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Modelling of Chlorophyll-*a* Concentration Patterns from Satellite Data Using Cubic Spline Function in Pattani Bay, Thailand

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ABSTRACT

The modelling of chlorophyll-*a* concentration helps to restrict the harmful effects in marine species caused by increased nutrient loads. The derived satellite data are often used for the monitoring of marine ecology. The common usage of satellite data is monthly average data to avoid the problem of missing values. In order to reduce the effect of missing data, this study employed the cubic spline model by using a satellite data for investigating seasonal variations of chlorophyll-*a* mapped in an eight-day interval consisting of missing values in Pattani Bay, Thailand from the year 2003 to 2017. This study further used the spline-fitted data for creating the baseline model of chlorophyll-*a* in Pattani Bay, and for examining the difference between spline fitted and monthly average data. This study revealed that the cubic spline method was able to handle the missing values in satellite data to gain the smoothness in data. When both models were compared, the spline-fitted observation yielded a smoother curve pattern than the monthly average observation. The spline fitted model was also able to display the chlorophyll-*a* data at any particular day of the year. It was also shown that the chlorophyll-*a* concentration level in the coastal area of Pattani Bay was higher in the inshore pixels, especially in rainy season.

INTRODUCTION

Chlorophyll-*a* is a photosynthetic pigment in plants essential for phytoplankton and is one of the important indicators of affluence and biomass in the aquatic ecosystems. Due to its healthy relationship with marine science, chlorophyll-*a* helps to measure the trophic level of water bodies and provide an understanding of oceanography (Ha et al. 2013). The content of phytoplankton depends on the oceanic surface water, which is useful for detecting the colour of chlorophyll-*a* (Zenkin et al. 2009). Several studies have been carried out on the occurrence, abundance of phytoplankton and their characteristics of harmfulness (Yoo et al. 2013). Among the several effects, the noteworthy observation is the appearance of eutrophication due to its nutrient loads in the water bodies (Intacharoen et al. 2018, Smith 2006); and its effect on marine species (Cheevaporn & Menasveta 2003). The study by Blondeau-Patissier et al. (2014) revealed that the global distribution of chlorophyll-*a* and biomass appearances are rich along the coastal line and continental shelves due to the strong nutrient supply. In addition, the significance of chlorophyll-*a* relevance over other water quality parameters and the importance of satellite data helps in the awareness, sensitivity of ecosystem drivers and feasibility to monitor aquatic bodies (Boyer et al. 2009). While the management of marine services is highly essential for the active detection and timely inspection of water bodies, the field monitoring of chlorophyll-*a* in water bodies is tedious, costly and inconvenient (Yunus et al. 2015).

In recent decades, various studies have investigated the implementation of satellite data for acquiring earthly information. Unlike field data, satellite data are more efficient since they cover a large area, have a higher availability and are less time consuming (Dörnhöfer & Oppelt 2016). This vital information from satellite sensors helps to acquire geological information including the monitoring of oceanography (Zhang et al. 2018). The utilization of remote sensing data noteworthiness could be eye-balled in the field of ocean and coastal environment (Ouellette & Getinet 2016). The ocean colour viewing sensors such as SeaWiFS, Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS-Aqua) (Ji et al. 2018, McClain 2009, Ouellette et al. 2016) have been used to obtain the global data. Since the commencement of MODIS-Aqua from 2002, monitoring of the chlorophyll-*a* concentration has been one of the pivotal features of remote sensing data to assess the aquatic environment, the significance of various biogeochemical characteristics and the substances present in the marine bodies (Schalles 2006, Stadelmann et al. 2001, WoŸniak et al. 2016).

Several studies have investigated the significance of chlorophyll-*a* concentration from satellite data in marine and coastal environment for the management and sustainability of the coastal area using ocean colour satellite data (Blondeau-Patissier et al. 2014, Hansen et al. 2015, Mélin et al. 2011, Nezlin & Li 2003, Ouellette & Getinet 2016, Park et al. 2010, Yunus et al. 2015, Zhang et al. 2011). The monthly average data were used for the analysis in most of these studies because of the problem caused by missing values from satellite due to cloud coverage and technical errors. Moreover, the monthly average seasonal variations for chlorophyll-*a* have been examined using annual order of the empirical orthogonal function by applying the principal component analysis function, bio-optical model, data assimilation and bias correlation method (Acker et al. 2008, Boyer et al. 2009, Ha et al. 2013, Mélin et al. 2011, Park et al. 2010, Saraceno et al. 2005, Tan et al. 2006). These results used from the aforementioned methods showed the changes in seasonal patterns using other water quality parameters along with chlorophyll-*a* concentration. However, with the usage of monthly average data, the details of each month could not be observed or the details have been diminished. The values obtained from the monthly average data are the same for the different days in a month due to the reason of the monthly mean effect.

Recently, the cubic spline function is widely used to deal with the problem of missing values in satellite time series data for investigating the seasonal variations. The study conducted by Mao et al. (2017) investigated the seasonal patterns of the carbon cycle in satellite time series data using cubic spline method to remove noise and verify the accuracy of data. Wongsai et al. (2017) and Sharma et al. (2018) used the spline method to assess the seasonal patterns using satellite data. Both the studies found that the use of cubic spline function improves the data by interpolating and estimating missing values for monthly average data to detect seasonality in the long-term satellite data. Another study by Deng & Chen (2006) found that the noise for seasonal trajectories using cubic spline fixed the problem of interpolation. The spline based model is competent in curve fitting for long time series data and the curve remains stable through data gaps (Bradley et al. 2007). Thus, the aim of this study is (i) to investigate the seasonal patterns and trend of chlorophyll-*a* concentration by using a cubic spline method, (ii) to gain the smoothness of missing data, and (iii) to create the baseline model for chlorophyll-*a* by predicting a particular day in any day of the year.

MATERIALS AND METHODS

Study area: The study was conducted in Pattani Bay, situated at the eastern coastal area in the lower Gulf of Thailand. The map of the study area consisting of the coastal area of Pattani Bay in the lower Gulf of Thailand with the respective geographical coordinates of the study site is shown in Fig. 1. The southern part of Thailand in the east coast has two seasons: rainy and dry season while the wettest period of the year is usually experienced from November to January (Limsakul et al. 2009). The study site located at the Gulf of Thailand is one of the important ecological parts of the Indo-Burma Hotspot, which is ranked in the top 10 hotspots of the world (Critical Ecosystem Partnership Fund 2012). The site was selected due to its significant valuable coastal wetland for conservation in Asia for the essential intertidal mudflat effect (Secretariat 1999). The marine ecology damages, such as pollution and toxic erosion along the coastal line, have been an aquatic hazard in the area of Pattani Bay (Sowana et al. 2011). The time series data from 2003 to 2017 retrieved from MODIS-Aqua sensor with the spatial resolution of 4×4 km, consisted a total area of 1,280 km^2 in the study site.

Data: The satellite chlorophyll-*a* data were used in this study for the investigation of seasonal patterns. The level-3 data converted from captured signals by MODIS-Aqua sensors were obtained from the ocean color website. The MODIS chlorophyll-*a* data obtained as raster images can be used in the various fields of oceanography to measure the environmental changes. In this study, eight-day mapped data for the spatial resolution of 4×4 km chlorophyll-*a* observations for Pattani Bay between the year 2003 to 2017 were downloaded from the ocean color website (https://oceandata.sci.gsfc.nasa.gov/MODISAqua/Mapped/8Day/4km/chlor_a). From the global chlorophyll-*a* data, the study area was defined by specifying appropriate co-ordinates and cropping the extent of the desired area as shown in Fig. 1.

The satellite data consisted of a total of 80 grids or pixels as displayed in Fig. 2. A satellite grid contained the information from the inshore and offshore pixels in the coastal area, therefore, the shape of the satellite pixel grids seemed rectangular in shape. Moreover, the resolution of pixel grids with eight columns and ten rows were in accordance with the pixels of the geographical location in the study area as shown in Fig. 2. The MODIS aqua sensor mapped for chlorophyll-*a* for every eight-day interval provided 46 downloadable files in a format of Network Common Data Form (NetCDF) per year, and consequently, a total of 690 files from 2003-2017 were acquired for each pixel. The obtained data had the same number of pixels in each file per observation. The pixels located in the land area contained missing values (for pixels 73-80). Hence, they were omitted from the study. In order to identify seasonal patterns and to get rid of spatial correlation problem for adjacent grids, each pixel was analysed separately.

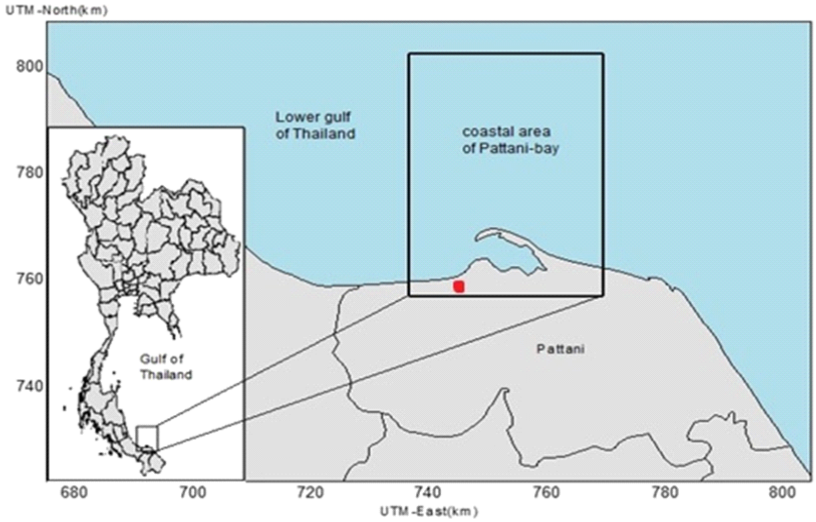

Fig. 1: Study area in the coastal area of Pattani Bay (demarked with a black box specifying Pattani district with red dot).

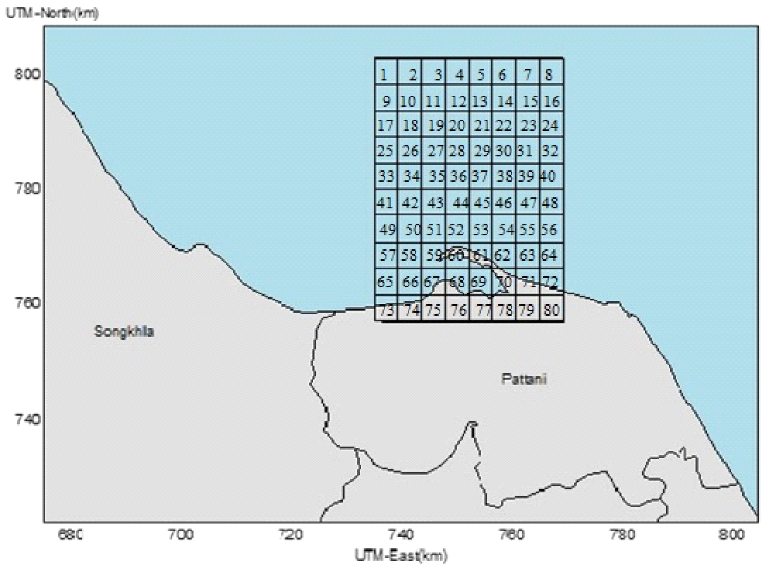

Fig. 2: Map of the study area showing 80 pixels (pixel grids demarked in a black box).

In the 15-year period, a total number of 49,680 observations were obtained for all pixels. From total observations, some observations were missing in each pixel during the study period due to the atmospheric and technical errors from the satellite. The heuristic eight-day period chlorophyll-*a* concentration, measured in the unit of mg/m^3, was used as the main variable for this study.

THE STATISTICAL METHOD

This study investigated both components of time series data, which include the seasonality and trend. In time series data, the trend shows the actual movement in the data over time; whereas, seasonal variation is the variation of data at specific seasonal frequencies. The process in time series analysis is to find whether the data are stationary or there is a trend in the series. In the case when the data are stationary, the seasonality effect would directly be examined. However, when the data are observed non-stationary, the time series influence (trend) would be subtracted from the original data for the seasonal analysis. In this study, the Augmented Dickey-Fuller test (ADF test) performed in R statistical software environment was used to check the stationarity of the data.

In order to fit the model into chlorophyll-*a* observations, the cubic spline function was used in this study. The cubic spline function is the piece-wise polynomial regression having a continuous second derivative and is an effective method to deal with the missing values in data by choosing a suitable knot vector written in linear form. Moreover, it is well-known and efficient in curve fitting with desirable derivatives and to smoothen data by interpolation with the suitable knots (Wongsai et al. 2017). The knots in cubic spline are the data points used to solve the problem of missing data by interpolation (Bradley et al. 2007). A cubic spline function with ten equidistance knots was fitted to the model by deciding the smoothness of curve fitted into the data. The general form of the cubic spline method is given in Eq. (1):

$$S_p = a + b + \sum_{i=1}^{k-2} c_i \left[(p - p_i)_+^3 - (p - p_{k-1})_+^3 \frac{(p_k - p_i)}{(p_k - p_{k-1})} + (p - p_k)_+^3 \frac{(p_{k-1} - p_i)}{(p_k - p_{k-1})} \right] \quad ...(1)$$

Where, S_p represents the chlorophyll-*a* concentration, a is a constant, b is the regression coefficient, C_K indicates time predictors for eight-day and monthly average chlorophyll-*a* observation, k is the knot loadings for the specified days of the year, P denotes time in Julian day, $P_1<P_2< ... <P_i$ are specified knots and $(P\text{-}P) + is\ P - x$ for $(P>P_K)$ and zero otherwise.

For the graphical representation, the graphs were plotted to investigate the seasonal patterns and trend in the data demonstrated by plotting the graph using cubic spline function. Later, to examine the difference in data, the spline fitted data and monthly average data were compared with the plots. To obtain the monthly average data, the monthly chlorophyll-*a* observations were averaged for each month from the total observations. Thus, for 72 pixels, the total of 12,960 observation records were obtained.

Lastly, level plot was represented in a graphical form as a study map to observe the chlorophyll-*a* concentration levels during the study period for all pixels. Moreover, level plot was also used to display plot for the day any particular day between the months. The graph could be adopted to exhibit the baseline model for chlorophyll-*a* data created by calculating the data points for the desired day in a year from the spline fitted model values. All data management, statistical analysis and graphical presentation in this study were performed using R statistical software environment version 3.3.1 (R-project, 2015).

RESULTS

For the statistical analysis of time series data, it is important to examine seasonal variation and trend in the dataset. The Augmented Dickey-Fuller test (ADF test) implemented in R showed that the p-value was less than 0.05. This affirmed that the data were stationary. For the investigation of seasonal variations, each pixel was examined individually. Each grid box in the chlorophyll-*a* seasonal pattern plot represent the study area consisting of 72 pixels. For the first attempt on data analysis, it was found that the data for chlorophyll-*a* concentration in the study area were more scattering in the middle period of the year (June and July). For a spline function to be fitted, the continuous data points are preferable. Therefore, the observations were orderly arranged starting from July and ending with June (JASONDJFMAMJ) instead of the conventional annual order from January to December. In order to normalize the distribution of data, the chlorophyll-*a* values were transformed into a natural log scale to reduce the effect of a dramatic fluctuation in data presentation.

A cubic spline model was fitted on the eight-day chlorophyll-*a* observations between the study period from 2003-2017, forming 72 models presented differently in the graph shown in Fig. 3. The model for the chlorophyll-*a* seasonal pattern comprised polynomial predictors from spline function. The ten equidistant knots were fitted in chlorophyll-*a* observations in this study, and they placed along the times of year. This particular number and positions of knots were selected arbitrarily to avoid the overfitting problem from having a greater number of knots, and to be adequate for the curve fitting and interpolation of the data. From Fig. 3, every grid box in the graph illustrates the chlorophyll-*a* concentration levels by fitting the spline model (pink solid line) to estimate the seasonal patterns of chlorophyll-*a*. The plot also illustrated an important feature for enhancing missing data with knots (blue cross). To observe the patterns of chlorophyll-*a* levels, the graph of the annual seasonal pattern was plotted. In each grid box, the maximum number of chlorophyll-*a* observations within the study period was a total of 690 observations. However, due to the problem of missing data, the plot displays the number of observations (n) ranged from 185 to 406 in each pixel between the study period in Fig. 3. In addition, each grid box in Fig. 3 illustrates the adjusted r-square of the model and both the longitude and latitude in the four corners of the grid box.

The coefficient of the model (adjusted r-square) in overall was around 44%. The adjusted r-square varied from 20% to 53% for all the grid boxes located inshore to offshore. Due to the abundance of chlorophyll-*a* concentration lev-

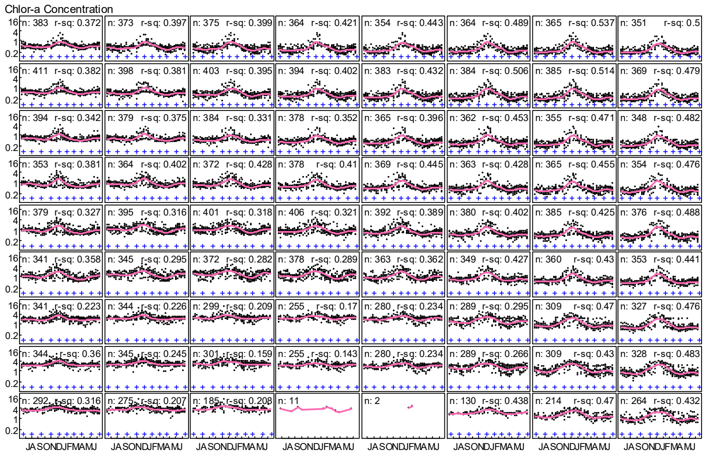

Fig. 3: Plot showing seasonal patterns of eight-day interval data by fitting cubic spline function for 72 pixels in 15-year period

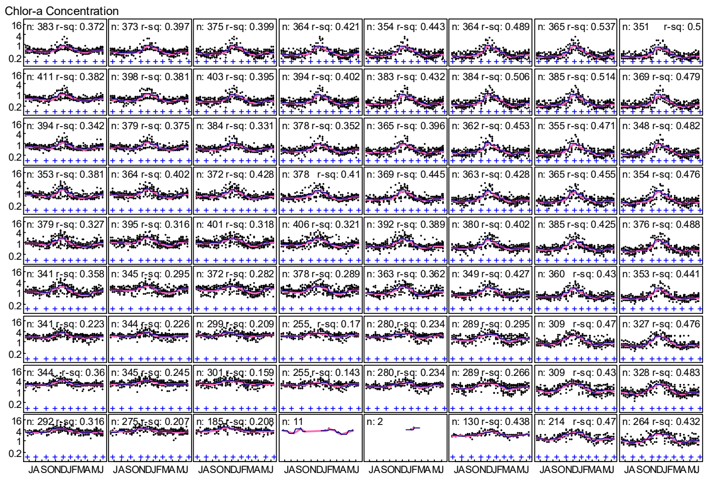

Fig. 4: Plot showing comparison between seasonal patterns of spline fitted eight-day data with pink solid line and monthly average data with blue solid.

els, the r-square values were inclined on inshore and offshore pixels. The result exhibited that there was an increase in concentration for the chlorophyll-*a* levels near inshore indicated by solid black dots shown in the Y-axis during the study period. The observed patterns for the inshore pixels near Pattani district (Fig. 1 with red dot) revealed that the seasonal patterns were slightly higher than the other pixels in the coastal area of Pattani Bay. Also, it is worthwhile to note that an increment of concentration levels observed within pixels reached up to 13 mg/m^3 in the inshore pixels near the coastal area. However, the concentration was decreasing towards the offshore pixels. In Fig. 3, it can be seen that an increasing pattern of chlorophyll-*a* started in November and ended in February. This period of the month falls during the rainy season of the year in the study site.

In Fig. 4, the difference in spline fitted chlorophyll-*a* observations (pink solid line) and monthly average chlorophyll-*a* observations (blue solid line) was compared. It was found that the monthly average observations had irregular patterns of chlorophyll-*a* observations due to the monthly mean effect in chlorophyll-*a* observations. Although the variations of chlorophyll-*a* observations were not relatively high, it is salient to note the details about the inadequacy of monthly average data. The monthly average observations showed fluctuations or flat curves for seasonal patterns due to the effect of outliers in the chlorophyll-*a* observations when observed in detail.

A more detailed comparison plot between spline fitted data and monthly average data is presented in Fig. 5. The samples of pixel numbers ranging from 37-40, 45-48, 53-56, 61-64 and 69-72 were chosen to observe the patterns, in particular, for a clearer presentation. It can be seen that the pattern of monthly average data changed along with the presence of outliers due to the inadequacy of data found mainly in the pixel numbers 53, 62 and 70, respectively. In addition, the monthly average data seemed to change the

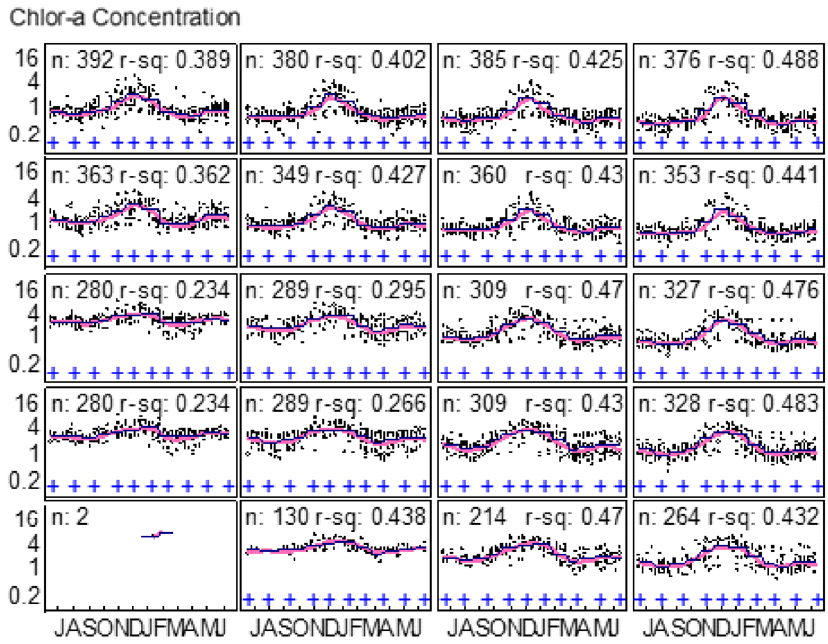

Fig. 5: Plot showing the seasonal patterns difference between monthly average data with blue solid line and spline fitted eight-day data with a pink solid line for 72 pixels in 15-years period for selected pixels.

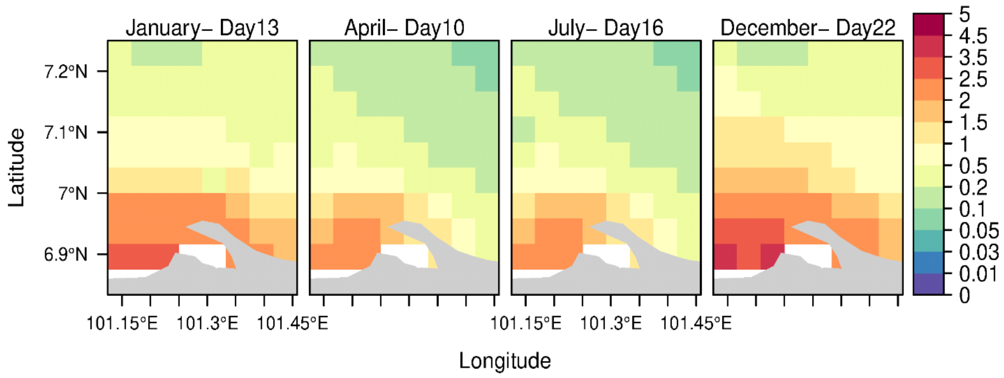

Fig. 6: Level plot for chlorophyll-*a* concentration for spline fitted eight-day data for random days in four months consisting of 72 pixels in 15-year period.

shape of the curve along with the outliers for the pixels in 39, 45, 48 and 56, respectively. On the other hand, the spline fitted data observations showed a dominant seasonal pattern in the overall pixels. Thus, a cubic spline fitted observation showed a smooth pattern compared to monthly averaged observations.

Furthermore, the spline fitted model values can also be used to plot the level plot with geographical physical vector masks to define the land area downloaded from natural earth website (www.naturalearthdata.com/downloads/10m-physical-vectors/) for the study area. For the extraction of the level plot, the spline fitted chlorophyll-*a* observations from the model used on a natural log scale were transformed back into an exponential form to obtain the original scale of the data. The level plot, displayed in Fig. 6 contained the concentration of chlorophyll-*a* for 72 pixels between 2003 and 2017. The plotted figure was represented as an example to observe the chlorophyll-*a* concentration levels at any day of the year by choosing random days of the year in the month of January, April, July, and December.

The level plot was displayed to capture the details of observations from the fitted cubic spline model by predict-

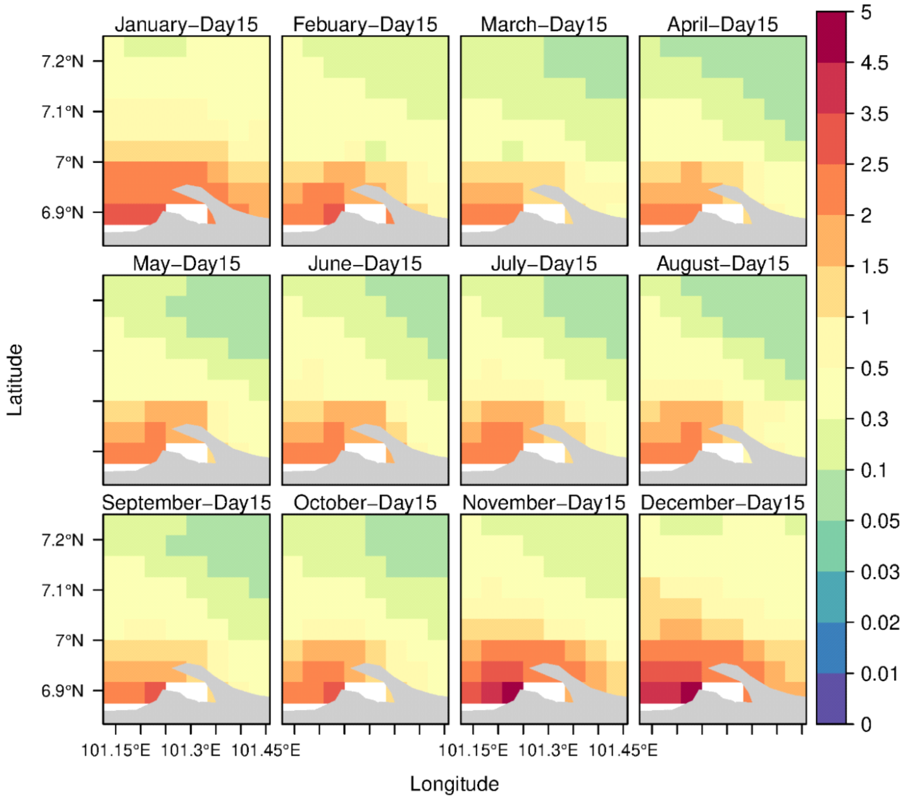

Fig. 7: Level plot for chlorophyll-*a* concentration for spline fitted eight-day data for day 15 in a year consisting of 72 pixels in15-year period.

ing the model values for any days of the year using model values from the original data. The model values were predicted by using the cubic spline equation by inputting the intercept and coefficient values from the model for 72 pixels as shown below in equation (2):

$$\hat{y} = a + b_1 x + b_2 s_1 + b_3 s_2 + b_4 s_3 + b_5 s_4 + b_6 s_5 + b_7 s_6 + b_8 s_7 \quad ...(2)$$

Where, *a* denotes intercept, *b* denotes β (coefficient from the model), *x* denotes the predicted days, S_1, S_2 ... S_7 denotes the spline piecewise polynomial regression.

To understand the extraction of level plot for the desired days, Table 1 is given as an example showing the piecewise polynomial function denoted as S_1, S_2 ... S_7. These values were obtained from the spline fitted chlorophyll-*a* data for the original data mapped in eight-day interval. To predict the days between eight-day intervals, the equation of spline function should be to obtain the model values for the desired days. Therefore, the values from Table 1 can be applied in equation (2). As an example, the results obtained for days 2, 106, 203, and 207 respectively, using random pixels were predicted using (2) and values in Table 1 is shown in Table 2.

From the obtained values given in Table 2, the difference of model values is shown for the different days in July for predicting the values by using cubic spline function. This is not possible for the monthly average data because there is no change in values due to the monthly mean effect. The benefit of using spline fitted value is shown in Fig. 7, by plotting level plot. The spline fitted values were extracted for the predicted days for the particular day 15 for all months and was demonstrated as an example in a level plot to observe chlorophyll-*a* level in any day of a year in Fig. 7.

The level plot in Fig. 7 displaying the concentration of chlorophyll-*a* at day 15 of each month shows the overall scenario of the year. The plot presents the increased level of chlorophyll-*a* concentration from the month of November to January for most of the pixels, confirming the result obtained from prior statistical model. The level plot displays the best example of a created baseline model to observe the data consistently for the original data and calculated points from the model for the desired days in a piecewise form, from the cubic spline function. The figure reveals that the

Table 1: Model values obtained for the chlorophyll-*a* observations for days 2, 58, 106, 138 and 207 respectively.

	Year				
	2009	2010	2012	2013	2014
Days	2	58	106	138	207
S_1	0	0	0	0	0
S_2	0	0	0	0	8
S_3	0	2197	0	0	50653
S_4	0	148877	4096	110592	373248
S_5	0	1030301	226981	804357	1601613
S_6	0	0	1030301	2352637	4251528
S_7	0	0	0	0	8242408
Pixel	2	9	24	46	68
Model Value	-0.73003	-1.08407	-1.08407	-1.08407	-0.54452
ExponentialValue	0.481894	0.338217	0.338217	0.338217	0.580119

Table 2: Difference between the model values obtained and the mean values after inputting the parameters form Table 1 in equation (2).

	Model values			Mean Value
Pixel	Day 197 (July 16)	Day 203 (July 24)	Day 209 (July 30)	Average values for July
1	0.4646218	0.445181	0.4561986	0.4889357
10	0.4832377	0.4592745	0.4726553	0.50529
21	0.3077348	0.2957641	0.302185	0.3433551
34	1.0073273	1.0038783	1.0066142	1.077119
42	1.3848131	1.3446034	1.3676119	1.4270782
50	2.0855312	2.0416567	2.0665652	2.1783519
60	2.1689982	2.1253003	2.1504334	2.1909411
72	0.8701816	0.8088683	0.8426502	1.0063647

chlorophyll-*a* concentration from November to February was considerably dominant for most of the inshore pixels when compared to the offshore pixels. The concentration level of chlorophyll-*a* varied with various colours indicates the chlorophyll-*a* levels in pixels as illustrated in Figs. 6 and 7.

DISCUSSION AND CONCLUSION

The spline fitted data and monthly averaged chlorophyll-*a* observations were used for the investigation of seasonal patterns in Pattani Bay, Thailand from 2003-2017. The spline fitted and monthly average chlorophyll-concentration observations showed similar seasonal patterns for 72 pixels used in this study; however, the details of the monthly-average data were not obtainable due to the monthly effect in the data. A noteworthy observation of this study was that the fitted values showed a smoother curve for the spline fitted chlorophyll-*a* observations than the monthly average chlorophyll-*a* observations. The coefficient of the model shows a goodness of fit for spline fitted eight-day observations where the adjusted r-square inclined on the availability of data. Furthermore, the data were apparently fluctuating due to the variation of chlorophyll-*a* levels from 2003 to 2017. The examined seasonal patterns were fluctuating mainly due to perspiration in the rainy season, monsoon variations and a stronger aridness in the dry season.

When the data were compared in Fig. 4, the average monthly data showed the irregular patterns of chlorophyll-*a* observations due to the monthly mean effect in chlorophyll-*a* observations. Although the variations of chlorophyll-*a* observations were not relatively high, it was also important to be aware of the inadequacy of monthly average data. The monthly average data showed a flatter curve due to the effect of outliers in the chlorophyll-*a* observations. The monthly averaged data exhibited the inadequacy for examining the seasonal patterns at different days in a month due to averaged effect. Furthermore, the results illustrated the effectiveness of cubic spline model in satellite chlorophyll-*a* data and to calculate the values for any day in a year. Moreover, the significance of using cubic spline method was well highlighted by Sharma et al. (2018), North & Livingstone (2013), and Wongsai et al. (2017). These aforementioned studies discussed the benefits of fitting a cubic spline to gain the seasonal patterns and to study the flaws of missing value, the fluctuation in satellite data and for the optimization of cubic spline knots.

The level plot given in Fig. 6 and Fig. 7 illustrates the usefulness of using spline fitted data to observe the chlorophyll-*a* level for any day of the year especially plotted as an example for random days in four months and particular day 15 in a year. The level plot displayed that the chlorophyll-*a* concentration was higher in offshore pixels during the rainy season from November to January. Therefore, the chlorophyll-*a* concentrations may have increased in Pattani district due to the increase in effluents in the soil/water. More interestingly, Lirdwitayaprasit et al. (2006) affirmed that red tides were observed more often in the rainy season to influence the concentration of chlorophyll-*a*. The study by Limsakul et al. (2009) revealed that chlorophyll-*a* concentration is expected to increase the rainy season. Furthermore, Matsumura et al. (2006) studied the monsoon wind and the river discharge effects on the coastal water, and the chlorophyll-*a* content was reported to be higher in the wet season than in dry season due to the loaded nutrients in the water (Intacharoen et al. 2018). Another study by Wang et al. (2015) discussed that the chlorophyll-*a* concentration was higher near the coast and lower in the open sea due to the treacherous area. It was also discussed that the runoff provides abundant nutrients for phytoplankton near the coast, which can similar insights as the scenario in Pattani Bay. Based on global water quality unit (μg/L) for chlorophyll-*a* (Sheldon & Alber 2011, Hanmer et al. 2003), the chlorophyll-*a* concentrations were grouped into three categories as follows: < 5 μg/L represents good condition, > 5 μg/L denotes fair condition, and > 20 μg/L represents a poor condition of water quality. The model result from this study found that the chlorophyll-*a* concentration is in the range of 5-20 μg/L. Thus, the coastal area of the lower Gulf of Thailand on the eastern coast is in fair condition of water quality along the coastal belt.

In conclusion, this study described the chlorophyll-*a* seasonal pattern which helps in obtaining vital information with the usage of satellite observations on the coastal area of Pattani Bay. The sample study site investigated the seasonal patterns and showed the significance of using spline fitted eight-day observations over monthly average data. The fitted model was used effectively to predict the model values for any particular day of the year. In addition, this study model can widen the knowledge on satellite time series data for water body and oceanic characteristics, and up to date monitoring purposes which provides information for the conservation of marine ecology. Furthermore, to gain more information of patterns for water quality, further studies on spatial locations for chlorophyll-*a* concentration along with other water parameters could provide better insight on satellite time series data using the same methodology presented in this study.

The limitation of this study is the presence of a number of missing values in satellite chlorophyll-*a* observations. Although, this study used the spline function to deal with the missing data, a more precise condition of the chlorophyll-*a* concentration in Pattani Bay would have been achieved if there were less missing data.

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