A Spatiotemporal Aerosol Optical Depth Forecasting in Thailand Using Deep Learning

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***Abstract*—Aerosol Optical Depth (AOD) is a key parameter in atmospheric science. Accurate AOD prediction plays a crucial role for environmental management, air quality assessment, and understanding the earth climate change. It also serves as a direct indicator of particulate matter pollution, which poses significant health risks. This study addresses the need for precise AOD forecasting by implementing SwinLSTM, a multi-step spatiotemporal deep learning model. A 6-hour forecasting horizon was selected to align with practical applications, with lookback periods of 12 and 24 h. Both lookback periods yielded comparable model performance, as evidenced by the following metrics: Mean Absolute Error of 0.04, Root Mean Square Error of 0.08, Structural Similarity Index of 0.97, and Peak Signal-to-Noise Ratio ranging from 44.4 to 44.95. By enhancing our understanding of AOD and its contributing factors, we can develop more effective strategies to mitigate the negative impacts of air pollution and protect human health and the environment. Additionally, AOD forecasting can aid in understanding the impact of atmospheric particles on the Earth's climate.**

***Keywords*—aerosol optical depth prediction, air pollution, climate change, spatiotemporal deep learning, SwinLSTM model**

I. Introduction

Aerosol Optical Depth (AOD) is a measure of how much light is blocked by particles suspended in the atmosphere. These particles, known as aerosols, include dust, smoke, sea salt, and pollutants. AOD has important applications in climate studies, air quality monitoring, and visibility assessments. It plays a key role in influencing Earth's energy balance and climate change. High AOD levels are often associated with poor air quality, leading to hazy conditions and reduced visibility. Air quality, particularly Particulate Matter (PM2.5), is a critical global issue. PM2.5, consisting of particles less than 2.5 micrometers in diameter, poses severe risks to public health and environmental sustainability. A large portion of the world's population lives in areas where air quality fails to meet safety standards. Air pollution is a major cause of premature deaths, particularly in various low- and middle-income countries. Thailand also faces challenges related to air pollution. Addressing AOD and PM emissions is crucial for improving public health and environmental sustainability.

Addressing air pollution requires a multifaceted approach, combining stringent air quality regulations with heightened public awareness and engagement. Implementing robust policies to limit emissions from industries, vehicles, and other major sources is crucial for mitigating air pollution at its root. Additionally, public education campaigns can play a key role by informing individuals about the health risks associated with poor air quality and encouraging behavioral changes that reduce exposure. These campaigns also promote sustainable practices to improve long-term air quality. The development of effective monitoring, forecasting, and mitigation strategies is also crucial for protecting both human health and the environment. Forecasting models enable timely interventions, such as public health advisories and traffic restrictions, by predicting future air quality.

Artificial Intelligence (AI) is driving transformative changes across multiple sectors, including healthcare, finance, education and environmental science. Its ability to analyze vast amounts of data, recognize patterns, and make highly accurate predictions offers opportunities for innovation and efficiency. AI has become a powerful tool for addressing complex environmental challenges, such as air pollution prediction [1]. AI-powered models can develop precise predictions of air quality by analyzing historical data and current conditions, enabling early warnings and proactive measures. Moreover, AI can be integrated with real-time monitoring systems to provide continuous updates on air quality conditions. This allows authorities to track pollution levels, identify hotspots, and issue timely alerts to the public. AI models used in these applications range from traditional machine learning algorithms to advanced deep learning techniques. Recent advancements of deep learning include Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs) and other neural networks [2].

In recent years, researchers have conducted extensive studies to predict air quality concentrations using a variety of data sources. These studies often incorporated satellite-based information, meteorological variables, land use data, and other relevant factors. Many studies have focused on the use of satellite-derived AOD, which plays a key role in addressing various environmental challenges, such as air quality, climate change, and disaster management. Since AOD is closely correlated with PM2.5, it serves as an important proxy for estimating PM2.5 concentrations [3]. AOD affects visibility, which is crucial for transportation, aviation, and outdoor activities. Accurate AOD predictions can help optimize these activities and minimize risks. Additionally, AOD measurements can pinpoint sources of air pollution, including industrial emissions, vehicle exhaust, and natural events like wildfires. Accurate AOD predictions are also crucial for understanding and modeling the impacts of aerosols on climate change. AOD data enhances climate prediction models by improving our ability to model aerosol behavior. This potentially offers deeper insights into future climate trends.

In this study, we developed a multi-step air pollution prediction model that incorporates the spatiotemporal relationships between air quality and various environmental factors. The objective of our model was to predict AOD values at multiple future time steps for a specified geographic region in Thailand as our case study. Due to the limited availability of ground-level PM2.5 data in Thailand, we focused on training the model using more comprehensive satellite-based AOD information. For this purpose, we selected the SwinLSTM model, an architecture combining SwinTransformer blocks with a simplified LSTM, as the foundation for our prediction model [4]. It was originally designed for next-frame prediction in image sequences. Due to its input format, the SwinLSTM is well-suited for our grid-level AOD data. This model structure allowed us to effectively capture both spatial and temporal dependencies, improving the accuracy of AOD predictions across multiple time steps.

II. Literature Review

Atmospheric aerosols play a crucial role in air quality, environmental pollution, climate change and human health [5–7]. Prior studies have explored various methods to predict AOD levels. Wang *et al.* employed multiple instance regression to forecast AOD, treating it as a collection of labeled instances from neighboring pixels [8]. Li *et al.* proposed nonlinear principal component analysis combined with geographically and temporally weighted regression for AOD prediction [9]. In addition, tree-based and multivariate linear regression models have been developed using climatic parameters [10]. More recently, Kou *et al.* introduced a geospatial-temporal heterogeneity embedded graph neural network to predict AOD at multiple sites [11]. They also integrated geographically and temporally weighted regression with a graph attention network to capture spatiotemporal patterns.

An alternative approach to regression-based methods involved utilizing support vector machines and multi-layer feed-forward neural networks with error back-propagation algorithms for AOD estimation [12]. With the advancement of Global Navigation Satellite System (GNSS) technology, Aliyu and Botai incorporated GNSS-derived Precipitable Water Vapor (PWV) into their AOD model [13]. They observed a correlation coefficient of -0.64 between AOD and PWV. Similarly, Zhao *et al.* proposed an adaptive AOD forecasting model using PWV data driven from GNSS [14].

Another related area of research with our work involved estimating missing AOD data [15]. Olcese *et al.* developed an automated method that utilized AOD data from other nearby stations, artificial neural networks, and air mass trajectories [16]. Instead of relying on simple artificial neural networks, Li *et al.* advanced this approach by employing a more sophisticated deep learning technique. They employed bootstrap aggregating of autoencoder-based residual deep networks, to robustly impute AOD and subsequently estimate PM2.5 levels [17]. A random forest model has also been used to generate high-resolution daily AOD estimates with full coverage [18]. More recently, Long *et al.* introduced a satellite-based AOD filling method using hourly level-3 Himawari-8 AOD products and random forest models [19].

III. Materials and Methods

A. Study Area and Data Collection

This study focused on the central region of Thailand, including the Bangkok Metropolitan Area. To accurately predict air quality in this region, we integrated a variety of data sources. These included high-resolution satellite imagery from Himawari 8, a geostationary satellite operated by the Japan Meteorological Agency [20], and two reanalysis datasets including MERRA-2 [21] and ERA-5 [22]. Himawari 8 provided real-time weather data with 5 km×5 km resolution, including cloud cover and atmospheric conditions. This information was essential for understanding the factors influencing air pollution. MERRA-2 was developed by NASA's Global Modeling and Assimilation Office which offered a spatial resolution of 0.5 degrees×0.625 degrees. Additionally, ERA-5 is a high-resolution atmospheric reanalysis dataset from the European Centre for Medium-Range Weather Forecasts. It has a resolution of 11,132 m×11,132 m and offers detailed atmospheric information.

For the data collection process, AOD data was directly downloaded from the Himawari-8 SFTP server under clear-sky conditions. Although Himawari-8 typically provides hourly AOD data, there can be major data gaps due to factors such as extended cloud cover or elevated surface reflectance. To address these gaps, we adopted a method like Liu *et al.* and supplemented the Himawari-8 data with MERRA-2 AOD data [23]. By integrating Himawari-8 and MERRA-2 data, we created a complete and continuous hourly AOD data for the region of interest. In addition to AOD, meteorological parameters, including precipitation, shortwave radiation, surface pressure, temperature, wind direction (u-component and v-component), and leaf area index, were obtained from the ERA5 dataset. This comprehensive dataset, combining hourly AOD and various meteorological parameters from multiple satellite sources. It provided a robust foundation for analyzing spatiotemporal patterns across the study region. Particularly, all collected variables were mapped to the central region of Thailand, resulting in a spatial resolution of 8×32×32 (C×H×W), where C represents the channels, H the height, and W the width.

B. Methodology

This study approached air pollution prediction as a spatiotemporal forecasting problem. It focused on predicting future events or conditions based on both spatial (location-based) and temporal (time-based) data. Our objective was to develop a model capable of accurately predicting AOD levels across the entire region of interest over multiple future time steps. To enhance model interpretability and training efficiency, we applied channel-wise normalization. This involved scaling the values within each channel to the range of 0 to 1. Training samples were constructed to predict AOD for a 6-hour forecasting horizon. To capture temporal dependencies, an experiment was conducted to evaluate the impact of different lookback periods. Specifically, we explored using 12-hour and 24-hour lookback windows to determine the suitable time frame for incorporating historical data into the prediction model. For model development, the entire dataset was divided into three subsets: training (2016–2022), validation (2022), and testing

(2023). This structured approach provided a solid foundation for developing a robust multi-step AOD prediction model.

To address the spatiotemporal nature of air pollution prediction, we selected SwinLSTM-D, a model renowned for its performance on such data. To further improve the model's robustness, we utilized OpenSTL, a bootstrapping technique within the PyTorch Lightning framework. For training, we employed Mean Absolute Error (MAE) as the loss function, focusing specifically on AOD prediction. This approach ensured that the model converged effectively on the target variable. By carefully selecting SwinLSTM-D and incorporating bootstrapping techniques, we aimed to capture the complex spatiotemporal relationships inherent in air pollution data. This approach was designed to optimize the model's performance for accurate AOD predictions.

C. Evaluation Metrics

To further assess the model's performance, we used a combination of pixel-wise error metrics and Image Quality Assessment (IQA) metrics. For pixel-wise errors, we calculated Root Mean Square Error (RMSE) and mean absolute error (MAE) to quantify the differences between predicted and actual AOD values at the individual pixel level. For the IQA metrics, Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) were employed to assess the overall quality of the predicted AOD images.

IV. Result and Discussion

After training multi-step spatiotemporal deep learning models to forecast AOD, we selected the best-performing model based on its validation loss. Particularly, the models underwent a rigorous training and evaluation process. The initial training phase utilized the training dataset to learn the underlying patterns. This was followed by hyperparameter tuning on the validation set to optimize performance. Subsequently, the fine-tuned model with optimized parameters was assessed on the held-out test set.

We evaluated the model's performance with the pixel-wise error metrics, and IQA metrics. For the pixel-wise error metrics, RMSE penalizes larger errors more severely due to the squaring operation. It is therefore often used in applications where large errors have serious consequences like ours. MAE is often used in applications where the absolute magnitude of the error is more important than the direction (positive or negative). For RMSE and MAE, we calculated grid-wise averages across samples and timesteps to obtain a comprehensive assessment of the model's performance. For the IQA metrics, SSIM considers three factors: luminance, contrast, and structural similarity. It calculates a similarity index between 0 and 1, where 1 indicates perfect similarity. PSNR measures the ratio of maximum possible signal power to the power of the noise. A higher PSNR indicates a better signal-to-noise ratio. Table 1 summarizes the evaluation results for both lookback periods (12-hour and 24-hour) on the training, validation, and testing datasets.

While the model exhibited comparable performance on both the training and validation sets, a slight decrease in performance was observed on the test set. However, these differences were relatively minor. This suggests that the model has a strong ability to generalize to unseen data. The absence of significant overfitting is a positive indicator of the model's robustness. To further bolster our confidence in the model's performance and ensure its applicability to real-world scenarios, incorporating an external test dataset would be beneficial. As more data becomes available, conducting additional evaluations on this external set can provide valuable insights into the model's generalizability and potential limitations.

Table 1. Evaluation metrics based on train, validation, and test data

(Lookback, Forecasting horizon)	Evaluation metrics	Train	Validate	Test
(12, 6)	MAE	0.0354	0.0390	0.0409
	RMSE	0.0704	0.0768	0.0827
	SSIM	0.9731	0.9715	0.9655
	PSNR	44.9768	44.3350	44.4414
(24, 6)	MAE	0.0339	0.0392	0.0402
	RMSE	0.0678	0.0788	0.0829
	SSIM	0.9741	0.9714	0.9663
	PSNR	45.5572	44.6839	44.9508

We selected a 6-hour forecasting horizon to align with the practical application of the model as an early warning system. A 6-hour prediction window allows for sufficient time to implement preventive measures based on the forecasted AOD values. To determine an appropriate lookback period, we experimented with 12-hour and 24-hour windows. While a longer lookback period provides the model with more historical information, it can also lead to increased risk of overfitting. As shown in Table 1, the differences in evaluation metrics between the 12-hour and 24-hour lookback periods were minimal. This indicates that adding more historical data did not essentially improve the model's performance. The 12-hour lookback period model may be preferred due to its smaller size and reduced computational demands. This model presented a balance between capturing historical trends and mitigating the risk of overfitting. Nonetheless, further research into the potential advantages of longer lookback periods in specific scenarios could be beneficial.

To comprehensively assess the model's performance at each forecast horizon within the 6 future time steps, we calculated all evaluation metrics for each predicted step. These metrics provided insights into the model's accuracy, precision, and overall predictive capability capturing pixel-wise errors and IQA metrics at different points in the future. Fig. 1 visually represents the distribution of these metrics across 6 forecast steps. These values were averaged across all grids in the region.

The model demonstrated its strongest performance at the initial forecasting horizon. However, a gradual decline in accuracy was observed as the prediction horizon extended into the future. This trend is intuitively understandable, as forecasting AOD values over longer periods becomes inherently more challenging. This potentially due to the increasing complexity and uncertainty associated with future atmospheric conditions. While the model's accuracy may diminish slightly with longer forecasting horizons, the ability to provide predictions for multiple future time steps remains valuable for real-world applications. This trade-off between accuracy and forecasting horizon allows decision-makers to make informed policy interventions based on anticipated AOD levels, even when predictions are subject to some degree of uncertainty.

To further observe the model performance, we visualized the real value compared to the predicted AOD values across grids in the region of interest. Fig. 2 represents a specific time point selected as an example. It illustrates this comparison using a color gradient from blue (lowest AOD) to red (highest AOD). The figure is arranged from the earliest prediction point on the left to the latest prediction point on the right. The color scale is based on the minimum and maximum AOD values in the ground truth data. While there are some differences between actual and predicted values, the overall trend can be captured effectively, and a strong correlation is evident between the two. This provides a clear visual representation of the model's ability to accurately predict AOD levels across the region, with only minor variations.

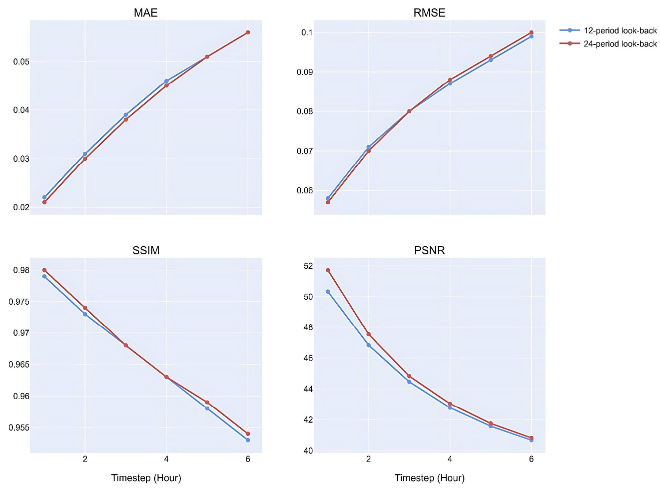

Fig. 1. Evaluation metrics across 6 forecasting horizons.

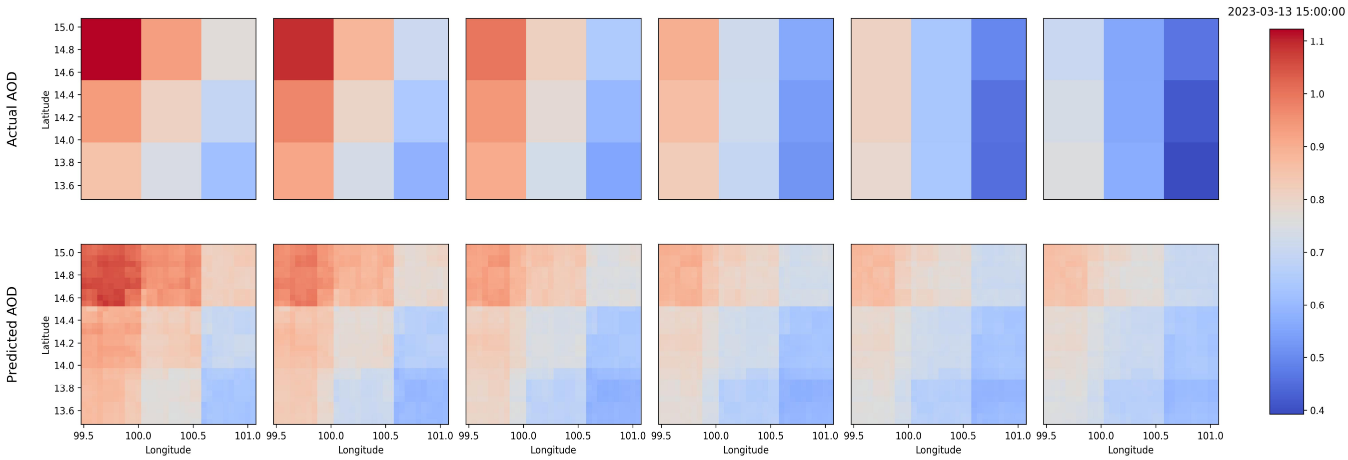

Fig. 2. An example of the real (top) and the predicted AOD (bottom).

The dataset employed in this study was derived from satellite-based observations centered on the central region of Thailand. To our knowledge, this research represents a pioneering effort in applying spatiotemporal deep learning techniques to AOD forecasting within this specific geographical context. The quality and availability of the AOD and meteorological data are important to the model's performance. Inaccuracies or biases in the data can introduce errors in the predictions. Additionally, limited access to high-quality data can hinder the model's training and evaluation. Due to the limited availability of comparable studies in the same area of interest, we were unable to conduct a thorough comparison with other widely used AOD prediction models in the scope of this study. Instead, we focused our attention on the SwinLSTM model, which was well-suited for our dataset. Future research should involve an in-depth comparison of the model with other state-of-the-art AOD forecasting approaches, with a specific focus on real-time capabilities. A broader comparison would provide a more complete understanding of its relative strengths and weaknesses.

While the SwinLSTM model demonstrates promising capabilities, its computational demands can be substantial, particularly for large datasets or real-time applications. In addition, the model's performance may exhibit regional variations due to differences in geographical features, meteorological conditions, and land use patterns. Furthermore, the model's ability to generalize across different time periods can be influenced by factors such as climate change, human activities, and other environmental variables. As more data becomes available, we intend to expand our research to encompass other regions and diverse time periods, thereby enhancing the model's applicability and generalizability.

As depicted in Fig. 2, the model's performance exhibited a decline with increasing prediction time. This presents a potential challenge for practical applications, especially with long-term forecast requirements. To mitigate this limitation, future research could explore alternative model development strategies. For instance, one-point prediction models, which predict a single step ahead at a time, might demonstrate superior accuracy compared to multi-step prediction models. This potential advantage of one-point prediction models stems from the fact that their loss functions focus on a single output value, while multi-step prediction models consider multiple output values simultaneously. This can lead to a more concentrated focus on accuracy for the prediction step in one-point models. A rolling window approach, where the model predicts one step ahead and uses its own forecast as input for the next prediction, could be another avenue to explore. This iterative process allows for promising accuracy for long-term predictions. Additionally, investigating more sophisticated models could be a promising direction for enhancing the model's performance. These models should be specifically designed for long-term forecasting and incorporate temporal dependencies or seasonal patterns.

V. Conclusion

This study introduced a spatiotemporal deep learning model for accurate AOD forecasting in the central region of Thailand. The model integrated historical satellite-based AOD data along with relevant meteorological parameters, including precipitation, shortwave radiation, surface pressure, temperature, wind direction, and leaf area index. The proposed framework demonstrated promising performance when evaluated using pixel-wise error and IQA metrics. This was achieved by effectively capturing both spatial and temporal patterns within the diverse data sources. Although challenges related to data quality and computational resources were encountered, the results highlighted the potential of deep learning approaches for AOD forecasting.

Future research should focus on overcoming the limitations of this study by improving data quality, increasing computational efficiency, and extending the model's applicability to other regions and time periods. A comprehensive comparison with other state-of-the-art AOD prediction models would provide valuable insights into the relative performance of the proposed framework. Refining the model development process through advanced training strategies and incorporating more sophisticated models is another promising direction. Moreover, exploring methods to quantify uncertainty in predictions could further enhance the model's utility. This provides decision-makers with more reliable and actionable insights. The development of accurate AOD forecasting models is essential for better understanding and mitigating the harmful effects of air pollution on both human health and the environment. Continued advancements in these models can support more informed policy decisions. They can also aid in disaster management and contribute to efforts to combat climate change.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

PW conceptualized; CC and VK implemented; all authors contributed to the methodology design; PW validated; CC and VK curated data; PW wrote the paper; PW supervised; all authors had approved the final version.

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