



TUYỂN TẬP BÁO CÁO HỘI NGHỊ TOÀN QUỐC

KHOA HỌC TRÁI ĐẤT VÀ TÀI NGUYÊN VỚI PHÁT TRIỂN BỀN VỮNG (ERSD 2024)

HÀ NỘI 14 - 11 - 2024

ERSD 2024



NHÀ XUẤT BẢN GIAO THÔNG VẬN TẢI

**TIỂU BAN
DỮ LIỆU LỚN VÀ CHUYỂN ĐỔI SỐ
TRONG KHOA HỌC TRÁI ĐẤT,
TÀI NGUYÊN MÔI TRƯỜNG**

Enhancing temporal sea surface temperature prediction using LSTM model

Tran Thi Hoa^{1,*}, Tran Thanh Ha¹, Nguyen Thi Mai Dung¹, Tran Thi Ngoc¹
¹*Hanoi University of Mining and Geology*

ABSTRACT

Sea surface temperature (SST) is one of important factors influencing numerous aspects of the Earth's climate, ecosystems, economies, and human societies. Monitoring and predicting trends and patterns of SST are essential for mitigating the impacts of climate change and ensuring the sustainability of marine and terrestrial environments. Historical records are available to directly retrieve and conduct several deep learning models in temporal SST prediction. However, in order to enhance to process of predicting SST data, there are several factors need considering which are trends, periodicities or other disturbances (weather, ocean currents or ocean oscillation). This paper proposes a recurrent neural network (RNN) – Long Short-Term Memory (LSTM) to an enhancement of time-series SST prediction by preventing a problem of several common regression model which is a vanishment and gradient of temporal relationship of input data and handling long-term dependencies. We use thermal bands of Landsat and MODIS images to set and select sample data for training LSTM model. Results are being expected to offer an effective architecture of SST prediction model based on LSTM mechanism.

Keywords: Landsat; MODIS; LSTM; SST; thermal bands

1. Introduction

Sea Surface Temperature (SST) refers to the temperatures of the ocean's surface, typically measured at a depth of a few meters below the surface (NOAA n.d.). SST is a critical variable in the study of climate because it influences and is influenced by various atmospheric and oceanic processes. SST plays several key roles in Earth's climate.

First of all, it gets impacts on regulating heat exchange between the ocean and the atmospheres. Warmer SST can encourage evaporation rates, which adds moisture to the atmosphere and can lead to increased precipitation and more intense weather systems, such as hurricanes, typhoons and cyclones. Hence, SST has a very closed relation to climate regulation.

Furthermore, SST is a driving factor in ocean currents and circulation patterns, such as the Gulf Stream and the El Niño – Southern Oscillation (ENSO) (NASA n.d.). These currents redistribute heat globally, affecting weather patterns and climate. For example, during and El Niño event, warmer SST in the central and eastern Pacific Ocean can lead to significant changes in weather patterns, including altered rainfall and temperature distributions across the globe (Nan Chen 2019). This also explains why during El Niño years, several regions (like the southern United States) are in wetter conditions, and others are in drier conditions (Australia, for instance).

Carbon cycle is also driven by SST regarding the solubility of gases, including carbon dioxide (CO₂). Warmer surface waters hold less CO₂, which can influence atmospheric CO₂ levels and thus global warming. Conversely, cooler waters can absorb more CO₂, acting as a carbon sink (H.-O. Pörtner 2019).

Lastly, marine ecosystems are additionally subjected by the sea surface temperature. Marine life, including the distribution and productivity of marine species, is very sensitive to changes in SST (ClaraDeser 2010). Coral reefs, for instance, under conditions of prolonged elevated temperatures can be bleached and potentially degraded (Gordon 1973).

* Corresponding author
Email: tranthihoa@humg.edu.vn

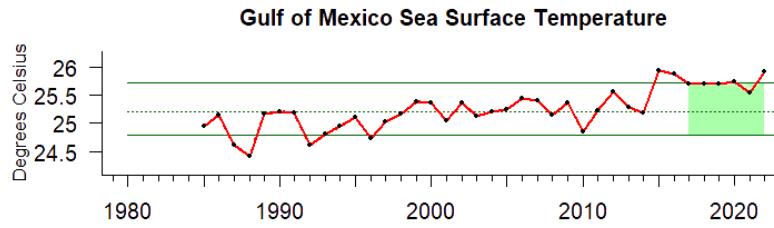


Figure 1. Gulf of Mexico SST product used for this analysis is the NOAA Coral Reef Watch CoralTemp v3.1 SST composited monthly.

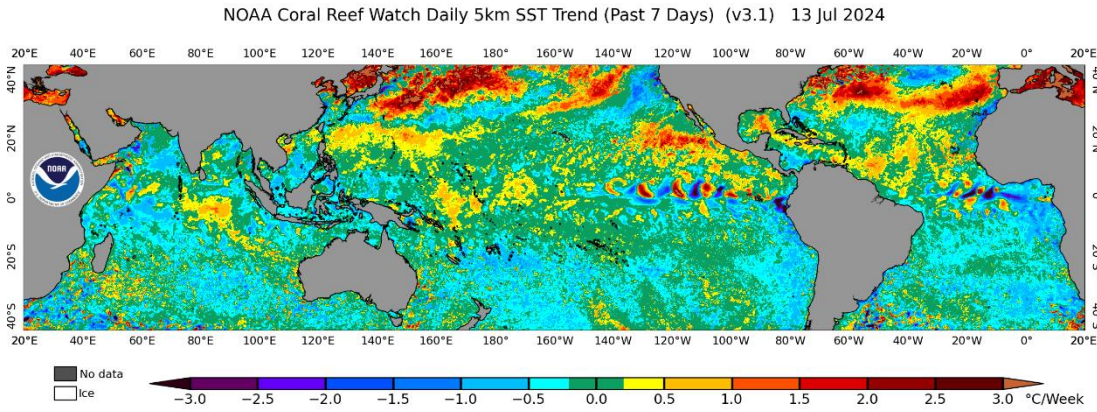


Figure 2. The 7 days SST trends for ocean areas at scale of daily Global 5km

It is undeniable that SST is a crucial factor in driving ocean currents, marine systems and climatic patterns. Understanding SST variations and trends is essential for predicting climate and environmental management.

Remote sensing technology is able to record and monitor any changes in SST at the time of observation daily or periodically taking advantages of thermal bands of optical sensors like MODIS or Landsat which are both free resources at coarser to moderate spatial scales (Ye, et al. 2022). In order to monitor time series SST, there is a need of a model contributing relevant factors to recognize patterns in sequences of data.

Current deep learning models have proven highly effective for predicting sea surface temperature due to their ability to learn complex patterns from large datasets (Liu 2017). Several common model can be counted as: the Convolution Neural Networks (CNNs) (Qiao, et al. 2022), the Recurrent Neural Networks (RNNs), the Long Short Term Memory Network (LSTMs) (Saxena, et al. 2023), the convolutional LSTMs or the hybrid model (Minkyu Kim 2020). Each of those models has their own strengths and weaknesses. For example, the CNNs are effective and easily accessible in capturing spatial features and patterns, however, there are lack of dependencies taken into account. The RNNs, though, are capable of capturing dependencies and long-term trends in SST, may suffer from vanishing and exploding gradient problems. Thus, they are often limited to short-term dependencies, which can be inadequate for tasks like SST prediction where long-term trends and cycles are important (Minkyu Kim 2020).

The LSTMs are specifically designed to overcome the limitations of standard RNNs by introducing a memory cell that can maintain information over long periods. This allows LSTMs to capture long-term dependencies and patterns in SST data more effectively. Furthermore, they use gating mechanisms to control the flow of information into and out of the memory cell. This gating mechanism enables the network to learn when to remember or forget information, addressing the vanishing gradient problem and improving learning efficiency. This study concerns an integration of LSTM networks with satellite data from sources like MODIS and Landsat to leverage their temporal resolution and spatial coverage for accurate SST predictions.

2. Methodologies

2.1. The LSTM Networks

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data (Hochreiter 1997). They address the limitations of traditional RNNs, which struggle with learning long-term dependencies due to the vanishing gradient

problem. LSTMs are particularly effective for tasks involving sequences, such as time series prediction, natural language processing, and speech recognition.

For architecture, an LSTM network identically consists of units called LSTM cells. Each LSTM cell contains three main components: input gate, forget gate, and output gate. These gates regulate the flow of information within the cell, allowing the network to maintain and update a memory cell state over long sequence. To be more specific, the input gate controls the extent to which new information flows into the cell state, while the forget gate determines how much of the past information to discard from the cell state. The output gate, on the other hand, decides how much of the cell state to output at the current time step.

The cell state is the key to LSTM's ability to remember information over long periods. It undergoes regulated updates at each time step, ensuring that important information is retained while irrelevant information is discarded.

The operations within an LSTM cell can be summarized by the following equations (Hochreiter 1997):

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \quad (2)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (3)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad (4)$$

$$h_t = o_t \odot \tanh(c_t) \quad (5)$$

Where:

- x_t is the input vector at time step,
- h_t is the hidden state vector at time step,
- c_t is the cell state vector at time step,
- W_{xi}, W_{hi}, W_{ci} are weight matrices for the input gate,
- W_{xf}, W_{hf}, W_{cf} are weight matrices for the forget gate,
- W_{xc}, W_{hc}, W_{cc} are weight matrices for the cell state,
- W_{xo}, W_{ho}, W_{co} are weight matrices for the output gate,
- b_i, b_f, b_c, b_o are bias vectors,
- σ is the sigmoid activation function,
- $\odot$ denotes element-wise multiplication.

2.2. Data resources

2.2.1. MODIS thermal bands

The MODIS (Moderate Resolution Imaging Spectroradiometer) onboard the Terra and Aqua satellites provides extensive temporal resolution data, capturing images twice daily, both during the day and at night. This high temporal resolution, then, makes MODIS an excellent resource for continuous monitoring. In detail, historical data from the Terra satellite is available since 2000, while Aqua has been providing data since 2002. Additionally, MODIS offers global coverage of 36 spectral bands, among which thermal infrared bands (TIR) at 1km spatial resolution are particularly used for surface temperature monitoring. MODIS resources can be accessed through NASA's Earth Observing System Data and Information System (EOSDIS), the LAADS DAAC, and other NASA portals, ensuring consistent and reliable data for environmental monitoring and analysis.

For calculating surface temperature, the split-window algorithm is commonly used (Wan 1996):

$$LST = T_{31} + a(T_{31} - T_{32}) + b + c(T_{31} - T_{32})^2 \quad (6)$$

Where:

- LST is the Land Surface Temperature (Kevil degree).
- T_{31} and T_{32} are the brightness temperatures in MODIS Bands 31 (10.78–11.28 μm) and 32 (11.77–12.27 μm), respectively.
- a, b, c are coefficients derived from regression analysis based on atmospheric condition.

2.2.2. Landsat thermal bands

The Landsat program, which includes multiple satellites such as Landsat 5, 7, 8, and 9, provides medium-resolution data with a 16-day revisit cycle. Landsat 5 operated from 1984 to 2013, while Landsat 7 has been providing data since 1999, despite experiencing data gaps due to the Scan Line Corrector (SLC) failure in 2003. Landsat 8 has been operational since 2013, and Landsat 9 was launched in 2021. The program's data spans from 1972 to the present, offering a rich historical archive.. Data from the Landsat program can be acquired via the USGS Earth Explorer, GloVis, and NASA Earthdata portals, providing

essential information for a wide range of applications, from environmental monitoring to urban planning.

Thermal bands provided by Landsat at different time scale are various in spatial resolutions and wavelengths. Landsat 5 and 7 offer one thermal band which is band 6 (10.40–12.50 μm) at 120 m and 60 m resolution, respectively. Otherwise, Landsat 8 and 9 provide two thermal bands which are band 10 (10.60–11.19 μm) and Band 11 (11.50–12.51 μm) at 100 m resolution. The variation of spatial resolution is one of the constraints of using Landsat archive in research adding one more step to harmonize the scale for data.

In general, LST is calculated base the radiative transfer equation (Du 2015):

$$\text{LST} = \frac{BT}{1 + \left(B10 \cdot \frac{BT}{\rho} \right) \ln(\epsilon)} \quad (7)$$

Where:

- LST is the Land Surface Temperature (Kevil degree).
- BT is the brightness temperature.
- B10 the wavelength of emitted radiance (10.9 μm for Band 10).
- $\rho = h \cdot c / \sigma$ ($1.438 \times 10^{-2} \text{ m} \cdot \text{K}$, with h as Planck's constant, c as the speed of light, and σ as the Boltzmann constant).
- ϵ is the surface emissivity.

2.3. Proposed workflow for building and training LSTM for SST prediction

Since, SST is a critical parameter in climate monitoring, oceanography and meteorology. For accurate prediction with the LSTM, it is necessary to provide a sufficient number of recorded observation, and auxiliary data, such as wind speed and sea level pressure for creating a long-time and various dependencies. Satellite images provide comprehensive and continuous data for SST monitoring. Other data need to be collected regarding timestamps for synchronizing. Below is our proposed workflow for MODIS data, this subject could change regarding different type of input and how sufficient and adequate auxiliary data are able to be acquired. Detailed architecture of LSTMs will be discussed in the future when data are completely processed.

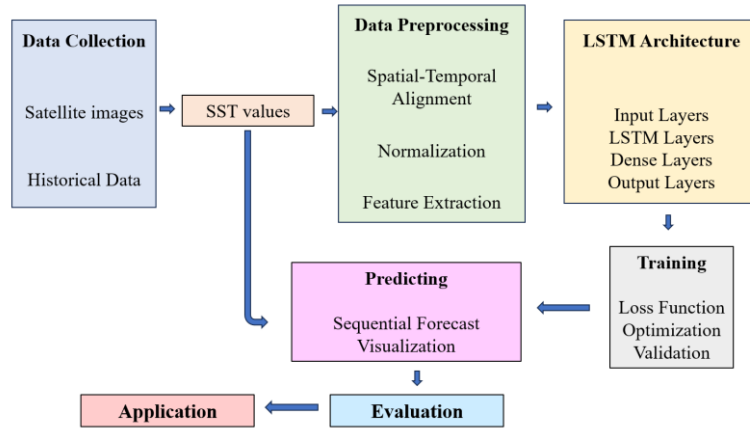


Figure 3. Our proposed workflow

3. Preliminary results and discussion

In the project, we investigated in learning the changes and predicting the SST along the coastal area of Vietnam during the observed time of 2021 to 2024 due our limitation of accessing dataset and the prolonged process time of equipment constrains. The area is defined as an extension from 103 to 116.5 degrees East longitude and 6 to 23 degrees North latitude covering entirely the Vietnames territorial border including Hoang Sa and Truong Sa islands.

Currently, we have conducted the sea surface temperature of each day from 2004 to July 2024 covering more 20 years of robustly historical data. However, we are still seeking for other types of records regarding auxiliary data of wind speeds, ENSO or tropical storms' occurences fulfill the list of dependencies for the model.

Figure 4, 5 and 6 below perform daily variation of the SST along Vietnames territorial border acquired in June 2022, June 2023 and June 2024 respectively. In general, the June average sea surface temperature (blue line in the graph) is around 32 Celcius degrees which is identically orange shade in the maps.

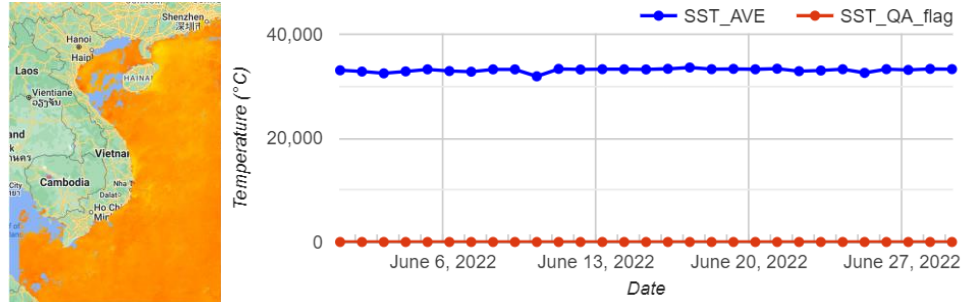


Figure 4. June 2022 sea surface temperature of our research area

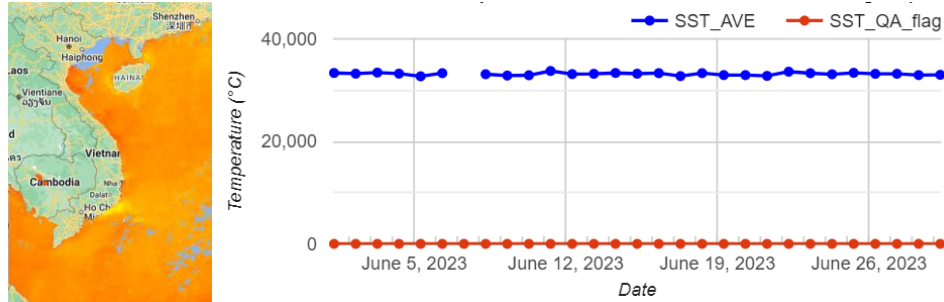


Figure 5. June 2023 sea surface temperature of our research area

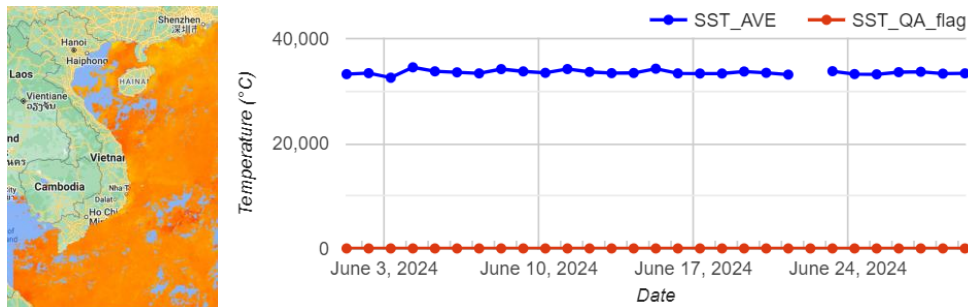


Figure 6. June 2024 sea surface temperature of our research area

4. Conclusion

In this study, we have done with acquiring and process data for the archive of almost 20 years MODIS sea surface temperature of our region of interest. Nevertheless, the process of predict SST patterns is quite complicated due to a large of amount of data and lacking records of dependencies. We are still in the search of identifying dependencies based on our availability of data resources. Future work could explore the integration of additional satellite data sources and the parameters for the architecture of our LSTM model, examine other deep learning model to further improve SST prediction accuracy. Additionally, real-time SST prediction systems could be developed to provide continuous monitoring and forecasting capabilities which mainly focuses on impact of SST on Vietnamese climate patterns.

Acknowledgements

We credit the sponsor from the research project T24-02 “Research on an integration of a Recurrent Neural Network – LSTM (Long Short-Term Memory) and USLE model in forecasting soil erosion”, at Hanoi University of Mining and Geology.

Figure 1 from “Sea Surface Temperature | National Marine Ecosystem Status (noaa.gov)”, and figure 2 from the website https://coralreefwatch.noaa.gov/product/5km/index_5km_sst-trend-7d.php under Copyright.

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TÓM TẮT

Nâng cao khả năng dự đoán nhiệt độ bề mặt nước theo thời gian bằng mô hình LSTM

Trần Thị Hòa¹, Trần Thanh Hà², Nguyễn Thị Mai Dung¹, Trần Thị Ngọc³

¹*Trường Đại học Mở -Địa chất*

Nhiệt độ bề mặt nước biển (SST) là một trong những yếu tố quan trọng ảnh hưởng đến sự điều hòa khí hậu Trái Đất, các hệ sinh thái, các nền kinh tế và xã hội của con người. Công tác giám sát và dự đoán xu hướng và hình thái của SST là điều cần thiết để giảm thiểu các tác động của sự biến đổi khí hậu và đảm bảo tính bền vững của môi trường biển và cả ở trên cạn. Các dữ liệu hay bản ghi về nhiệt độ là nguồn tư liệu để truy xuất trực tiếp và xây dựng các mô hình học sâu trong dự đoán thay đổi nhiệt độ nước biển. Tuy nhiên, để nâng cao khả năng dự đoán từ nguồn dữ liệu đó, một số yếu tố cần phải xem xét kỹ càng, ví dụ như : xu hướng, thời kì hoặc các yếu tố khí hậu (thời tiết, dòng hải lưu hay các dao động đại dương). Nghiên cứu này đề xuất ứng dụng mạng nơ-ron hồi quy – bộ nhớ dài hạn – ngắn hạn (LSTM) để nâng cao khả năng dự đoán SST theo chuỗi thời gian bằng cách ngăn ngừa vấn đề chung của một số mô hình hồi quy là sự mất mát các mối quan hệ giữa các dữ liệu đầu vào theo thời gian để xử lý các dữ kiện dài hạn. Dữ liệu đầu vào là kênh nhiệt của các vệ tinh Landsat và MODIS để thiết lập và lựa chọn dữ liệu mẫu để huấn luyện mô hình LSTM. Kết quả dự kiến sẽ cung cấp một kiến trúc hiệu quả của mô hình dự đoán SST dựa trên cơ chế của LSTM.

Từ khóa: Landsat; MODIS; LSTM; SST; kênh nhiệt