.32)	(4.95, 6.28)
Jan 2018	(1.74, 3.27)	(3.17, 4.85)	(3.61, 5.56)
Feb 2018	(1.75, 3.08)	(1.84, 3.21)	(3.39, 5.18)
Mar 2018	(1.87, 3.37)	(1.80, 3.03)	(2.75, 4.05)
Apr 2018	(1.10, 2.64)	(1.28, 2.89)	(3.03, 4.19)
May 2018	(2.02, 3.30)	(1.66, 3.04)	(4.77, 6.45)

The forecast plots for the fisheries sites are displayed in Figures 7, 8 and 9 respectively. The solid black line in the plot represents the historical (observed) data (time series), while the solid red line represents the forecasted values for twelve months ahead (June 2017 - May 2018).

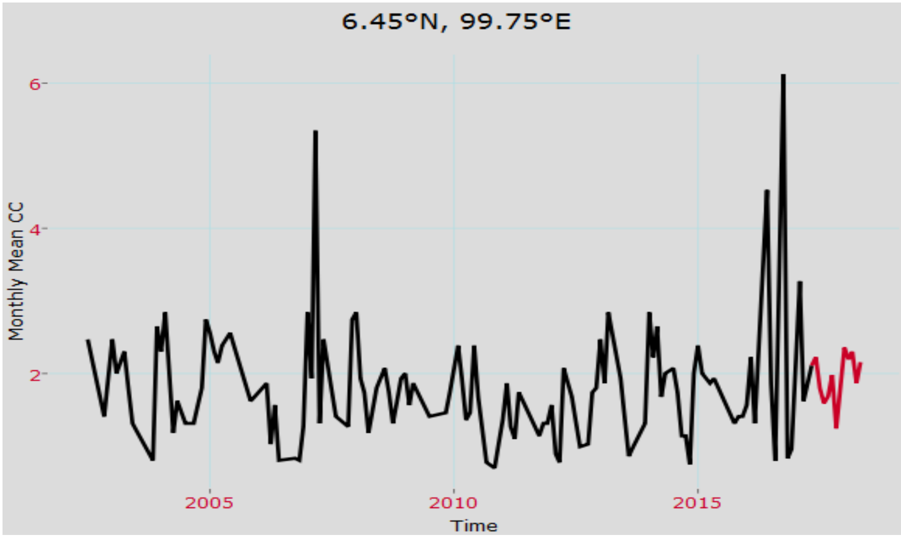

Figure 7: Forecast plot of 6.45°N, 99.75°E.

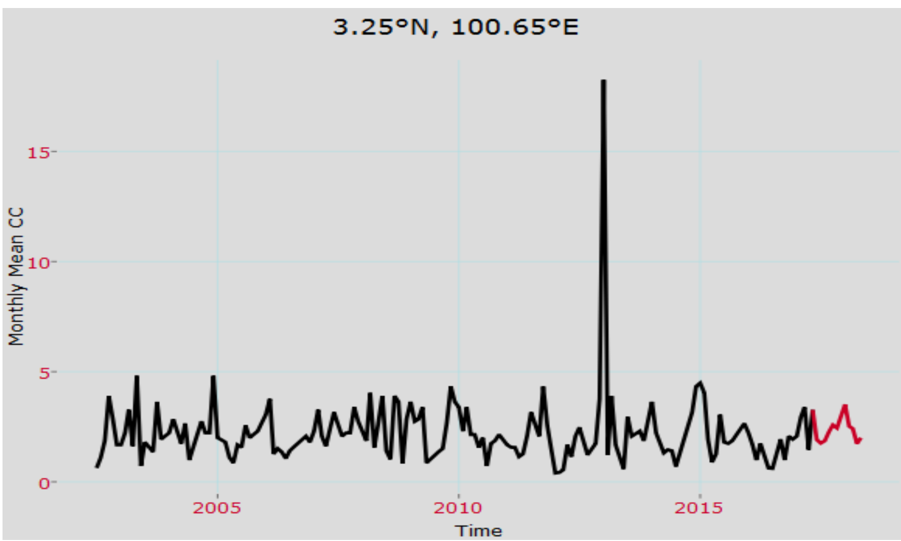

Figure 8: Forecast plot of 3.25°N, 100.65°E.

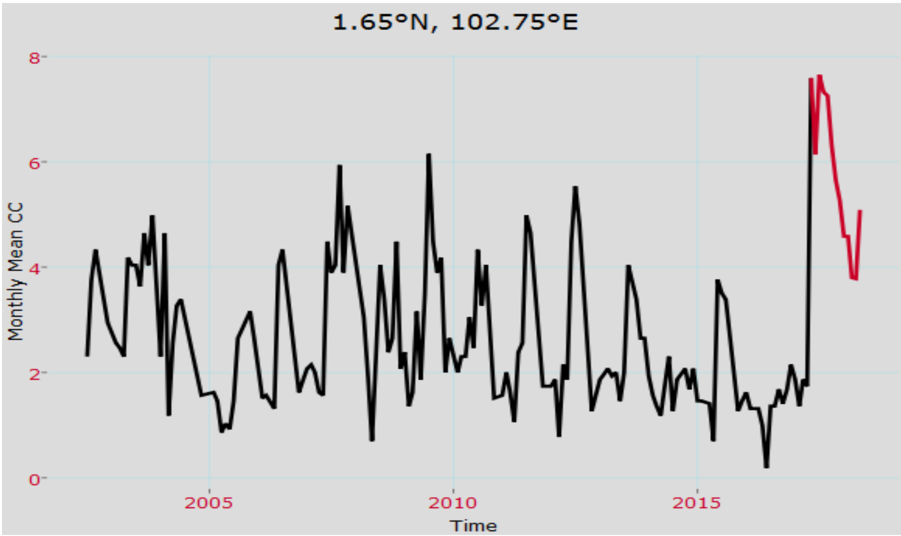

Figure 9: Forecast plot of 1.65°N, 102.75°E.

4. Conclusions

The aim of this paper was to develop a web portal to forecast the monthly mean CC of the waters off Peninsular Malaysia's west coast within the EEZ of Malaysia. The developed portal addresses the typical challenge in fisheries by narrowing down the fishing ground search utilising the underlying relationship amongst CC, phytoplankton and the food chain of small pelagic fishes.

The portal can be regarded as a tool to assist fishermen especially those operating devices to catch small pelagic fishes to enhance their fishing efforts in a far more efficient manner, which in turn may increase profitability and make life at sea less stressful for them. Subsequently, it could help to optimise cost and time involved in fishing trips as compared to the manual operation in which fishermen may have to move from one to another point in the sea to find a fruitful fishing ground at a given time.

The information conveyed in the form of monthly mean CC values in the portal shall be used by fishermen prior to their fishing trips, in which it can be used either to select a fisheries site with the highest mean CC value for a fixed month or to select a month with the highest mean CC value for a fixed fisheries site. This would help them to plan their fishing trips ahead to decide where or when to fish instead of deciding it during a fishing trip.

The major advantage of using this portal is the easy accessibility provided using computers or smartphones with internet connection. Furthermore, the user interface provides both graphical and numerical outputs that are readable and simple. Additionally, the development of this portal can also be seen as a supporting initiative for Peninsular Malaysia's west coast fisheries, as more attention was always given to the east coast fisheries. On the other hand, the drawback of using CC is that it only helps to confine the fishing ground search but it does not guarantee a catch at any rate. An issue of concern in the portal is the belated availability of the most recent data from source database ensuing delayed data update process in the portal.

Further research to enhance fishing grounds identification can be conducted by incorporating other vital environmental variables such as dissolved oxygen content, nutrients content, sea surface salinity and sea surface height which may also play a significant role in fisheries besides CC, subjected to consistency in data availability.

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