The Chlorophyll-a Modelling over the Andaman Sea using Bi-Directional LSTM Neural Network

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Abstract—The topography of the south of Thailand is the peninsula between the Andaman Sea and the South China Sea. The global measurement of chlorophyll-a is the NASA satellite image product. 16-year monthly time series (from 2003 to 2018) of the Moderate Resolution Imaging Spectroradiometer (MODIS), the data in both space and time. The approximation and component detailed from the original series of MODIS chlorophyll-a were considered sources of chlorophyll-a stationary level anomalous variability. The paper created Bi-Long Short Memory (Bi-LSTM) modeling, that kind of neural network. Six positions in the province area, Ranong, Phangnga, Phuket, Krabi, Trang, and Satun, were studied. The model was evaluated using four performances as, mean squared error (MSE), root mean square error (RMSE), the sum of square error (SSE), and correlation coefficient. Phangnga was given a good chlorophyll-a prediction. However, the model has been validated to predict chlorophyll-a using Bi-LSTM.

Keywords—Chlorophyll-a, Bi-Directional, Neural Network.

I. Introduction

The Andaman sea is located in the southeast of the Bay of Bengal, the north covering Myanmar, the east covering Thailand, Myanmar, Malaysia, and the west covering the Andaman Islands. The behavior of the monsoon season is the most impact on the Andaman area. Two seasonal monsoons are the winter monsoon and summer monsoon. The winter monsoon during November runs as late as October. The summer monsoon typically runs from June to October. The monsoon circulation interaction between the Indian Ocean and South Asia provides dynamic instabilities as chaotic [1].

The most important for understanding monsoon variability is the relation between sea surface temperature (SST) and land surface condition, large-scale circulation as the El Nino-Southern Oscillation (ENSO) [2]. However, sea surface temperature is close to the land or surface of the sea. The water temperature depends on the sun; the temperature decreases according to the sea depth. Zhao et al. [3] emphasize that the nutrient of phytoplankton by the tropical storm and the concentration of Chlorophyll-a near the coastline is higher due to the supplied nutrient from the mainland directly. Therefore, climate variability usually changes the coast or mainland and the sea. Kavak and Karadogan [4] focused on the relationship between Chlorophyll-a and sea surface temperature (SST) on the black sea using sea-viewing Wide Field-of-view Sensor (SeaWiFS) and Advanced Very High-Resolution Radiometer (AVHRR) satellite imagery.

In recent years, deep learning or deep neural networks predict everything in the real world. The machine learning model that learning data like time series data. The machine learning algorithm includes a support vector machine, decision tree, artificial neural network, long short-term memory neural network, etc. Long short term memory (LSTM) neural network model can use continuous sample data usually used in time series, which is a good result in prediction. Hochreiter and Schmidhuber [5] use LSTM to improve time series. However, it is limited by computer memory. LSTM includes forget gate, an input gate, and an output gate, and it has been applied to predictions such as the weather data, stock price, and data from real life. The LSTM learns faster than other neural networks and has better resolution than recurrent neural networks [5].

Schuster and Paliwal [6] developed a bi-directional LSTM neural network in 1997. They were using input data from the past and future and spitted the neuron into positive and negative time directions. The output is separated from forwarding states and backward states, and the training process bi-LSTM is trained in both forward and backward directions. This work focus on using Bi-LSTM to predict Chlorophyll-a.

This research aims to predict Chlorophyll-a in six regions of the south of Thailand. The problem is approached using Bidirectional Long Short Term Memory (Bi-LSTM) due to having a memory for previous time-series data and good for predicting the future value.

II. Data and Methods

A. Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an instrument from the National Aeronautics and Space Administration (NASA). MODIS provides global image products of the land surface, sea surface temperature, and Chlorophyll-a. Dataset provides the time series of the monthly data from 2003 -to 2018, shown in Fig. 1, and Fig. 2 describes the change in Chlorophyll-a data in time series, while Fig. 2 shows the spatial area of Chlorophyll-a.

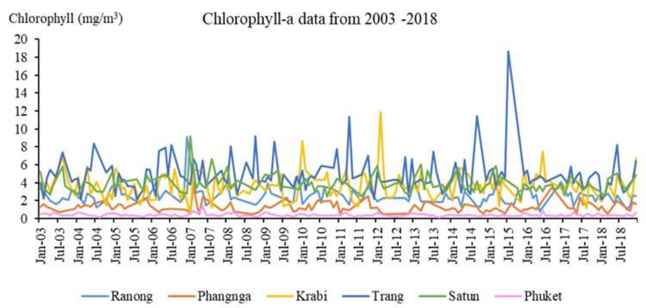

Fig. 1. The change of Chlorophyll-a in 2003-2018.

According to Fig. 1, the period of Chlorophyll-a data from 2003 - to 2018 for six positions in each province shows on Table I, such as Ranong, Phangnga, Phuket, Krabi, Trang, and Satun. The data show that in July, Chlorophyll-a increase caused the southwest monsoon. Southwest monsoon produced the strong wind from India ocean to Andaman area then Chlorophyll-a moved another area to Andaman sea. Fig. 1 shows that Phuket's Chlorophyll-a data is lower than other positions, and Trang provides a higher value because of the different geography of each area. Fig. 2 clearly shows the shading of Chlorophyll-a. The red color is the maximum of Chlorophyll-a, and the blue color is the minimum of Chlorophyll-a. The Andaman area provides Chlorophyll-a between 3.23-5.6. Then, this dataset for study into training and testing with 8:2 ratios to learn and evaluate the experiment models.

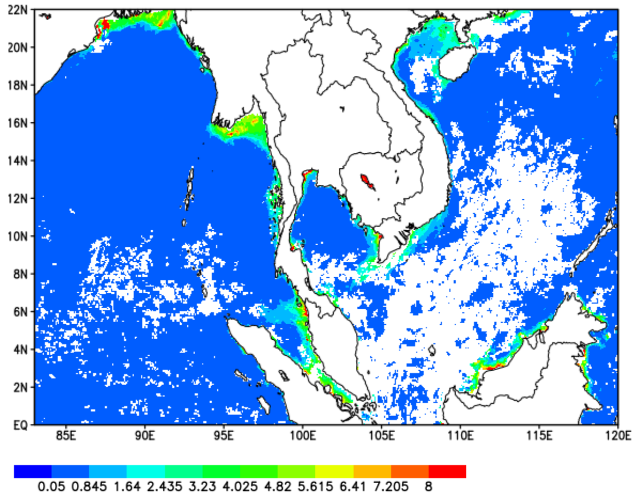

Fig. 2. The area of Chlorophyll-a.

TABLE I. AREA POSITION FOR STUDIES

Area	Latitude	Longitude
Ranong	9.65	98.43
Phangnga	8.86	98.25
Phuket	7.76	98.33
Krabi	7.98	98.90
Trang	7.22	99.49
Satun	6.56	99.96

B. *Long Short Term Memory (LSTM)*

Long Short Term Memory (LSTM) was developed for solve the vanishing gradient problem of Recurrent Neural Network (RNN) [8]. LSTM has included the input gate, forget gate, and output gate. LSTM could connect the historical data and return back to check results (unlike RNN, which only forward results) [9]. LSTM could control the information flow into each gate. However, LSTM is better than RNN and suitable for time series data because it could select good data for memory or remove it. [5] Fig. 3 shows the process of LSTM, the input layer, and the output layer consists forget gate and output gate.

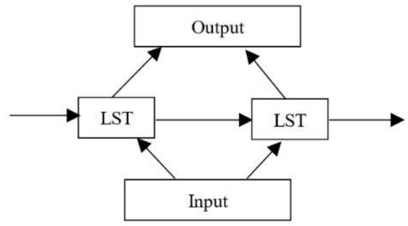

Fig. 3. LSTM Process.

C. *Bidirectional Long Short Term Memory (Bi-LSTM)*

The template Bi-LSTM is a mixing between Long Short Term Memory (LSTM) and Bi-directional Recurrent Network (Bi-RNN). The Recurrent Neural Network RNN was developed with time-series data from Long Short Term Memory (LSTM). LSTM and RNN consist of input, hidden, and output layers .The input layer is called the input gate, and the output layer is called forget gate and output gate. Fig. 4. shows the process between LSTM and Bi-RNN combined together .Graves and Schmidhuber [7] created architectures of Bi-directional RNN .For time step t, input $X_t \in \mathbb{R}^{n\times d}$ and hidden layer. Bi-direction assumed that the forward and backward hidden state is $\vec{H}_t \in \mathbb{R}^{n\times h}$ and $\overleftarrow{H}_t \in \mathbb{R}^{n\times h}$, where h is the hidden unit, as follows

$$\vec{H}_t = \phi\left(X_t W_{xh}^{(f)} + \vec{H}_{t-1} W_{hh}^{(f)} + b_h^{(f)}\right) \tag{1}$$

$$\overleftarrow{H}_t = \phi\left(X_t W_{xh}^{(b)} + \overleftarrow{H}_{t+1} W_{hh}^{(b)} + b_h^{(b)}\right) \tag{2}$$

where $W_{xh}^{(f)}, W_{xh}^{(b)}$ is weight and $b_h^{(f)}, b_h^{(b)}$ is bias

$$O_t = H_t W_{hq} + b_q \tag{3}$$

where O_t is the output layer.

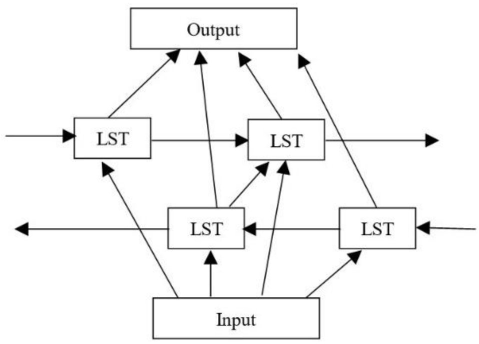

Fig. 4. Bi-LSTM Process.

The performance metrics in time series prediction are MSE, RMSE, MAE, and MAPE**.** Each statistic shows a different meaning in time series prediction. MSE is the average square of error, and RMSE shows how residual spread by the standard deviation of error. The following equation of error as

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(y - \hat{y}\right)} \tag{5}$$

$$MSE = \frac{1}{n}\sum_{1}^{n}\left(y - \hat{y}\right)^2 \tag{6}$$

where $y, \hat{y}$ represent the actual value and predicted value from the model.

D. Experimental Settings

To prepare the training and test dataset of Chlorophyll-a monthly in 2015 – 2019, divided into 80% and 20% of training data for the bi-LSTM neural network model. Furthermore, the training dataset was used for validating it for each epoch of training. Therefore, this paper prediction model was trained and evaluated using the training and evaluation datasets. The training and testing processes were performed on Intel Core i7-8750H CPU @ 2.20GHz 2.21GHz. and Matlab program (License 40512557).

III. Results

The experimental results are shown in Fig. 5 focus on Chlorophyll-a from the bi-LSTM model in six provinces; Krabi, Phangnga, Phuket, Ranong, Satun, and Trang. The x-axis represents monthly, and the y-axis shows the quantity of Chlorophyll-a. The predicted Chlorophyll-a is represented by the black dash line and the actual data as the black line. The results indicated that the predicted Chlorophyll-a from the bi-LSTM model in Phangnga matches the actual values. On the contrary, the predicted Chlorophyll-a from the bi-LSTM model in Trang does not obtain good results. Therefore, Phangnga is suitable for Chlorophyll-a prediction.

The best performance in this research could be seen from the indicator of the training dataset and testing dataset as scores. Training and testing scores could be seen from MSE and RMSE values. The smaller the MSE and RMSE values, show the better the performance system. For the training results, the minimum and maximum values of RMSE are 0.014919 and 0.098909, respectively; for testing results, the minimum and maximum are 0.00067 and 1.42950, respectively. Table II shows the performance of the training and testing dataset, showing that Phangnga provided good performance. Table III shows the correlation coefficient of Chlorophyll-a prediction. Again, Phangnga was given good value than other provinces, and Ranong provided a lower correlation coefficient.

TABLE II. PERFORMANCE OF TRAINING AND TESTING DATASET

Province	**Training dataset**			
	MSE	**RMSE**	**Error Mean**	**Error Std.**
Krabi	0.0048549	0.069677	7.6323e^{-5}	0.070028
Phangnga	0.0008493	0.029143	2.0916e^{-5}	0.029290
Phuket	0.0002226	0.014919	4.1679e^{-5}	0.014982
Ranong	0.0097830	0.098909	15.073e^{-5}	0.099533
Satun	0.0006694	0.025873	42.955e^{-5}	0.026041
Trang	0.0088384	0.094013	115.99e^{-5}	0.094521
	Testing dataset			
Krabi	2.04340	1.42950	0.151210	1.51960
Phangnga	0.00067	0.025884	0.0081678	0.02653
Phuket	0.06624	0.257380	-0.016363	0.26828
Ranong	31.9674	5.654000	1.439900	6.69630
Satun	0.85432	0.924290	-0.11532	1.29690
Trang	35.9183	5.99320	-3.11810	5.72230

TABLE III. THE CORRELATION COEFFICIENT FOR CHLOROPHYLL-A PREDICTION

Province	**Correlation Coefficient (r)**
Krabi	0.94602
Phangnga	0.99918
Phuket	0.87352
Ranong	0.67118
Satun	0.99117
Trang	0.9829

IV. Conclusion

In this paper, we applied the bi-LSTM neural network to predict Chlorophyll-a. Six areas representative of the south of Thailand around the Andaman sea. For sixteen years of data (2003-2018), predictions were performed. The MSE, RMSE, and correlation coefficient (r) were used to evaluate the forecasting accuracy of the model. The results indicate that the proposed prediction has the best prediction accuracy with the benchmarks. The suggestion bi-LSTM has demonstrated forecasting accuracy for Chlorophyll-a forecasting.

Acknowledgment

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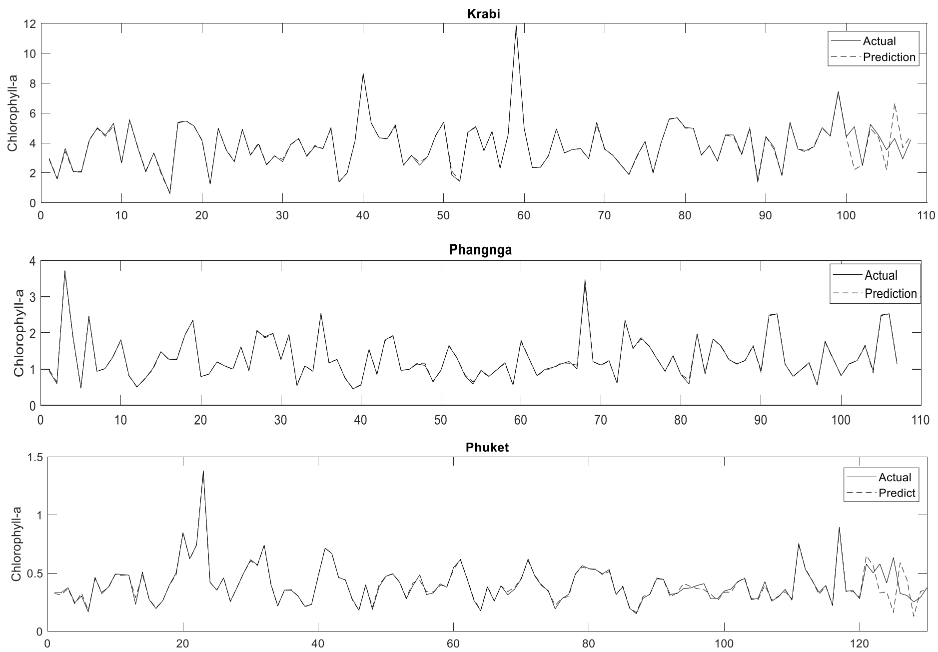

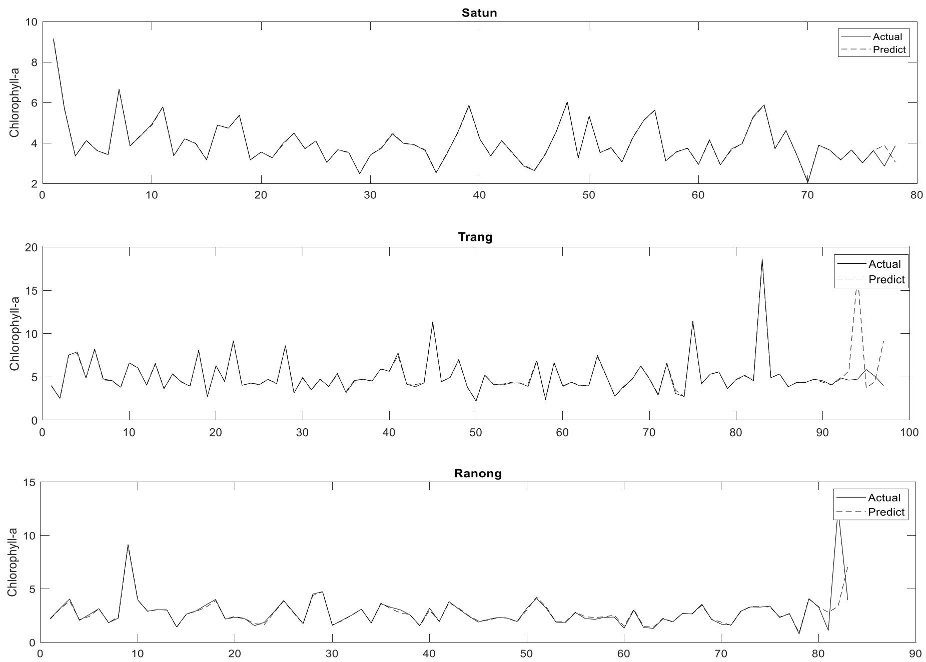

Fig. 5. Results of the bi-LSTM method with ground truth values on the testing data set.

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