Remote Sensing Applications: Society and Environment 33 (2024) 101117

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Long term of sea surface temperature prediction for Indonesia seas using multi time-series satellite data for upwelling dynamics projection

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ARTICLE INFO

Keywords:
Sea surface temperature
Upwelling
Indonesian seas
Deep learning
Convolution neural network
Long sort term memory

ABSTRACT

Global warming, which impacts global temperatures, has led to an increase in sea surface temperature (SST). This rise significantly affects marine ecological systems, especially in Indonesia. As a result, long-term forecasting of SST dynamics is essential for shaping various policies. However, most studies on SST forecasting have focused on short-term predictions in local or medium-sized areas and often overlook the dynamic upwelling that influences SST. In this paper, we propose a five-year SST prediction for the Indonesian seas, incorporating multi-time-series satellite data to project upwelling dynamics. We utilized two deep learning time series models to construct a predictive model that estimates monthly SST values. This model employs extensive multiple satellite data, encompassing 14,934 points (including SST with a resolution of 0.090, wind, ENSO, heat flux, and solar radiation) from 2003 to 2021. To enrich the training data and mitigate overfitting, we applied data augmentation for time series. Experimental results reveal that all satellite datasets correlate with SST over five years. The 1D-Convolution Neural Network outperformed the Long-Short Term Memory model, exhibiting the lowest mean absolute error of 0.39 °C compared to 0.45 °C. Our model detected a consistent upwelling dynamic over a five-year pattern in the Indonesian seas. These findings suggest that our proposed model offers accurate and efficient long-term monthly SST predictions, crucial for upwelling projections.

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https://doi.org/10.1016/j.rsase.2023.101117
Received 20 August 2023; Received in revised form 3 November 2023; Accepted 30 November 2023
Available online 9 December 2023
2352-9385/

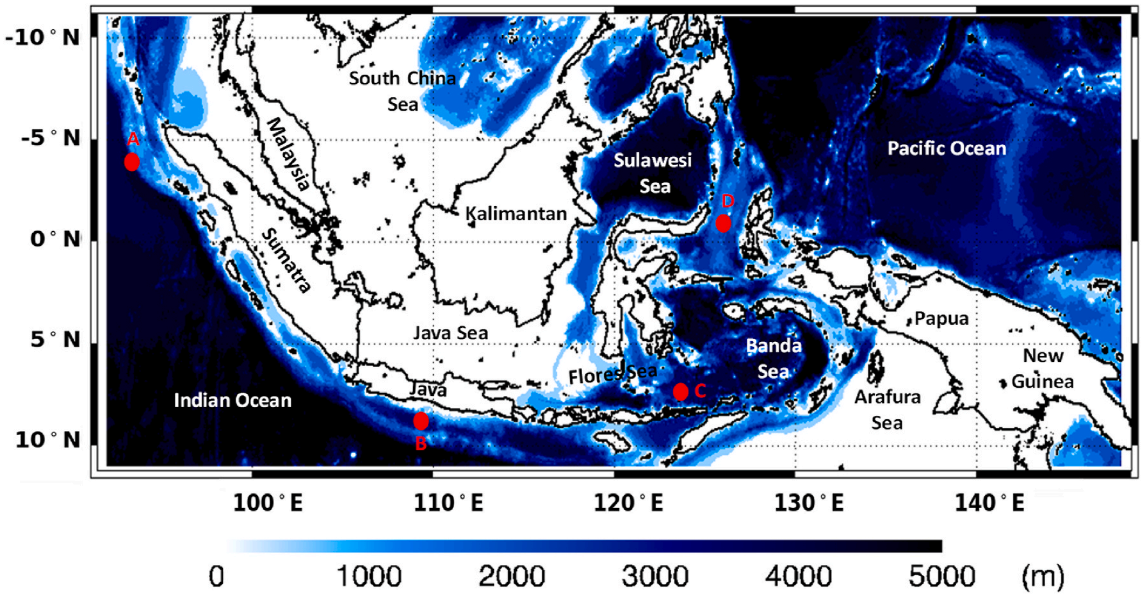

Fig. 1. Indonesian Seas with its major Islands and bathymetry. The red points denote the validation points as shown in Fig. 4. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

1. Introduction

Sea Surface Temperature (SST) is an essential parameter in global oceanic and atmospheric systems (Xu et al., 2021) and dramatically influences the marine ecological system, especially in Indonesia (Qu et al., 2005). Unexpected shifts in SST can retain an effect on marine biological systems (Xu et al., 2010; Wirasatriya et al., 2017), marine resources (Solanki et al., 2016), and also the livelihoods of fishers. In addition, SST can correspondingly be employed to represent the dynamics of upwelling to increase global fisheries production (Kudela et al., 2010). The upwelling phenomenon can be identified by SST cooling and seasonally varying abundance of nutrients (El Aouni et al., 2021). Therefore, the observation and projection of the upwelling phenomenon can utilize SST and its importance for forecasting unexpected temperature changes in the ocean.

SST observation data was collected over ship sensing and satellite remote sensing observations (e.g., Xu and Ignatov, 2016). Ship sensing observations initially cover small areas throughout the ocean area; therefore, usually employed for validation data with satellite data. The validation process was utilized to select the most appropriate SST remote sensing data to determine oceanographic phenomena (Zhou, 2020). Today, satellite remote sensing observations or marine satellites can produce nearly 8 Exabyte of data annually. It forms part of a sizeable oceanographic data, but almost 80% of this data has yet to be explored (Qian et al., 2022). Big data is the latest trend in managing super-large and complex data with at least three common characteristics: volume, velocity, and variety (Gartner, 2013). Big data analytics examines data to uncover hidden patterns, correlations, and other insights (Russom, 2011). Baoleerqimuge and Guoyu (2013) summarized some commonly used SST observation methods and presented four datasets, such as Optimum Interpolation Sea Surface Temperature Analysis (OISSTA) and Extended Reconstructed Sea Surface Temperature (ERSST). Several SST observation and prediction studies use reanalysis datasets (Sun et al., 2022) and models with small resolutions. This dataset does not show the natural and extreme conditions that occur in the sea, especially related to extreme conditions. In our previous study, merged microwave and infrared optimal interpolation (MW_IR_OI) data was shown to have the highest validity compared to other data, primarily to determine extreme temperature cooling, such as tropical cyclone events and upwelling (Tresnawati et al., 2022). Satellite data with tight resolution and can show extreme conditions can potentially use more real SST predictions.

SST prediction research has been remarkably prompt recently (Murphy et al., 2021) leveraging artificial intelligence for short-term and long-term predictions. Artificial intelligence utilizing deep learning for time series forecasts is featured in comprehensive data analysis, such as Convolution Neural Networks (CNN) (Zheng et al., 2020; Han et al., 2019) and Long Sort Term Memory (LSTM) (Kim et al., 2020; Zhang et al., 2020). CNN carries the advantage of being able to ascertain hidden features from input data and process acceleration because it is not a sequentially based model. LSTM includes several benefits in sequence modeling due to its extended memory function and solving the problem of gradient loss and gradient implosion in the long sequence training process (Jia et al., 2022). However, it has drawbacks in parallel processing and always takes longer to train. Both of these methods were used for short and long-term predictions. Short-term predictions start from hour to daily predictions. Short-term predictions are proper for the prediction of extreme SST changes briefly within a given region, such as marine heatwave (HWT) (Kim et al., 2020). Meanwhile upwelling events are events in a very long range. Hence, they are more precise with long-term predictions. Long-term predictions start from monthly to year predictions. Using five years of data, Sun et al. (2021) use a graph neural network to predict SST in the northwestern Pacific Ocean area. Additionally, predictions with multi-dimensional inputs can be a solution for SST data processing (Kang et al., 2018; de los Campos et al., 2018), especially in the territory of Indonesia in general.

Table 1
Data source and resolution.

Data	Source	Period	Spatial Resolution	Total data
Sea Surface Temperature	https://podaac.jpl.nasa.gov/datasetlist	2003–2021	0.09°	1.148.396.054
Wind	https://www.remss.com/measurements/wind/ https://www.remss.com/measurements/ccmp/	2003–2021	0.25°	149.130.240
Surface latent heat flux	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form	2003–2021	0.25°	149.130.240
Solar Radiation	https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form	2003–2020	0.25°	149.130.240
Oceanic Nino Index (ONI)	https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php	2003–2020		228

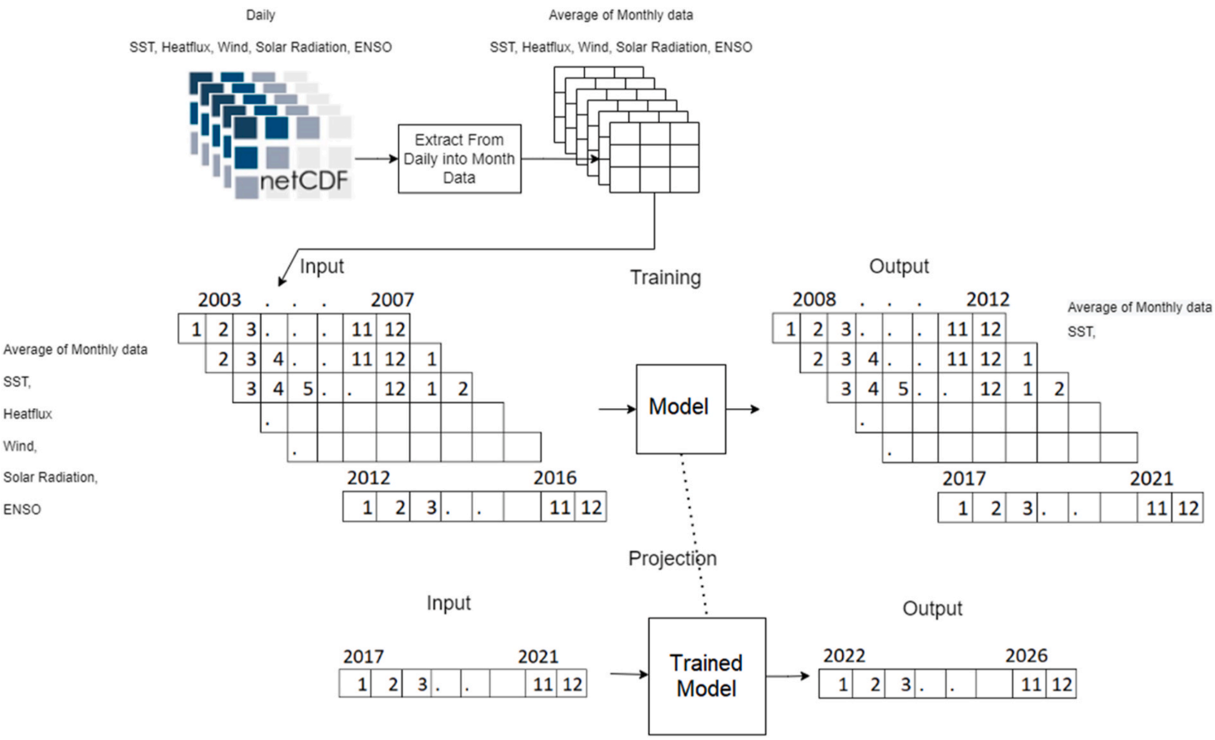

Fig. 2. Data preparation and augmentation.

In recent years, the availability of high-resolution SST data, with a spatial granularity of 0.09°, has provided researchers with a detailed view of the temperature variations in the Indonesian seas (Tresnawati et al., 2022). However, the high resolution, combined with the expansive geographical expanse of Indonesia, poses unique challenges. Not only does it result in a substantial volume of data, but it also introduces computational complexities, especially when using deep learning models for prediction and analysis (Sun et al., 2022). This study focuses on forecasting extreme events, such as upwellings, manifesting as local patterns in the SST time series data (Armstrong, 2000). The Convolutional Neural Network (CNN), especially its 1D variant, is adept at capturing these local patterns due to its architectural design (Qian et al., 2023). On the other hand, given the temporal nature of our data, Long Short-Term Memory (LSTM) networks, with their ability to capture long-term dependencies in sequential data, become an essential tool in our analytical arsenal (Zhang et al., 2020). While there are numerous state-of-the-art deep learning architectures available (Sun et al., 2021) computational efficiency becomes a paramount concern, given the high resolution and volume of our data. Complex architectures, although potentially more accurate, often demand significant computational resources, both in terms of memory and processing power (Sun et al., 2022). The SOTA architecture can introduce challenges regarding training time, resource allocation, and real-time applicability. Hence, our choice of 1D-CNN and LSTM is also influenced by the need to balance accuracy and computational feasibility. In contrast to graph networks (Sun et al., 2021), which are fundamentally designed for interconnected, non-sequential data and focus on capturing relationships and dependencies between different data points or series, our chosen models are more aligned with the sequential and local pattern detection required for our study.

Focusing on the vast expanse of the Indonesian seas, which stretch from 91°–147°E to 12°S–12°N, a semi-enclosed sea providing a

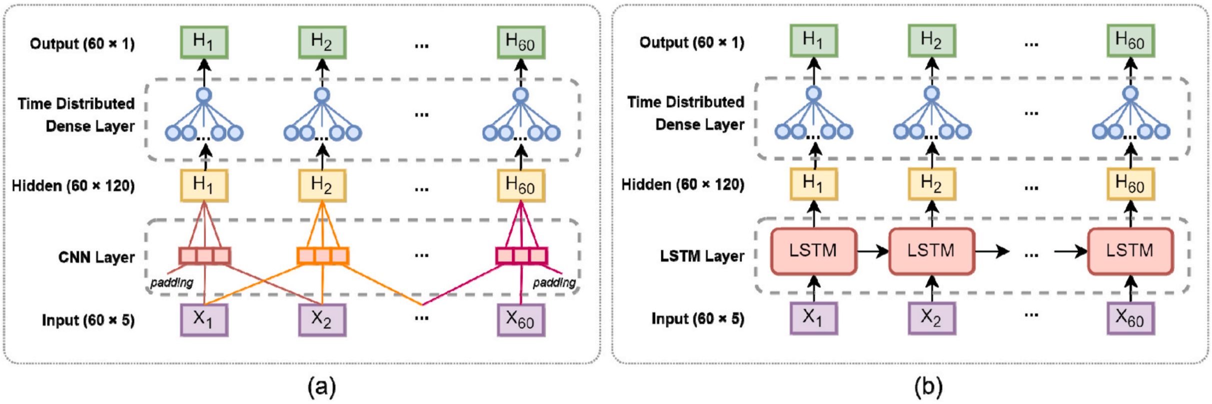

Fig. 3. Deep learning Architecture of (a) 1D-CNN, and (b) LSTM.

substantial transfer route from the Pacific Ocean to the Indian Ocean and the world's largest marine ecosystem (Fig. 1). The SST variability within the Indonesian seas is very complex since it varies diurnally due to the day-night difference (Wirasatriya et al., 2020a), monthly due to tidal influence (Nugroho et al., 2018; Ray and Susanto, 2016), intra-seasonally as influenced by Madden-Jullian Oscillation and other planetary waves (Balbeid et al., 2016), seasonally due to the monsoon wind (Setiawan and Habibi 2011; Setiawan and Kawamura 2011; Wirasatriya et al., 2019, 2020b, 2021), and inter-annually due to El Niňo Southern Oscillation and Indian Ocean Dipole (Susanto et al., 2001; Susanto and Marra 2005; Setiawan et al., 2019, 2020; Wirasatriya et al., 2017). Thus, the accurate and early SST prediction can determine the dynamics and characteristics of future upwelling that can be used to determine various policies (Xiao et al., 2019; Rosario et al., 2019). For upwelling case study, we focus on the Maluku Sea since this is well known area for strong upwelling that occurs during Southeast monsoon season (Setiawan and Habibi, 2011; Wirasatriya et al., 2017; Sari et al., 2018; Atmadipoera et al., 2018).

2. Data and method

2.1. Data

This study used multi-satellite data for SST and surface wind; and reanalysis data for heat flux, as shown in Table 1 (accessed 1 October 2022). The input of SST dataset was obtained from multiple data sources remote sensing almost the overcast pixel contamination. By avoiding the diurnal cycle after the associated corrections were implied on raw data, valid SST data was represented (https://podaac.jpl.nasa.gov/dataset/MW_IR_OI-REMSS-L4-GLOB-v5.0). We also consider Oceanic Niňo Index (ONI) which is index for ENSO as an input for SST prediction since Susanto et al. (2006) indicated that ENSO is the main driver for the interannual variability within the Indonesian seas. Datasets were extracted via Python programming (available on https://git.hub/bowo.adi/) that plots images to data representative from the netCDF dataset.

2.2. Method

Beyond the mere application of 1D-CNN and LSTM, our methodology introduces several novel techniques tailored for SST prediction in the Indonesian seas. We've employed a unique data augmentation technique, constructing monthly averages in diverse manners, which not only enriches our training dataset but also simulates unforeseen SST situations. This not only ensures our model's robustness to diverse scenarios but also prepares it for potential anomalies. Additionally, our sliding-window method, adapted specifically for our dataset's nature, ensures that the model is fed with a rich variety of patterns, enhancing its predictive capabilities.

The workflow of the study is briefly summarized in Fig. 2. Following previous studies' results, the satellite data used in this study MW_IR_OI with the spatial resolution is 0.090. Other data with a spatial resolution greater than SST are interpolated to equate with MW_IR_OI resolution with the reference mechanism of the smallest Euclidian distance value with the SST point. The hours' data was changed in the form of a daily average. Then the data in the daily form is transformed into monthly average data. The monthly average data was obtained from the daily data to get the extreme situation and generate unexpected situations from augmentation data. Data augmentation expands the deep learning model training data and develops an unexpected situation. Augmentation is accomplished by constructing the monthly average for an entire month and the monthly average for 20 days randomly for each month and selecting ten times. The SST data available at the lengthiest period accessed is 2003–2021; therefore, the data were separated into training data from 2003 to 2016 and data validation from 2017 to 2021. The feature time series was five years with a 5-year predicted output. The training set is built by the sliding-window method, a back sliding window of 1 month at a time. With data augmentation, 1848 months of training data were obtained with 1188 sets of sliding windows. In the validation data, no augmentation is performed to retrieve the best model in the training process. Moreover, in the SST projections scenario for the next five years, the 2017–2021 validation data is retained in the best model to cast the 2022–2026 SST prediction.

1D-CNN and LSTM were executed in this study to receive the most suitable model for long-term SST prediction in the expansive ocean. The model runs for data at an individual point with multivariate data input. The architecture of the 1D-CNN and LSTM

Table 2
Pearson correlation results.

Variables	Correlation with SST
SST	1.000
Wind Vector U	−0.117
Wind Vector V	−0.479
Heat flux	0.542
Solar Radiation	0.542
ONI	−0.542

employed in this study can be seen in Fig. 3.

Convolution with multi-layer perceptron extends a prior neural network from one hidden layer to multiple layers with convolution layers as feature extraction. As the layers and neurons increase, the organized structure gets to be more complicated than a primary neural network, which is capable in apprehending nonlinear issues. According to Zhao et al. (2019), CNN architecture is categorized as one-Dimension (1D) and n-Dimension. 1D is focused on feature extraction of sequential data, and n-Ds were utilized for extraction features on images, video, or multidimensional data. 1D-CNN approach is proposed in this study to untie with fast computing of the features from time series sequential sensor data.

The complete process of 1D-CNN is illustrated in Fig. 3a. A layer of one-dimensional sequential data as input $[X_1, X_2, \ldots\ldots, X_N]$, where N is data length time of remote sensing data sequences. Multidimensional time series data will be convoluted as a feature mapping using kernel. Convolutional layers utilize a channel matrix for feature extraction and the pooling layer for feature dimensionality reduction, compressing the sum of data and parameters and decreasing overfitting. Recognizable valuable data can be filtered to some extent when data pass through the pooling layer within the proposed method. In the convolutional layer operation, the convolutional filter slides over each sample and executes the convolutional process. In 1D-CNN, multiple filter kernels can be applied in the convolutional layer with different filter lengths (Arunthavanathan et al., 2021; Li et al., 2018).

The repetitive neural network (RNN) is typically employed for time series prediction. While RNNs ordinarily endure the vanishing gradient problem. To crush this problem, LSTM was introduced to control the time series data's memory data (Hochreiter and Schmidhuber, 1997). The LSTM contains three gate structures: input, forget, and output gates. Input and forget gates are planned to control the memory cell state. Fig. 3b shows the architecture of the LSTM block used in this paper.

Pearson correlation is used to determine the degree or severity of the relationship between two variables or two features of an object (Conover, 1979). The magnitude of the Pearson correlation value can be seen in the following equation:

$$r_{xy} = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{\left[n\sum x^2 - (\sum x)^2\right]\left[n\sum y^2 - (\sum y)^2\right]}} \tag{1}$$

where x is the first variable, y is the second variable and n is the number of observations Mean Absolute Error (MAE) is a method to measure the level of accuracy of a forecasting model. The MAE value represents the average error between the forecasting result and the actual value (Yaffee and McGee, 2000).

$$MAE = \frac{\sum_{n=1}^{N} [\widehat{r}_n \text{-} r_n]}{N} \tag{2}$$

with $\widehat{r}_n$ is the value of the i-th forecasting data, r_n is the i-th actual data value, and N is the existing sample size. The metric evaluation R^2 *score* (3), weighted by the variance s^2 of each output, is used to evaluate the results.

$$R^2\ score = 1 - \sum_{t=1}^{q} \frac{\sum_{i=1}^{n} \left(y_{t,i} - z_{t,i}\right)^2}{\sum_{i=1}^{n} \left(y_{t,i} - \mu_t\right)^2} \bullet s_t^2. \tag{3}$$

3. Result and discussion

3.1. Validation result

Pearson correlation expresses the influence of each input variable on SST to see the relationship between variables, i.e., the independent and the dependent variable (Archdeacon, 1994). The Maluku Sea site sample points were used to determine the variables' Pearson correlation in Indonesia, as shown in Table 2. Based on the correlation, the SST was likely to be retained by the latent heat flux and solar radiation with a score of 0.542, which means that it is moderately correlated (Asuero et al., 2006). The ENSO correlation value was negative at −0.524, which means that there is an inverse relationship between the ENSO index and SST; the more significant the ENSO value will cause SST cooling in Indonesian seas and vice versa. Meanwhile, in the wind, both vector winds u and v have negative values of −0.117 and −0.479, meaning that there is an inverse relationship between the wind variable and SST, which indicates that if the wind speed increases, it causes SST cooling in Indonesian waters. These variables have their respective contributions to SST because no single variable has a correlation value of 0 (zero). Therefore, its intention be included as input for the SST prediction

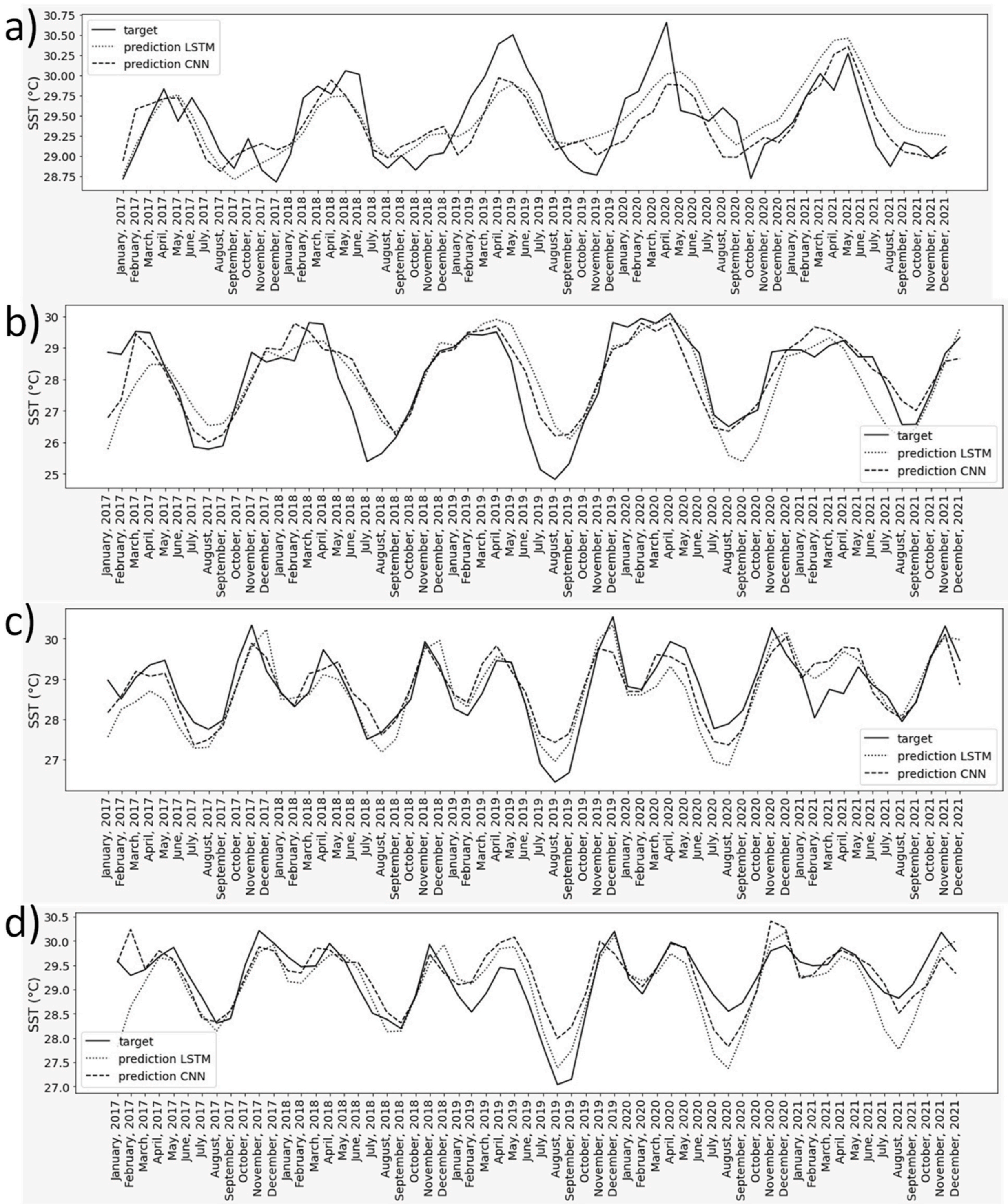

Fig. 4. Validation Results of 4-point as shown in Fig. 1 for (a) West Sumatra, (b) South Java, (c) Flores Sea, and (d) Maluku Sea.

Table 3
Performance comparation 1D-CNN and LSTM.

Area	1D-CNN		LSTM	
	MAE	R^2 score	MAE	R^2 score
A (West Sumatera)	0.284	0.536	0.286	0.542
B (South Java)	0.559	0.706	0.702	0.533
C (Flores Sea)	0.387	0.684	0.443	0.605
D (Maluku Sea)	0.336	0.587	0.375	0.468
Average	0.3915	0.628	0.4515	0,537

Table 4
MAE for each month for validation 2017–2021 in the Indonesian Seas.

Month	2017	2018	2019	2020	2021
Jan	0.82	0.37	0.48	0.54	0.50
Feb	0.44	0.41	0.45	0.35	0.52
Mar	0.34	0.28	0.40	0.38	0.40
Apr	0.26	0.29	0.33	0.41	0.39
May	0.38	0.37	0.30	0.37	0.30
Jun	0.38	0.43	0.40	0.42	0.30
Jul	0.35	0.49	0.48	0.43	0.30
Aug	0.33	0.41	0.59	0.50	0.36
Sept	0.41	0.39	0.67	0.64	0.44
Oct	0.48	0.40	0.65	0.52	0.39
Nov	0.41	0.30	0.37	0.42	0.44
Dec	0.36	0.34	0.38	0.36	0.46
Average	0.41	0.37	0.46	0.44	0.40
Max	0.82	0.49	0.67	0.64	0.52
Min	0.26	0.28	0.30	0.35	0.30
Total Average	0.42				

process.

Indonesia is a tropical region crossed by the equator. The solar movement across the Indonesian equator occasionally occurs in two different seasons. The Northwest monsoon season occurs in December, January, and February. The Southeast monsoon season takes place in June, July, and August. The wind that blows in Indonesia is influenced by the seasons; therefore, this wind system is called monsoon wind (Alifdini et al. (2021). In the first step, 1D-CNN and LSTM models were tested at several territorial ocean samples. The results of this trial are used as a comparison of the best models operated for Indonesia seas prediction. Four sample points of the Indonesian seas were considered to represent the condition, namely: West of Sumatra, South of Java, Flores Sea, and Maluku sea.

Fig. 4 shows the plot results of five years of validation data predictions for the four points. Based on Fig. 4, the four regional samples above demonstrate different SST patterns. Still, the prediction results show a pattern similar to the actual values. This result indicates that the model is satisfactory for predicting SST values from 2017 to 2021. Fig. 4 shows that LSTM provides too modest a prediction for the fluctuations; therefore, it retains a higher error value than 1D-CNN as shown in Table 3. This error is especially noticeable in seas with extreme temperatures, such as in the south of Java and Flores Seas. In Maluku and the west Sumatra Sea, the MAE for both models doesn't look so much different.

At the sample point of the western Sumatra Sea, as shown in Fig. 4b, a pattern of ups and downs routine of the actual value was inducted and followed the pattern of the rise and fall of the prediction, even though the projections carried out were long-term periods. The annual SST pattern can also be well read by the both prediction model, except during extreme conditions (cooling or heating) of SST such as in December 2017 where the average actual value of 28.5 °C predicted results are only able to produce a value of 29.5 °C. Likewise, when extreme warming occurred in March 2020 to reach 30.5 °C, the expected outcome was 29.75 °C.

Flores seas is the area which is strongly affected by the monsoon wind system. Monsoon wind systems affect ocean variations such as wind, currents, and temperature distribution. Fig. 4c shows the effect of monsoon wind systems on the SST variations. There are 2 peaks of SST cooling which occur during the peak Northwest monsoon (February) and Southeast monsoon (August). In general, this pattern can be well captured by the prediction results.

The Maluku Sea is also strongly influenced by the Northwest and Southeast monsoon winds (Setiawan and Habibi 2011) as shown in Fig. 4d. In the Northwest monsoon season, SST warms up to 30 °C, while generally, in the Southeast monsoon season, SST cools up to 27 °C. This pattern can be captured sufficiently by models using both methods. Nevertheless, there is a fairly noticeable difference between the predicted results and their actual values, especially during the extreme SST cooling in August 2019 of 27 °C, where the predicted result is only around 28 °C. Considering that Maluku Sea and Flores Sea are the major pathways for Indonesian Throughflow (ITF) (Sprintall et al., 2009), the small errors of the SST prediction generated from both models may be benefit for the study of future projected ITF.

For the southern Java, the sampling point is located inside the eastern pole of Indian Ocean Dipole (IOD) (Saji et al., 1999). Thus, IOD strongly influences the SST variation in this area. Although both SST models can capture the pattern of monsoon wind induced

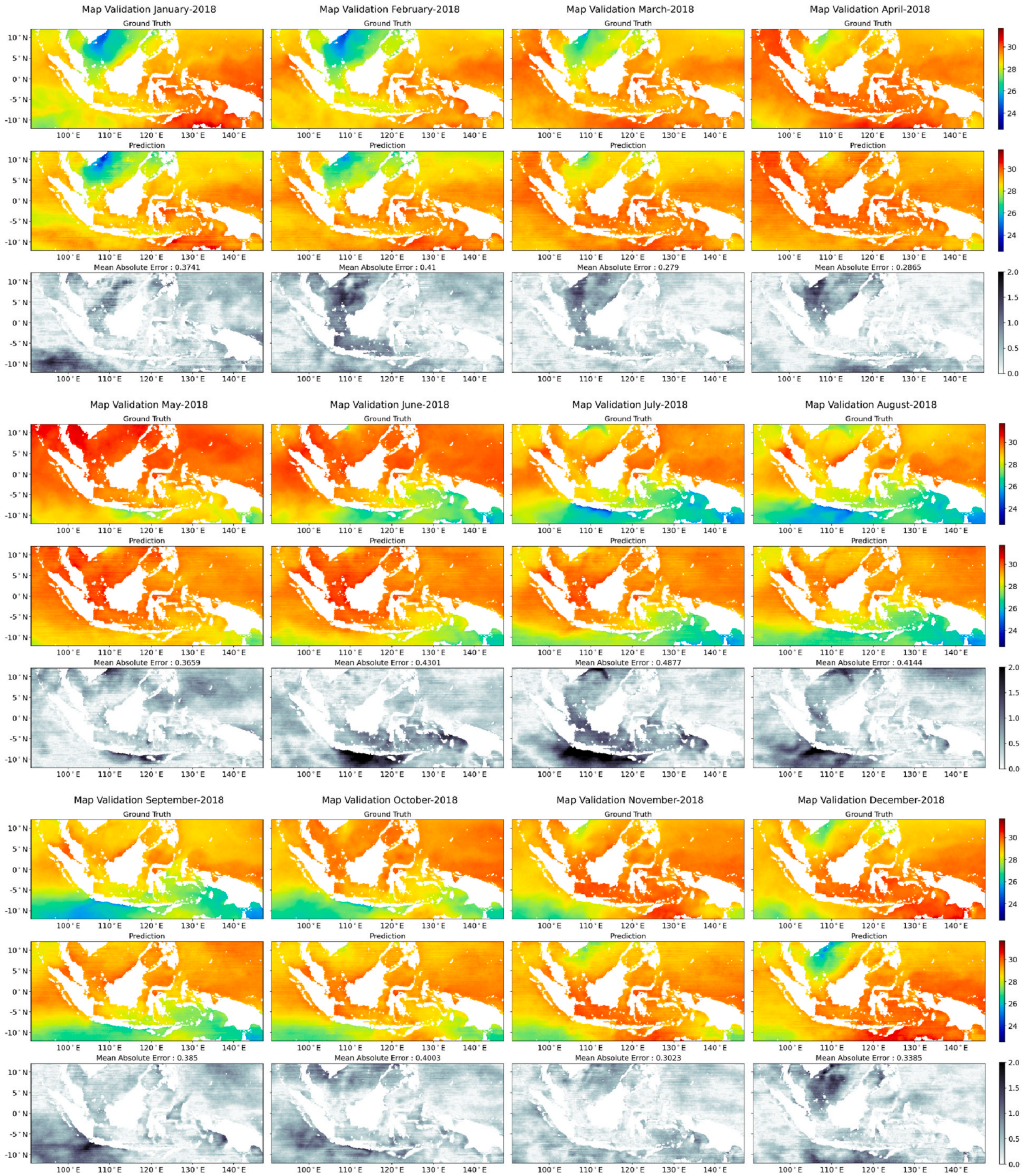

Fig. 5. Plotting monthly satellite data as ground truth (upper figures), prediction result (middle figures) and MAE of each point (lower figures) with the color bars represent the SST values in °C for Indonesia seas in 2018. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

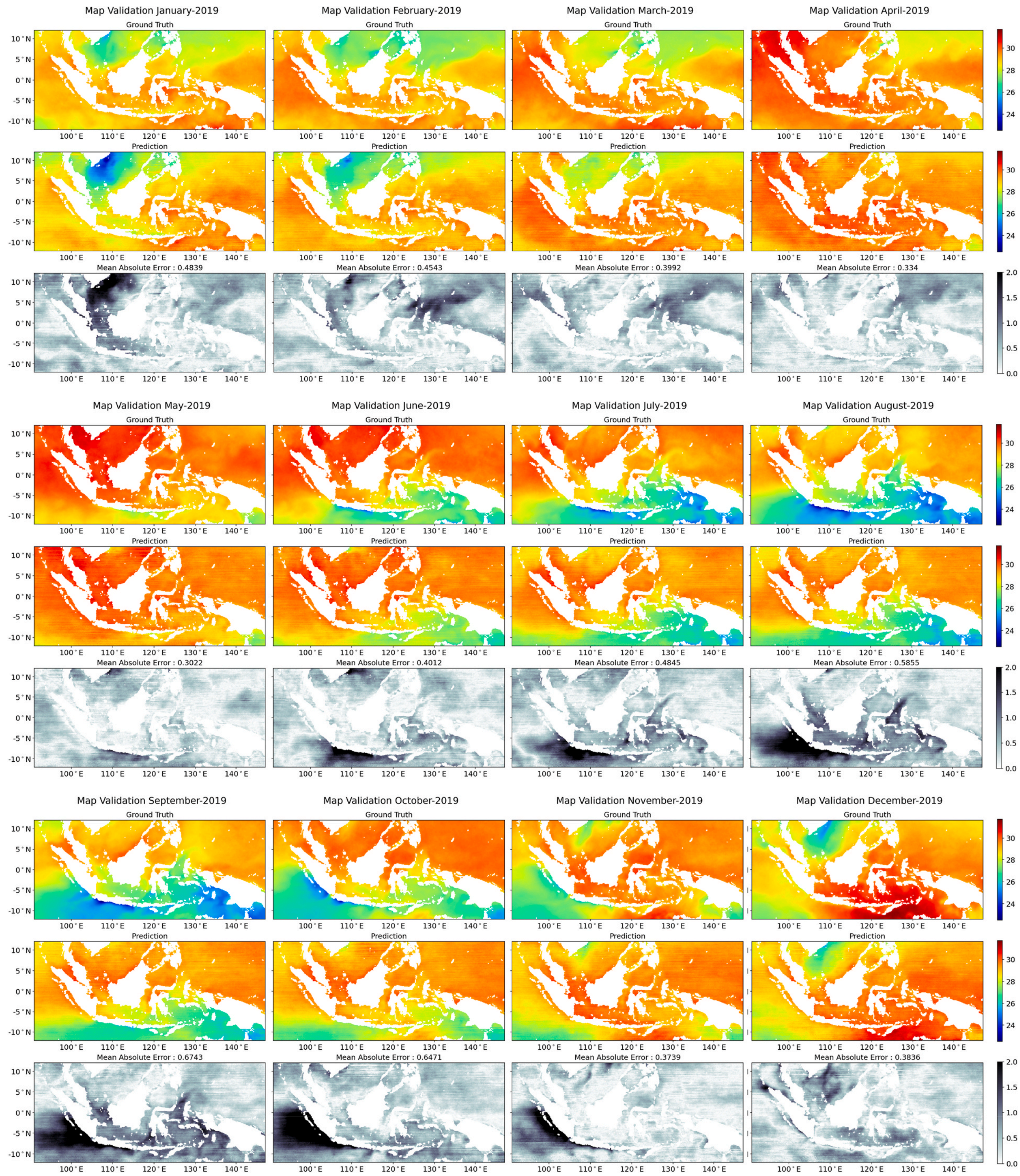

Fig. 6. The same as Fig. 5 but for 2019.

Table 5
MAE for each month for validation 2017–2021 in the Maluku Sea.

Month	2017	2018	2019	2020	2021
Aug	0.20	0.18	0.73	0.67	0.26
Average	0.41				

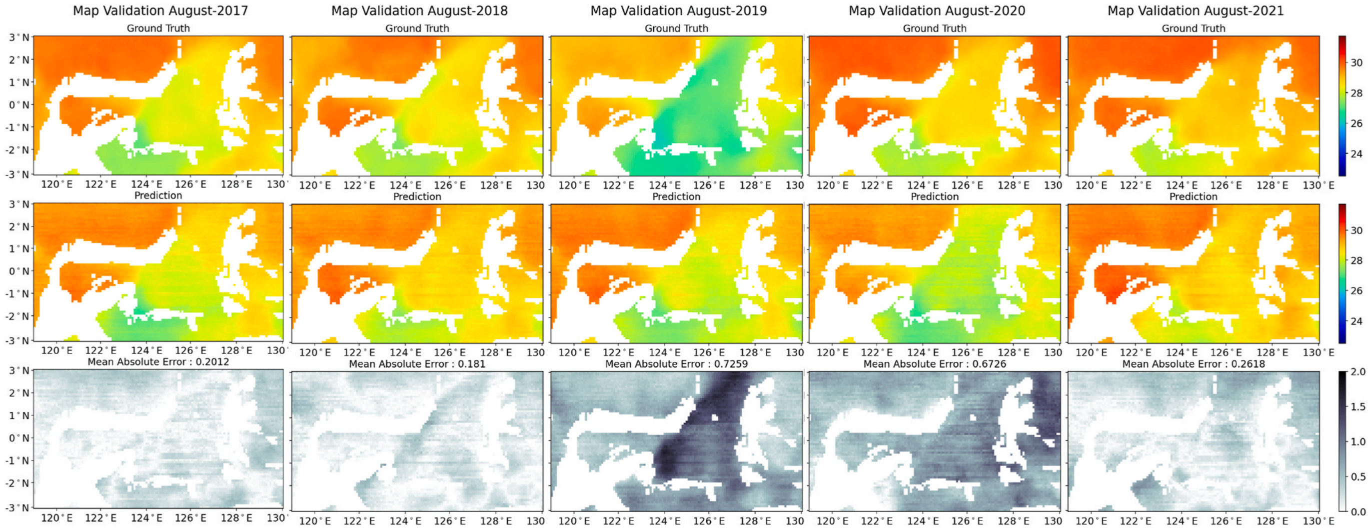

Fig. 7. Plotting monthly satellite data as ground truth average (upper figures), prediction result (middle figures) and MAE (lower figures) for Maluku Sea in August 2017–2021.

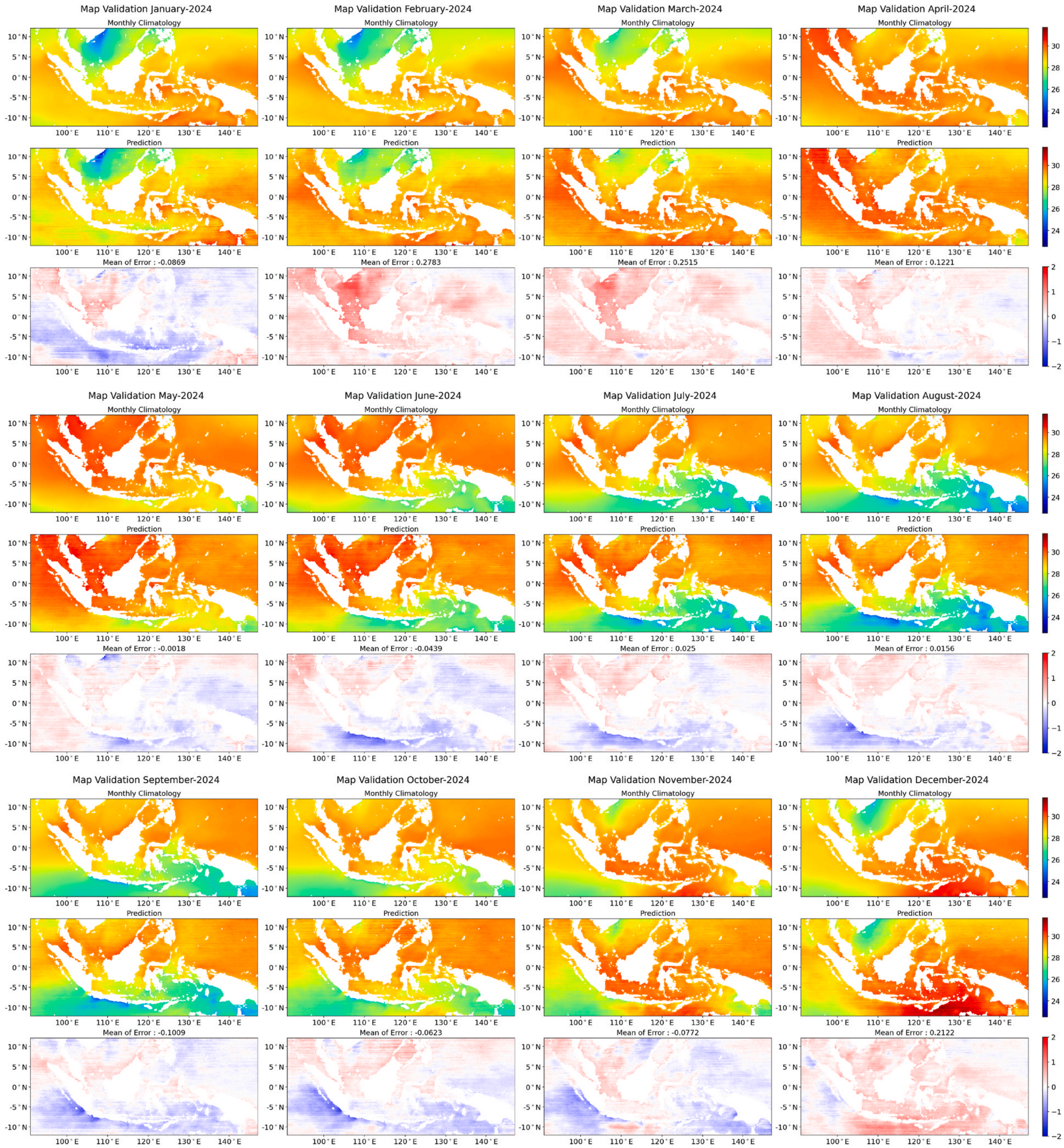

Fig. 8. Plotting monthly climatology of Satellite data (2003–2021) (upper figures), prediction result (middle figures) and SST anomaly (prediction-monthly climatology) (lower figures) for Indonesia seas in 2024.

coastal upwelling denoted by the minimum SST in September, they fail to catch the signal of extreme upwelling event during the positive IOD in 2019. Both models overestimate about >1 °C from the actual SST in August, September and October 2019. For other years, 1D-CNN has closer value to the actual SST than LSTM.

To compare the overall performance of 1D-CNN and LSTM in predicting SST, MAE was calculated for 4 areas (Table 3). Table 3 shows that 1D-CNN outperforms LSTM, with the lowest MAE value. Therefore, 1D-CNN was then used for training and validation for data throughout the Indonesia seas.

Training and validation of models in the same period were carried out for all regions of Indonesia. The results of global SST prediction and validation in Indonesian waters can be seen in Table 4, resulting in a minimum average MAE value of 0.37 °C in 2018 and a maximum of 0.46 °C in 2019. The ground truth, prediction results, and MAE value in each point using the CNN method can be

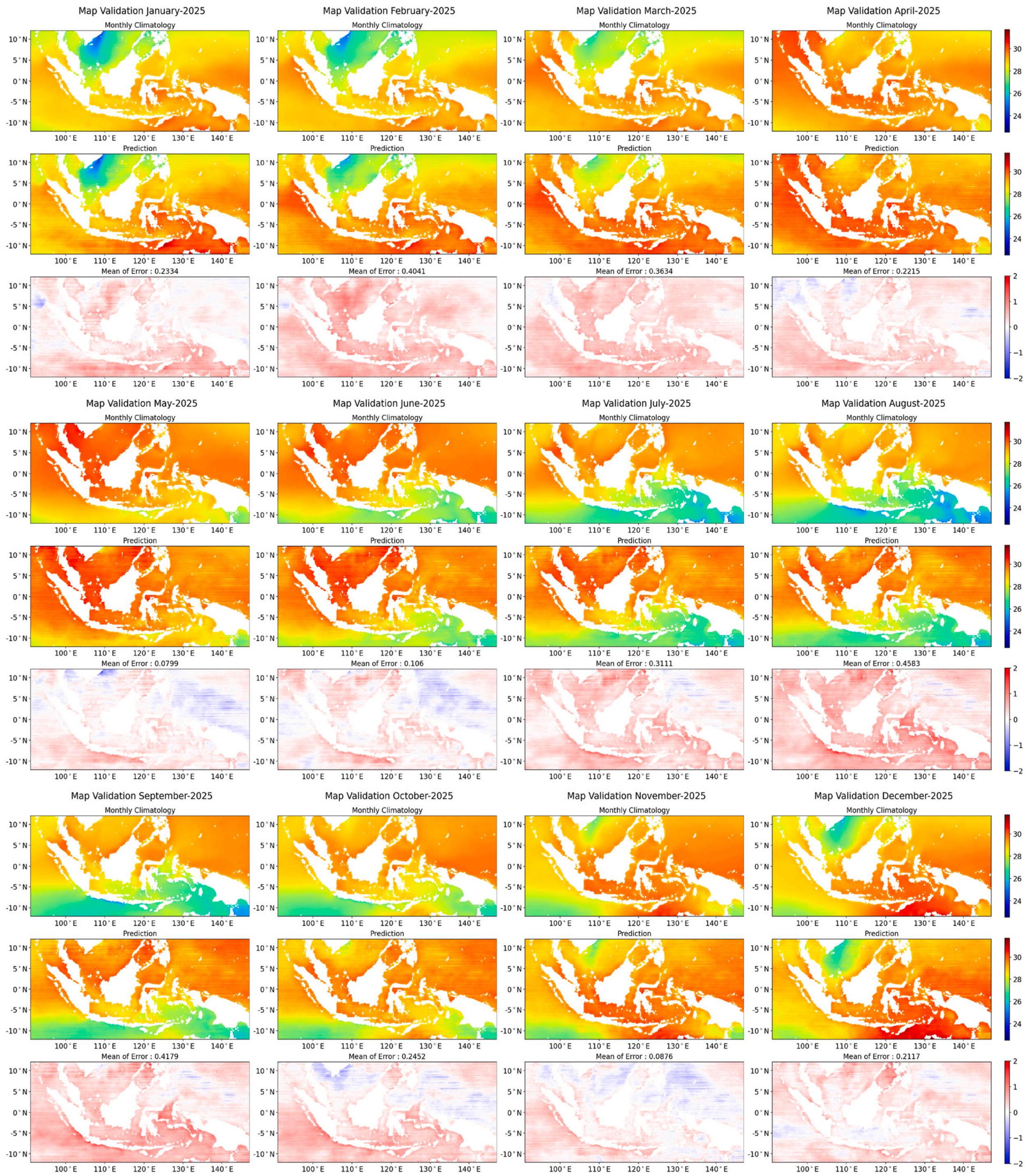

Fig. 9. The same as Fig. 8 but for 2025.

seen in Figs. 5 and 6 with the MAE value of the month. The predicted results for August 2017–2021 have an average MAE of 0.42 °C, a minimum MAE value of 0.26 °C in 2017, and a maximum of 0.82 °C in 2017.

The detection of upwelling in the Maluku Sea area in August 2017–2021 obtained results that the cooling of the 27.5 °C SST < that occurred in 2017 and 2018 could be well read by the prediction model as evidenced by MAE 0.20 °C and 0.18 °C as shown in Table 5. The year 2019 is over-estimated with the largest MAE value of 0.72 °C. In 2020 the results are predicted under estimated MAE value of 0.62 °C. In 2021 the MAE value is 0.26 °C where SST cooling can be predicted quite well as shown in Fig. 7.

The 2017 predictions gave results similar to the actual situation where temperatures ranged from 27 to 28.5 °C, the lowest SST of about 27 °C was around the border of Tomini Bay to Banggai Island, a MAE value of 0.20. In 2018, it seems that the prediction results are warmer than the actual situation but the MAE value ranges from 0.25 to 0.50 °C. The 2019 prediction looks warmer than it actually is, and this year the MAE value is the largest compared to other years' predictions of 0.72 °C around Banggai Bay and the Northern Maluku Sea region. In 2020 the predicted results look colder SST in the Maluku Sea area than the actual situation ranging from 26.5 to 27.5 °C, with MAE in general only around 0.62 °C. As for 2021, the prediction results look very similar to the actual situation with SST values ranging from 27.5 to 29.5 °C, MAE values represent quite good results with a <value of 0.5 °C, which is 0.26 °C.

3.2. Projected sea surface temperature 2022–2026

The SST projection of Indonesia seas using the multi-dimensional input CNN method for 2022–2026. This projection was compared with climatological value from monthly average for each month from 2003 to 2021. SST predictions in 2024 and 2025 are depicted in Figs. 8 and 9, respectively. Based on the experiment result as shown in Table 6, a minimum anomaly result was 0.04 °C in 2024. The SST that is projected to be colder than climatological in January, May, June, September, October and November while other months are projected to be warmer. The maximum anomaly of 0.26 °C is 2025, the SST in 2025 is projected to be warmer than the climatological value.

The projection of SST in the Maluku Sea in August 2022–2026 provides assistances, one of which is to determine the detection of upwelling in the region as shown in Table 7 and Fig. 10. In general, the Maluku Sea during 2022–2026 is projected to have a positive anomaly of SST value of 0.431 °C, which means that warmer conditions will occur than the climatological of 2003–2021. Meanwhile, the projection of upwelling in the Maluku Sea in August 2022–2026 based on the SST value <27.5 °C has the potential to occur in 2024 with a fairly extreme SST cooling ranging from 26 to 27 °C. Meanwhile, in August 2022 and 2023 in the Maluku Sea, it is projected that there is a potential for upwelling but not as large as in 2024, with SST ranging from 27 to 28 °C seen in the west and south of Banggai Island. In 2025 and 2026, it is projected that there will be a weakening of upwelling by looking at the SST value of the region which is quite warm, which is around 28–29 °C except on the west and south sides of Banggai Island there is an SST of around 27.5 °C.

The abundance of nutrients in the Maluku Sea area can be caused by upwelling events. Maluku Sea has the highest average productivity in August (Setiawan and Habibi, 2011). However, this seasonal phenomenon also has significant inter-annual variability, ENSO plays a very important role in controlling the spatial pattern of chlorophyll concentration in Indonesia (Susanto et al., 2006). Chlorophyll concentration due to upwelling greatly affects the condition of capture waters The application of these projection results can have implications for forecasting fish catch policies in the Maluku Sea area. For example, in the Leihitu water area, Central Maluku Regency, the potential of the fishery is dominated by pelagic fisheries including tuna (*Thunnus* spp), kitefish (*Decapterus* spp), mackerel (*Scommberamorus* spp), and others. Data from Maluku Fisheries Statistics shows that fishery production in 2009 was 429,892.2 tons, of which 10% of fishery production was mackerel (Maluku Provincial Fisheries Service, 2010). One of the properties of pelagic fish resources is that they are very fond of temperatures ranging from 18 to 31 °C (Collete, 1983), Where in the temperature range is one of them can be caused by the strengthening of the upwelling phenomenon.

The results of SST predictions and projections in this study can already be used in general by taking the prediction patterns previously described, but still need to be considered and justified, especially for the waters of the southern region of Java-Bali Island to West Sumatra where the extreme cooling of SST in 2019 cannot be fully read by the prediction model. We suspect that this condition is strongly influenced by strong positive IOD activity in 2019 since along the southern coast of Java, IOD is more dominant to control the interannual variability of SST than ENSO (Wirasatriya et al., 2020b). Furthermore, Iskandar et al. (2022), shows extreme positive IOD event in 2019 induced anomalously strong upwelling event, particularly along the southern coast of Java and Sumatra. Another phenomenon that is alleged to be the strong cause of SST cooling is the strong tidal mixing that occurs at the southern Bali to Lombok Island (Ray and Susanto, 2019).

Predictions and projections of the emergence of upwelling are needed in estimating the condition of the waters in an area, so it is necessary to conduct in-depth and continuous research. The community, especially fishermen, is expected to be more familiar with the global climate phenomenon of ENSO and also IOD as well as the use of remote deterrence technology as a detection of the emergence of upwelling.

The 1D-CNN prediction model, which utilizes surrounding parameters as the latest model in Indonesian waters, has generally produced prediction patterns that correspond to the actual value or with the climatological value, as evidenced by a monthly average MAE of <0.5 °C. In certain cases, this model still does not show optimal results, especially in capturing potential extreme events such as SST cooling <27 °C, so it is necessary to trial other prediction models that are more reliable or daily data analysis with longer series so that more extreme value information will be obtained.

3.3. Discussion

The Pearson correlation, as a measure of the influence of various input variables on SST, shows the intricate interplay between various oceanographic and meteorological factors. The validation using sample points from the Maluku Sea highlights the effects of latent heat flux, solar radiation, the ENSO index, and wind vectors on SST. The moderate correlation value of 0.542 between SST and the combined influence of latent heat flux and solar radiation points towards a significant, albeit not overwhelming, influence of these factors on SST. On the other hand, the negative ENSO correlation signifies the cooling effect of a higher ENSO value on Indonesian seas, echoing the known inverse relationship between the ENSO index and SST.

The monsoonal wind patterns, characteristic of Indonesia due to its location around the equator, play a pivotal role in shaping the SST. The prediction models, 1D-CNN and LSTM were tested across different territorial ocean samples, with results from these trials intended to identify the best model for the Indonesian seas. Interestingly, while the LSTM model showed modest predictions with larger errors, especially for seas with extreme temperatures, the 1D-CNN model generally outperformed LSTM. This disparity was

Table 6
Monthly anomaly for 2022–2026 from their monthly climatology in the Indonesian Seas.

Month	2022	2023	2024	2025	2026
Jan	−0.28	0.15	−0.09	0.23	0.08
Feb	0.29	0.33	0.28	0.40	0.20
Mar	0.22	0.28	0.25	0.36	0.17
Apr	0.12	0.09	0.12	0.22	0.05
May	−0.03	0.00	0.00	0.08	−0.02
Jun	−0.03	−0.06	−0.04	0.11	0.12
Jul	0.17	0.05	0.03	0.31	0.37
Aug	0.28	0.15	0.02	0.46	0.50
Sept	0.23	0.16	−0.10	0.42	0.42
Oct	0.22	0.13	−0.06	0.25	0.32
Nov	0.08	0.02	−0.08	0.09	0.20
Dec	0.24	0.13	0.21	0.21	−0.02
Average	0.13	0.12	0.04	0.26	0.20
Max	0.29	0.33	0.28	0.46	0.50
Min	−0.28	−0.06	−0.10	0.08	−0.02
Average All year = 0.15					

Table 7
Monthly anomaly for 2022–2026 from their monthly climatology in the Maluku Sea.

Month	2022	2023	2024	2025	2026
August	0.56	0.46	0.16	0.34	0.64
Average all year	0.43				

particularly noticeable in the south of Java and Flores Seas.

The intricate patterns of SST, with their seasonal highs and lows, were largely captured by both models. Yet, they sometimes faltered during extreme SST conditions. For example, in December 2017, the models underestimated the actual SST, and in March 2020, they overestimated it. This suggests potential limitations in the models' capabilities to predict extreme events or sudden shifts in SST, which are critical for a myriad of applications, from fisheries to climate modeling.

Furthermore, the Maluku Sea's strong influence by the Northwest and Southeast monsoon winds results in seasonal variations in SST, which the models managed to capture fairly well. However, again, during extreme cooling events, the models showed discrepancies with actual values, further emphasizing the need for refining their predictive capabilities. The monsoon wind systems, influencing the south of Java, Maluku Sea and Flores seas, have been shown to affect SST variations. While the prediction models captured the general trend, they still struggled to predict extreme conditions. This is evident in July 2017 and August 2019, where there was a notable overestimation by the models.

It's noteworthy that the 1D-CNN model, despite its occasional shortcomings, still generally performed better than the LSTM model, as evidenced by lower Mean Absolute Error (MAE) values. The success of the 1D-CNN model, in general, may be attributed to its ability to capture spatial patterns effectively, making it suitable for oceanographic data.

However, the limitations of the models become more pronounced when considering phenomena like the strong positive IOD activity in 2019, which strongly influenced SST cooling. The models' inability to capture this event suggests that external factors like the IOD and ENSO play a significant role in SST fluctuations. Furthermore, other factors like tidal mixing, as seen at the southern Bali to Lombok Island, can also influence SST, and their omission in the current modeling approach might be another limitation. The 1D-CNN prediction model's overall good performance, as evidenced by a monthly average MAE of <0.5 °C, is commendable. However, its occasional failures to predict extreme events point towards the need for further refinement. One potential way forward could be the inclusion of more input parameters, such as IOD and tides, which might enhance the model's predictive capabilities.

To date, many products of SST datasets are constructed based on the blended of multi satellite sensors that is limited only on the near real-time SST product (e.g., Donlon et al., 2007; Sandra et al., 2016; JPL OurOcean Project 2010; Beggs et al., 2011). The present study managed to develop the SST dataset projected for the future using the 1D-CNN method with high accuracy. This present study will be benefit for climate change research which need accurate future projection of SST data.

4. Conclusion

This paper proposed five years of SST prediction for the wide-size area Indonesia Sea using multi-time-series satellite data for upwelling dynamics projection. Two deep learning time series models were utilized to construct a predictive model to estimate the monthly SST value by employing big multiple satellite data 14.934 point (SST with resolution 0.090°, Wind, ENSO, Heat flux, and solar radiation) from 2003 to 2021. Data augmentation for time series is applied to enrich the training data model to avoid overfitting. Based on the experimental result, all satellite datasets correlate with SST in five years, and 1D-Convolution Neural Network has the lowest mean absolute error evaluation compared to the Long-Short Term Memory model with 0.39 and 0.45, respectively for four points in Indonesia seas. Prediction and validation of SST globally in Indonesia's territorial waters in 2017–2021 resulted in a minimum average MAE value of 0.37 °C in 2018 and a maximum of 0.46 °C in 2019. The detection of upwelling in the Maluku Sea area in August

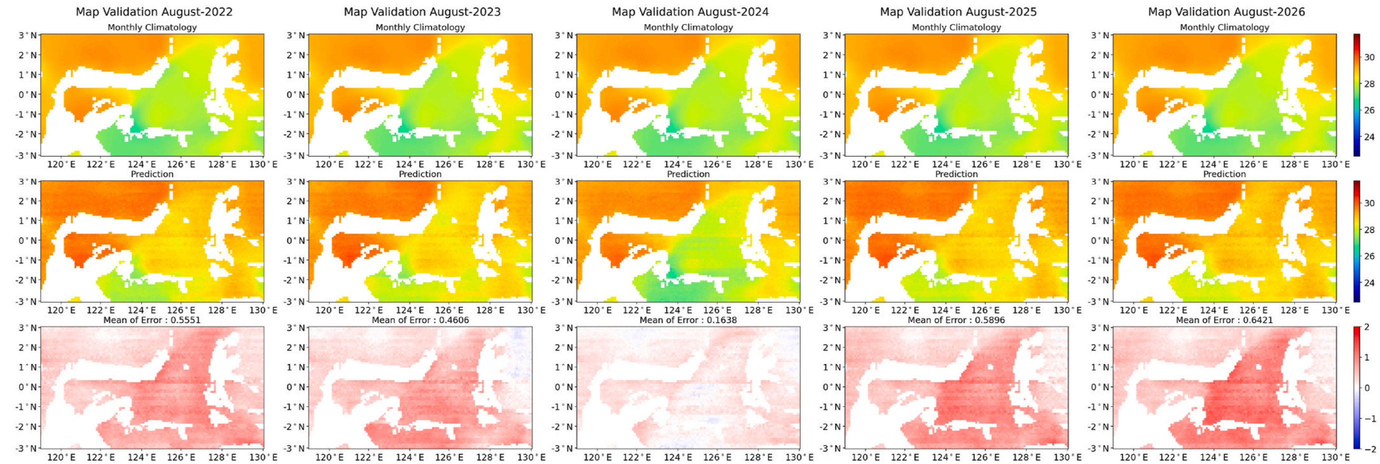

Fig. 10. Plotting August monthly climatology of Satellite data (2003–2021) (upper figures), prediction result (middle figures) and SST anomaly (prediction-monthly climatology) (lower figures) for Maluku Sea in 2022–2026.

2017–2021 obtained results that the cooling of the 27.5 °C SST < that occurred in 2017 and 2018 could be well read by the prediction model as evidenced by MAE 0.20 °C and 0.18 °C. The year 2019 is over-estimated with the largest MAE value of 0.72 °C. In 2020 the results are predicted under estimated MAE value of 0.62 °C. In 2021 the MAE value is 0.26 °C where SST cooling can be predicted quite well. The SST projection of Indonesia's territorial waters using the multi-dimensional input CNN method for 2022–2026 gets a minimum anomaly result of 0.04 °C in 2024, SST which is projected to be colder than climatological in January, May, June, September, October and November while other months are projected to be warmer. The maximum anomaly of 0.26 °C is 2025, the SST in 2025 is projected to be warmer than the climatological. Attenuation upwelling is expected to be a reference for mitigation and adaptation of fishery conditions in the Maluku Sea area in the future.

Ethical statement

We declare that research article entitled "Long Term of Sea Surface Temperature Prediction for Indonesia Seas using multi time-series satellite data for Upwelling Dynamics Projection" that is submitted to Journal "Remote Sensing Applications: environment and society" is our original work and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data are open source. The download links are presented in Table 1.

Acknowledgement

This work was supported by the Matching Fund Kedaireka Grant – Indonesia, Directorate General of Higher Education, Research and Technology; Ministry of Education, Culture, Research and Technology, Republic of Indonesia under Grant Number 94/UN7.A4/DK/IX/2022 with Anindya Wirasatriya as PIC Investigator. R. Dwi Susanto was supported by National Aeronautics and Space Administration (NASA; grant #80NSSC18K0777) through the University of Maryland.

References

Alifdini, I., Shimada, T., Wirasatriya, A., 2021. Seasonal distribution and variability of surface winds in the Indonesian seas using scatterometer and reanalysis data. Int. J. Climatol. 41 (10), 4825–4843. https://doi.org/10.1002/joc.7101.
Archdeacon, T.J., 1994. Correlation and Regression Analysis: a Historian's Guide. Univ of Wisconsin Press.
Armstrong, E.M., 2000. Satellite derived sea surface temperature variability off California during the upwelling season. Remote Sens. Environ. 73 (1), 1–17. https://doi.org/10.1016/S0034-4257(99)00072-3.
Arunthavanathan, R., Khan, F., Ahmed, S., Imtiaz, S., 2021. A deep learning model for process fault prognosis. Process Saf. Environ. Protect. 154, 467–479. https://doi.org/10.1016/j.psep.2021.08.022.
Asuero, A.G., Sayago, A., González, A.G., 2006. The correlation coefficient: an overview. Crit. Rev. Anal. Chem. 36 (1), 41–59. https://doi.org/10.1080/10408340500526766.
Atmadipoera, A.S., Khairunnisa, Z., Kusuma, D.W., 2018. Upwelling characteristics during El Nino 2015 in Maluku Sea. IOP Conf. Ser. Earth Environ. Sci. 176, 012018 https://doi.org/10.1088/1755-1315/176/1/012018, 2018.
Balbeid, N., Atmadipoera, A.S., Koropitan, A.F., 2016. Response of sea surface temperature (sst) and chlorophyll-a on Madden Julian Oscillation (MJO) in Indonesian seas. J. Ilmu Dan Teknol. Kelautan Trop. 7 (2) https://doi.org/10.29244/jitkt.v7i2.11035.
Baoleerqimuge, B., Guoyu, R., 2013. Sea surface temperature observation methods and comparison of commonly used sea surface temperature datasets. Adv. Meteo Sci. Tech. 3 (6), 52–57. https://doi.org/10.3969/j.issn.2095-1973.2013.06.007.
Beggs, H., et al., 2011. RAMSSA - an operational, high-resolution, Regional Australian Multi-Sensor Sea surface temperature Analysis over the Australian region. Austr. Meteorol. Oceanogr. J. 61 (1), 1–22. https://doi.org/10.22499/2.6101.001.
Collete, B.B., 1983. FAO Species Catalogue, Vol 2. Scombrids of the World: an Annotated and Illustrated Catalogue of Tunas, Mackerels, Bonitos and Related Species Known to Date, vol. 125. FAO Fish. Synop., pp. 1–137
Conover, W.J., 1979. Practical Nonparametric Statistics, vol. 350. John Wiley & Sons.
de los Campos, G., Vazquez, A.I., Hsu, S., Lello, L., 2018. Complex-trait prediction in the era of big data. Trends Genet. 34 (10), 746–754. https://doi.org/10.1016/j.tig.2018.07.004.
Donlon, C., et al., 2007. The global ocean data assimilation experiment high-resolution sea surface temperature pilot project. Bull. Am. Meteorol. Soc. 88 (8), 1197–1214.
El Aouni, A., Daoudi, K., Minaoui, K., Yahia, H., 2021. Robust detection of the North-west African upwelling from SST images. Geosci. Rem. Sens. Lett. IEEE 18 (4), 573–576. https://doi.org/10.1109/LGRS.2020.2983826.
Gartner, I.T., 2013. Glossary. Big Data Defintion. http://www.gartner.com/it-glossary/big-data/.
Han, M., Feng, Y., Zhao, X., Sun, C., Hong, F., Liu, C., 2019. A convolutional neural network using surface data to predict subsurface temperatures in the Pacific Ocean. IEEE Access 7, 172816–172829.
Hochreiter, J., Schmidhuber, S., 1997. Long short-term memory. Neural Comput. 9 (8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735.
Iskandar, I., Lestari, D.O., Saputra, A.D., Setiawan, R.Y., Wirasatriya, A., Susanto, R.D., Mardiansyah, W., Irfan, M., Rozirwan, Setiawan, J.D., et al., 2022. Extreme positive Indian Ocean Dipole in 2019 and its impact on Indonesia. Sustainability 14, 15155. https://doi.org/10.3390/su142215155.
Jia, X., Ji, Q., Han, L., Liu, Y., Han, G., Lin, X., 2022. Prediction of Sea Surface temperature in the East China sea based on LSTM neural network. Remote Sens. 4 (14), 3300.
JPL OurOcean Project, 2010. G1SST L4 SST Analysis. Ver. 1. PO.DAAC. CA, USA. Dataset accessed [20200401] at. https://doi.org/10.5067/GHG1S-4FP01.
Kang, G.K., Gao, J.Z., Chiao, S., Lu, S., Xie, G., 2018. Air quality prediction: big data and machine learning Approaches. Int. J. Environ. Sci. Dev. 9 (1), 8–16. https://doi.org/10.18178/ijesd.2018.9.1.1066.

Kim, M., Yang, H., Kim, J., 2020. Sea surface temperature and high water temperature occurrence prediction using a long short-term memory model. Remote Sens. 12 (21), 1–21. https://doi.org/10.3390/rs12213654.
Kudela, R.M., Seeyave, S., Cochlan, W.P., 2010. The role of nutrients in regulation and promotion of harmful algal blooms in upwelling systems. Prog. Oceanogr. 85 (1–2), 122–135. https://doi.org/10.1016/j.pocean.2010.02.008.
Li, X., Ding, Q., Sun, J.Q., 2018. Remaining useful life estimation in prognostics using deep convolution neural networks. Reliab. Eng. Syst. Saf. 172, 1–11. https://doi.org/10.1016/j.ress.2017.11.021.
Murphy, S.C., Nazzaro, L.J., Simkins, J., Oliver, M.J., Kohut, J., Crowley, M., Miles, T.N., 2021. Persistent upwelling in the Mid-Atlantic Bight detected using gap-filled, high-resolution satellite SST. Remote Sens. Environ. 262, 112487 https://doi.org/10.1016/j.rse.2021.112487.
Nugroho, D., Larrouy, A.K., Gaspar, P., Lyard, F., Reffray, G., Tranchant, B., 2018. Modelling Explicit tides in the Indonesian seas: an important process for surface sea water properties. Mar. Pollut. Bull. 131, 7–18. https://doi.org/10.1016/j.marpolbul.2017.06.033.
Qian, C., Huang, B., Yang, X., Chen, G., 2022. Data science for oceanography: from small data to big data. Big Earth Data 6 (2), 236–250. https://doi.org/10.1080/20964471.2021.1902080.
Qian, H., Ma, P., Gao, S., Song, Y., 2023. Soft reordering one-dimensional convolutional neural network for credit scoring. Knowl. Base Syst. 266, 110414 https://doi.org/10.1016/j.knosys.2023.110414.
Qu, T., Du, Y., Strachan, J., Meyers, G., Slingo, J., 2005. Sea surface temperature and its variability in the Indonesian region. Oceanography 18 (SPL.ISS. 4), 50–61. https://doi.org/10.5670/oceanog.2005.05.
Ray, R.D., Susanto, R.D., 2016. Tidal mixing signatures in the Indonesian seas from high-resolution Sea Surface temperature data. Geophys. Res. Lett. 43 (15), 8115–8123. https://doi.org/10.1002/2016GL069485.
Ray, R.D., Susanto, R.D., 2019. A fortnightly atmospheric 'tide' at Bali caused by oceanic tidal mixing in Lombok Strait. Geosci. Lett. 6 (6), 1–9. https://doi.org/10.1186/s40562-019-0135-1.
Rosario, J.J.A.D., Pérez, J.M.V., Gómez, E.B., 2019. On the prediction of upwelling events at the Colombian caribbean coasts from modis-SST imagery. Sensors 19 (13). https://doi.org/10.3390/s19132861.
Russom, P., 2011. fourth quarter. Big Data Analytics. TDWI Best Practices Report, vol. 19, pp. 1–34.
Saji, N.H., Goswami, B.N., Vinayachandran, P.N., Yamagata, T., 1999. A dipole mode in the tropical Indian Ocean. Nature 401, 360–363. https://doi.org/10.1038/43854.
Sari, Q.W., Siswanto, E., Setiabudidya, D., Yustian, I., Iskandar, I., 2018. Spatial and temporal variability of surface chlorophyll-a in the Gulf of Tomini, Sulawesi, Indonesia. Biodiversity 19 (3), 743–751. https://doi.org/10.13057/biodiv/d190306.
Setiawan, R.Y., Habibi, A., 2011. Satellite detection of summer chlorophyll-a bloom in the Gulf of Tomini. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 4 (4), 944–948. https://doi.org/10.1109/JSTARS.2011.2163926.
Setiawan, R.Y., Kawamura, H., 2011. Summertime phytoplankton bloom in the south sulawesi sea. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 4 (1), 241–244. https://doi.org/10.1109/JSTARS.2010.2094604.
Setiawan, R.Y., Setyobudi, E., Wirasatriya, A., Muttaqin, A.S., Maslukah, L., 2019. The influence of seasonal and interannual variability on surface chlorophyll-a off the western Lesser sunda Islands. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 12 (11), 4191–4197. https://doi.org/10.1109/JSTARS.2019.2948385.
Setiawan, R.Y., Wirasatriya, A., Hernawan, U., Leung, S., Iskandar, I., 2020. Spatio-temporal variability of surface chlorophyll-a in the Halmahera Sea and its relation to ENSO and the Indian Ocean Dipole. Int. J. Rem. Sens. 41 (1), 284–299. https://doi.org/10.1080/01431161.2019.1641244. Advance online publication.
Solanki, H.U., Bhatpuria, D., Chauhan, P., 2016. Applicationsof generalized additive model (GAM) to satellite-derived variables and fishery data forprediction of fishery resources distributions in the Arabian Sea. Geocarto Int. 32 (1), 1–29. https://doi.org/10.1080/10106049.2015.1120357.
Sprintall, J., Wijffels, S.E., Molcard, R., Jaya, I., 2009. Direct estimates of the Indonesian throughflow entering the Indian Ocean: 2004-2006. J. Geophys. Res.: Oceans 114. https://doi.org/10.1029/2008JC005257. C07001.
Sun, Y., Yao, X., Bi, X., Huang, X., Zhao, X., Qiao, B., 2021. Time-series graph network for Sea Surface temperature prediction. Big Data Res. 25, 100237 https://doi.org/10.1016/j.bdr.2021.100237.
Sun, T., Feng, Y., Li, C., Zhang, X., 2022. High precision Sea Surface temperature prediction of long period and large area in the Indian ocean based on the temporal convolutional network and internet of things. Sensors 22 (4). https://doi.org/10.3390/s22041636.
Sun, Z., Sandoval, L., Crystal-Ornelas, R., Mousavi, S.M., Wang, J., Lin, C., Cristea, N., Tong, D., Carande, W.H., Ma, X., Rao, Y., 2022. A review of earth artificial intelligence. Comput. Geosci. 159, 105034 https://doi.org/10.1016/j.jksuci.2021.08.007.
Susanto, R.D., Marra, J., 2005. Effect of the 1997/98 El Nino on chlorophyll-a variability along the southern coasts of Java and Sumatra. Oceanography 18 (4), 124–127.
Susanto, R.D., Gordon, A.L., Zheng, Q., 2001. Upwelling along the coasts of Java and Sumatra and its relation to ENSO. Geophys. Res. Lett. 28 (1), 1.559–1.602.
Susanto, R.D., Moore, T.S., Marra, J., 2006. Ocean color variability in the Indonesian Seas during the SeaWiFS era. Geochem., Geophys., Geosyst. 7 (5), 1–16. https://doi.org/10.1029/2005GC001009.
Tresnawati, R., Wirasatriya, A., Wibowo, A., 2022. Accuracy performance of satellite-derived Sea Surface temperature products for the Indonesia seas. Geogr. Tech. 17 (2), 69–83. https://doi.org/10.21163/GT_2022.172.07.
Wirasatriya, A., Setiawan, R.Y., Subardjo, P., 2017. The effect of ENSO on the variability of chlorophyll-a and Sea Surface temperature in the Maluku Sea. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 10 (12), 5513–5518. https://doi.org/10.1109/JSTARS.2017.2745207.
Wirasatriya, A., Sugianto, D.N., Helmi, M., Setiawan, R.Y., Koch, M., 2019. Distinct characteristics of SST variabilities in the sulawesi Sea and the northern part of the Maluku Sea during the Southeast monsoon. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 12 (6), 1763–1770. https://doi.org/10.1109/JSTARS.2019.2913739.
Wirasatriya, A., Setiawan, J.D., Sugianto, D.N., Rosyadi, I.A., Haryadi, Winarso, G., Setiawan, R.Y., Susanto, R.D., 2020a. Ekman dynamics variability along the southern coast of Java revealed by satellite data. Int. J. Remote Sens. 41 (21), 8475–8496. https://doi.org/10.1080/01431161.2020.1797215.
Wirasatriya, A., Hosoda, K., Setiawan, J.D., Susanto, R.D., 2020b. Variability of diurnal Sea Surface temperature during short term and high SST event in the western Equatorial pacific as revealed by satellite data. Remote Sens. 12 (19), 3230. https://doi.org/10.3390/rs12193230.
Wirasatriya, A., Susanto, R.D., Kunarso, Jalil, A.R., Ramdani, F., Puryajati, A.D., 2021. Northwest monsoon upwelling within the Indonesian seas. Int. J. Remote Sens. 42 (14), 5433–5454. https://doi.org/10.1080/01431161.2021.1918790.
Xiao, C., Chen, N., Hu, C., Wang, K., Gong, J., Chen, Z., 2019. Short and mid-term sea surface temperature prediction using time-series satellite data and LSTM-AdaBoost combination approach. Remote Sens. Environ. 233, 11358.
Xu, F., Ignatov, A., 2016. Error characterization in iQuam SSTs using triple collocations with satellite measurements. Geophys. Res. Lett. 43 (20), 10–826.
Xu, N., Duan, S., Li, A., Zhang, C., Cai, Z., Hu, Z., 2010. Effects of temperature, salinity and irradiance on the growth of the harmful dinoflagellate Prorocentrum donghaiense Lu. Harmful Algae 9 (1), 13–17. https://doi.org/10.1016/j.hal.2009.06.002.
Xu, Z., Ji, F., Liu, B., Feng, T., Gao, Y., He, Y., Chang, F., 2021. Long-term evolution of global sea surface temperature trend. Int. J. Climatol. 41 (9), 4494–4508. https://doi.org/10.1002/joc.7082.
Yaffee, R.A., McGee, M., 2000. An Introduction to Time Series Analysis and Forecasting: with Applications of SAS®and SPSS®. Elsevier.
Zhang, Z., Pan, X., Jiang, T., Sui, B., Liu, C., Sun, W., 2020. Monthly and quarterly sea surface temperature prediction based on gated recurrent unit neural network. J. Mar. Sci. Eng. 8 (4) https://doi.org/10.3390/JMSE8040249.
Zhao, J., Mao, X., Chen, L., 2019. Speech emotion recognition using deep 1D & 2D CNN LSTM networks. Biomed. Signal Process Control 47, 312–323. https://doi.org/10.1016/j.bspc.2018.08.035.
Zheng, G., Li, X., Zhang, R.-H., Liu, B., 2020. Purely satellite data–driven deep learning forecast of complicated tropical instability waves. Sci. Adv. 6 (29) https://doi.org/10.1126/sciadv.aba1482.
Zhou, X., 2020. Application of deep learning in ocean big data mining. J. Coast. Res. 106 (SI), 614–617.