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Satellite remote sensing and deep learning for aerosols prediction

Mirkov, Nikola S.; Radivojevi#, Dušan S.; Lazovi#, Ivan M.; Ramadani, Uzahir R.; Nikezi#, Dušan P.
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Original scientific papers

Satellite remote sensing and deep learning for aerosols prediction

Спутниковое дистанционное зондирование и глубокое обучение при прогнозировании распространения аэрозолей

Сателитско осматрање и дубоко учење за предвиђање аеросола

Nikola S. Mirkov a
University of Belgrade, Serbia
nmirkov@vin.bg.ac.rs
https://orcid.org/0000-0002-3057-9784

Dušan S. Radivojević b
University of Belgrade, Serbia
dusanr@vin.bg.ac.rs
https://orcid.org/0000-0003-1959-3152

Ivan M. Lazović c
University of Belgrade, Serbia
ivan.lazovic@vin.bg.ac.rs
https://orcid.org/0000-0002-3877-5157

Uzahir R. Ramadani d
University of Belgrade, Serbia
uzahir@vin.bg.ac.rs
https://orcid.org/0000-0002-3702-0094

Dušan P. Nikezić e
University of Belgrade, Serbia
dusan@vin.bg.ac.rs
https://orcid.org/0000-0002-8885-2683

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Abstract:

Introduction/purpose: The paper presents a new state-of-the-art method that involves NASA satellite imagery with the latest deep learning model for a spatiotemporal sequence forecasting problem. Satellite-retrieved aerosol information is very useful in many fields such as PM prediction or COVID-19 transmission. The input data set was MODAL2_E_AER_OD which presents global

Author notes

a University of Belgrade, “Vinča” Institute of Nuclear Sciences - National Institute of the Republic of Serbia, Belgrade, Republic of Serbia

b University of Belgrade, “Vinča” Institute of Nuclear Sciences - National Institute of the Republic of Serbia, Belgrade, Republic of Serbia

c University of Belgrade, “Vinča” Institute of Nuclear Sciences - National Institute of the Republic of Serbia, Belgrade, Republic of Serbia

d University of Belgrade, “Vinča” Institute of Nuclear Sciences - National Institute of the Republic of Serbia, Belgrade, Republic of Serbia

e University of Belgrade, “Vinča” Institute of Nuclear Sciences - National Institute of the Republic of Serbia, Belgrade, Republic of Serbia

dusan@vin.bg.ac.rs

AOT for every 8 days from Terra/MODIS. The implemented machine learning algorithm was built with ConvLSTM2D layers in Keras. The obtained results were compared with the new CNN LSTM model.
Methods: Computational methods of Machine Learning, Artificial Neural Networks, Deep Learning.
Results: The results show global AOT prediction obtained using satellite digital imagery as an input.
Conclusion: The results show that the ConvLSTM developed model could be used for global AOT prediction, as well as for PM and COVID-19 transmission.

Keywords: Aerosol optical thickness, NASA Earth observations, Con- vLSTM2D, COVID-19, particulate matter dispersion..

Р е з ю м е :

Введение/цель: В данной статье представлен новый современный метод, использующий спутниковые снимки НАСА с новейшей моделью глубокого обучения для решения задачи прогнозирования пространственно-временных последовательностей. Полученная со спутников информация об аэрозолях очень полезна во многих областях, таких как диспергирование частиц или передача COVID-19. Для входных данных послужила модель MODAL2_E_AER_OD, которая представляет глобальный прогноз оптической толщины аэрозоля на каждые 8 дней с Terra/MODIS. Реализованный алгоритм машинного обучения включает составные нейронные слои ConvLSTM2D в библиотеке Keras. Полученные результаты были сопоставлены с новой моделью CNN LSTM.
Методы: Вычислительные методы машинного обучения, искусственные нейронные сети, глубокое обучение.
Результаты: Результаты показывают глобальный прогноз оптической толщины аэрозоля с использованием цифровых спутниковых снимков в качестве входных данных.
Выводы: Полученные результаты показывают, что разработанная модель ConvLSTM пригодна для глобального прогнозирования толщины атмосферного аэрозоля, а также для распространения атмосферных частиц и COVID-19.

К л ю ч е в ы е   с л о в а : Оптическая толщина аэрозоля, наблюдения Земли НАСА, Con- vLSTM2D, COVID-19, дисперсия твердых части.

Abstract:

Увод: Изложена је унапређена метода која укључује Насине сателитске снимке са најновијим моделом дубоког учења који се односи на проблем предвиђања просторно-временских сигнала. Информација о аеросолима са сателитских снимака је врло значајна за предвиђање дисперзије честица у атмосфери и преноса вируса COVID-19. Улазни подаци MODAL2_E_AER_OD представљају глобални AOT за осам дана са Terra/MODIS. Алгоритам машинског учења је сачињен од композитних неуронских слојева ConvLSTM2D у библиотеци Keras. Добијени резултати су упоређени са новим моделом CNN LSTM.
Методе: Прорачунске методе машинског учења, вештачке неуронске мреже, дубоко учење.
Резултати: Резултати приказују глобално предвиђање оптичке дебљине аеросола са дигиталним сателитским снимцима који су коришћени као улазни подаци.
Закључак: Показано је да је развијени модел ConvLSTM погодан за глобално предвиђање атмо-сферске дебљине аеросола, као и за пренос атмосферских честица и вируса COVID-19.

Keywords: оптичка дебљина аеросола, NASA Earth Ob- servations, ConvLSTM2D, COVID-19, дисперзија честиц.

Introduction

Technological development together with rapid development of information technologies forms a modern basis for various scientific disciplines. One of such disciplines is Environment and Environmental protection. In recent decades, the development of remote sensing and open access of satellite images, as a part of the big data revolution, has provided scientists with a new opportunity for their research (Lin et al., 2018; Wang et al., 2013). One of many remote sensing applications is satellite data sets of aerosol optical thickness (AOT) or aerosol optical depth (AOD) (Shi et al., 2020; Wei et al., 2020). It is the same measurement that may be made from the ground using a sun photometer or from satellites like Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra satellite. Satellite measurements of aerosols are based on the fact that particles change the way the atmosphere reflects and ab sorbs visible and infrared light.

Today, scientists use arrays of satellite, aircraft, and ground-based instruments to monitor aerosols. The key quantity they report on is AOT, a measure of the amount of light that aerosols scatter and absorb in the atmosphere (Filonchyk et al., 2019). AOT is the fundamental measurement of quantity and distribution of aerosols. The Sun provides the energy that drives Earth's climate, but not all of the energy that reaches the top of the atmosphere finds its way to the surface. That is because aerosols, and clouds seeded by them, reflect about a quarter of the Sun's energy back to space (Colbeck & Lazaridis, 2013).

AOT is a measure of in what amount airborne particles prevent [K1] [K2] light from traveling through the atmosphere. Aerosols absorb and scatter incoming sunlight, thus reducing visibility and increasing optical thickness. An optical depth of less than 0.05 indicates a clear sky with relatively few aerosols and maximum visibility, whereas a value of 1 indicates hazy conditions. Optical depths above 2 or 3 represent very high concentrations of aerosols.

Aerosol particle pollution, i.e. [K3] [K4] airborne solid particles and liquid droplets, comes in a range of sizes. Particles smaller than 2.5 micrometers pose the greatest risk to human health because they are small enough to be breathed deep into the lungs and, in some cases, to enter the bloodstream.

These fine particles, about 30 times smaller than the width of a human hair, are also a major cause of poor visibility. Different specialists describe particles based on their shape, size, and chemical composition. Toxicologists refer to aerosols as ultrafine, fine, or coarse matter. Regulatory agencies, as well as meteorologists, typically call them particulate matter $PM_{2.5}$ or PM_{10}, depending on their size. In some fields of engineering, they are called nanoparticles. The media often uses everyday terms that hint at aerosol sources, such as smoke, ash, and soot (Nikezić et al., 2017).

Aerosols or airborne particulate matters (PM), which originate from both natural and anthropogenic emission sources, substantially influence the cli- mate, environment and human health. Satellite remote sensed AOT represents columnar aerosol loading of the atmosphere and can be empirically converted into PM mass as the primary predictor (You et al., 2016). In litera- ture review of the related work, there are studies that show a connection and a relationship between aerosols and PM prediction (Elperin et al., 2017; Kumar et al., 2007). It follows that the model presented in this study can also be applied to forecast PM and not only AOT.

Data and methodology

In the era of big data, to find the right piece of data as well as to prepare it for use, is quite a challenge. With globalization and the Internet, many data sets are available as open sources. NASA's data policy ensures that all NASA data are available fully, openly, and without restrictions. Satellite imagery from NASA Earth Observations (NEO) is available for bulk downloading and analysis. The resolution of satellite images varies depending on the instrument used and the altitude of the satellite's orbit. Different global data sets are represented with daily, weekly, and monthly snapshots, and images are available in a variety of formats.

Scientists use measurements from the MODIS sensor aboard NASA's Terra and Aqua satellites to map the amount of aerosol that is in the air all over the world. Because aerosols reflect visible and near-infrared light back to space, scientists can use satellites to make maps of where there are high concentrations of these particles. Although most aerosols remain suspended in the atmosphere for short periods, typically between 4 days and a week, they can travel vast distances. Particles moving within the atmosphere at 5 meters per second will travel thousands of kilometers in a week.

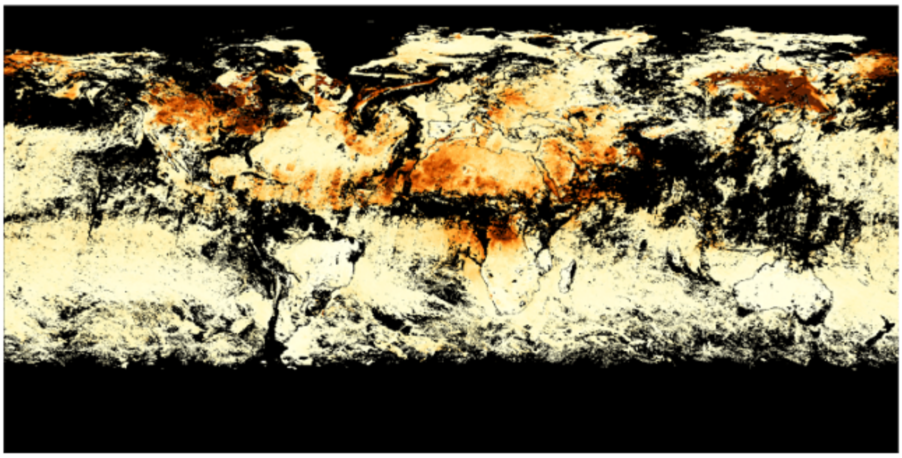

FIGURE 1
AOT from TerraMODIS on 2021-07-12
Рис. 1 – AOT от Terra/MODIS на 12.07.2021 г.
Слика 1 – AOT са Terra/MODIS на дан 12.07.2021.

Dust plumes from the Sahara frequently cross the Atlantic and reach the Caribbean. Winds sweep a mixture of Asian aerosols - particularly dust from the Gobi Desert and pollution from China - eastward over Japan and toward the central Pacific Ocean. Smoke from wildfires in Siberia and Canada can find its way to the Arctic ice cap.

NEO data sets are available in RGB as PNG files among other formats and all files are at full NEO resolution (3600x1800 pixels). Fig. 1 shows one sample of the data set MODAL2_E_AER_OD which presents global AOT for every 8 days from the Terra/MODIS (NASA NEO Nasa Earth Observations, 2022a; NASA NEO Nasa Earth Observations, 2022b). Optical thickness of less than 0.1 (palest yellow) indicates a crystal clear sky with maximum visibility, whereas a value of 1 (reddish brown) indicates very hazy conditions.

The MODIS aboard NASA's Terra and Aqua satellites is used to monitor AOT over most of the globe (oceans and the moist parts of the continents) on a daily basis, every 8 days and monthly. The MODIS is used to monitor aerosols' mass concentration, optical properties, and radiative forcing. MODIS' aerosol information is used to study aerosol climatology, to monitor the sources and sinks of specific aerosol types (such as sulfates and other industrial/urban aerosol and biomass burning aerosol), to serve as inputs for climate modeling and detection of the fingerprints of anthropogenic climate change, and to perform atmospheric corrections of remotely-sensed surface reflectance over the land. By (Kumar et al., 2007) MODIS' aerosol information can be used for PM prediction. The report by (Lin et al., 2018) states that the estimation of PM2.5 concentrations from AOT requires a vertical correction and a humidity correction. Except for the prediction of AOT and PM, MODIS' aerosol information can be used for COVID-19 transmission (Tang et al., 2020; Zoran et al., 2021; Eleftheriadis et al., 2021). By (Zoran et al., 2021) it has been more than one year since the first cases of the new coronavirus variant SARS CoV-2 that invades host cells using an endocytic pathway were detected in Wuhan, Hubei province in China. This coronavirus is a new enveloped virus positive-sense, single-stranded RNA with roughly spherical or moderately pleomorphic virions of approximately 60–140 nm with an average to 0.1 μm in diameter (Zoran et al., 2021). Several epidemiologic studies linked exposure to ambient air pollution with PM and gaseous pollutants and occurrence of numerous respiratory viral infectious diseases transmission during several seasons (Zoran et al., 2021). Under laboratory conditions, it was demonstrated that there is a long time viability of SARS-CoV-2 in ambient aerosols, as an important source of COVID-19 transmission (Zoran et al., 2021). The report by (Tang et al., 2020) presents prevention and control countermeasures to reduce the potential aerosol transmission under different occasions because current evidence on SARS-CoV-2 has limitations, but is strongly indicative of aerosols as one of several routes of COVID-19 transmission (Tang et al., 2020). The present study takes satellite-retrieved AOT from MODAL2_E_AER_OD which presents the snapshots from the year 2000 to present time on every 8 days (NASA NEO Nasa Earth Observations, 2022a; NASA NEO Nasa Earth Observations, 2022b). This data set is input data in the used deep learning (DL) model. The promise of DL is that it can solve complex problems automatically, faster and more accurately than a manually specified solution and at a larger scale. Traditional time series forecasting methods focus on univariate data with linear relationships and fixed and manually-diagnosed temporal dependence. Neural networks add the capability of learning possibly noisy and nonlinear relationships with arbitrarily defined but fixed numbers of inputs and outputs supporting multivariate and multi-step forecasting.

DL is part of a broader family of ML methods based on artificial neural networks (ANN) with representation learning. In DL, a convolutional neural network (CNN, or ConvNet) is a class of ANN, most commonly applied to analyze visual imagery. In a CNN, the input is a tensor with the shape: (number of inputs) x (input height) x (input width) x (input channels). After passing through a convolutional layer, an image becomes abstracted to a feature map, also called an activation map, with the shape: (number of inputs) x (feature map height) x (feature map width) x (feature map channels) (Valueva et al., 2020; Vaddi & Manoharan, 2020). A common application of a CNN is to extract spatial information from images.

Recurrent neural networks (RNN) add the explicit handling of ordered observations and the promise of learning temporal dependence from con- text. Long Short-Term Memory (LSTM) networks are a type of RNN that are capable of learning the relationships between elements in an input sequence. LSTM can process not only single data points (such as images), but also entire sequences of data. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series (Hochreiter & Schmidhuber, 1997).

Spatio-temporal prediction (STP) in DL is usually done by a CNN and LSTM where a CNN (Convolution2D) serves well for capturing image or spatial features, whilst LSTM is used to detect correlations over time (Dey et al., 2021). However, by stacking these kinds of layers, the correlation be- tween space and time features may not be captured properly. To solve this, the authors in (Shi et al., 2015) proposed a network structure capable of capturing spatiotemporal correlations, namely ConvLSTM (Shi et al., 2015). In Keras, this is reflected in the ConvLSTM2D class, which computes convolutional operations in both the input and the recurrent transformations to capture spatiotemporal data at the same time. ConvLSTM2D is a Recurrent layer, just like LSTM, but internal matrix multiplications are exchanged with convolution operations. As a result, the data that flows through the ConvL- STM cells keeps the input dimension instead of being just a 1D vector with features (Shi et al., 2015; Donahue et al., 2015; Hu et al., 2020; Valueva et al., 2020). The main difference between ConvLSTM and LSTM is the number of input dimensions. As LSTM input data is one-dimensional, it is not suitable for spatial sequence data such as video, satellite, or a radar image data set. ConvLSTM is designed for 3D data as its input.

Deep Learning Model

Shapes of the required input and output data for individual layers may vary with different types of layers used in the Deep Neural Networks. There are many possibilities to manage and manipulate data shapes through the network to achieve the desired goal. For reshaping data between two layers, we can use additional Reshape layers with the condition that the number of el ements that are reshaped stays the same. If we need to add time steps for recursive purposes, we can add a TimeDistributed layer. Also, in the existing recursive layers like LSTM and ConvLSTM, there are attributes called return_sequences that allow that layer input and output data stay in the same shape for next layer.

The data input shape for an LSTM layer is always in the form (samples, time steps, features) that is a 3D tensor, and its output is the same with the option return_sequences = True. When this option is False, the output is in the form (samples, features). Considering that ConvLSTM combines the performance of both Conv and LSTM layers, its data input shape is (samples, time steps, rows, cols, channels), that is a 5D tensor. Its output with the option return_sequences = True has a similar 5D shape except that the number of channels becomes the number of filters. When this option is set to False, time steps are restricted (Xavier, 2019).

The DL model used in this study consists of 3 x ConvLSTM2D layers and the final layer Conv3D as an output. The Conv3D layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs, i.e. height, width, and channel of the image. The ConvLSTM2D layer was followed by Dropout and BatchNormalization. In ML, early stopping is a form of regularization used to avoid overfitting and it was used in the model with a Reduce learning rate when a metric has stopped improving. The DL model is done in Keras. Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library.

The input data set was MODAL2_E_AER_OD, a set of PNG satellite retrieved images from 2000-02-18 to 2021-09-14 on every 8 days (993 snapshots in PNG format with 3600x1800 pixels resolution). The images were resized to 288x144 pixels (hardware could not support original resolution of images), converted to JPG, normalized by dividing with 255 and stored in the NumPy array with a sequence of 10 frames. MODAL2_E_AER_OD data set was split on train and test subsets. The train/test ratio during the testing phase was 70/30, 80/20 and 90/10. The optimum was achieved with the 80/20 train/test split.

After many trials and tests, it was concluded that the most optimal re- sult was obtained for the batch size=5 and epochs=50. Also, the best results gave the activation function 'hard_sigmoid' for the Conv3D layer and the optimizer 'adam' (learning_rate = 0.001) for a model compile. An activation function is a mathematical gate between the input feeding the current neuron and its output and the idea of activation functions is derived from the neuron-based model of the human brain which consists of a complex network of biological neurons in which a neuron is activated based on certain input from the previous neuron.

As part of the optimization algorithm, the error for the current state of the model must be estimated repeatedly. This requires the choice of an error function, conventionally called a loss function, which can be used to estimate the loss of the model so that the weights can be updated to reduce the loss on the next evaluation. A regression predictive modeling problem involves predicting a real-valued quantity, so, for the loss function, the Mean-Squared Error (MSE) was used, and for the metrics Root-MeanSquared Error (RMSE). Figure 2 depicts the used DL model.

After the process of DL model training was finished, prediction of the first image from the test dataset was done and it was compared with the original first image from the test dataset. This type of prediction is known as sequence-to-one and it is possible to predict more images (sequence- to-sequence type of prediction) (Nikezić et al., 2022).

Results and discussions

The saved DL model was loaded to predict the first image from the test dataset, Fig. 3a. Fig. 3b shows the original first image from the test dataset.

The evaluation of the DL model is based on the evaluation metrics i.e. MSE=0.0116. The MSE is always positive regardless of the sign of the predicted and actual values and a perfect value is 0.0 while the range is from zero to infinity. These results prove that the proposed ML model can be used for AOT forecasts. Figure 4 shows the line plots of loss over 50 training epochs.

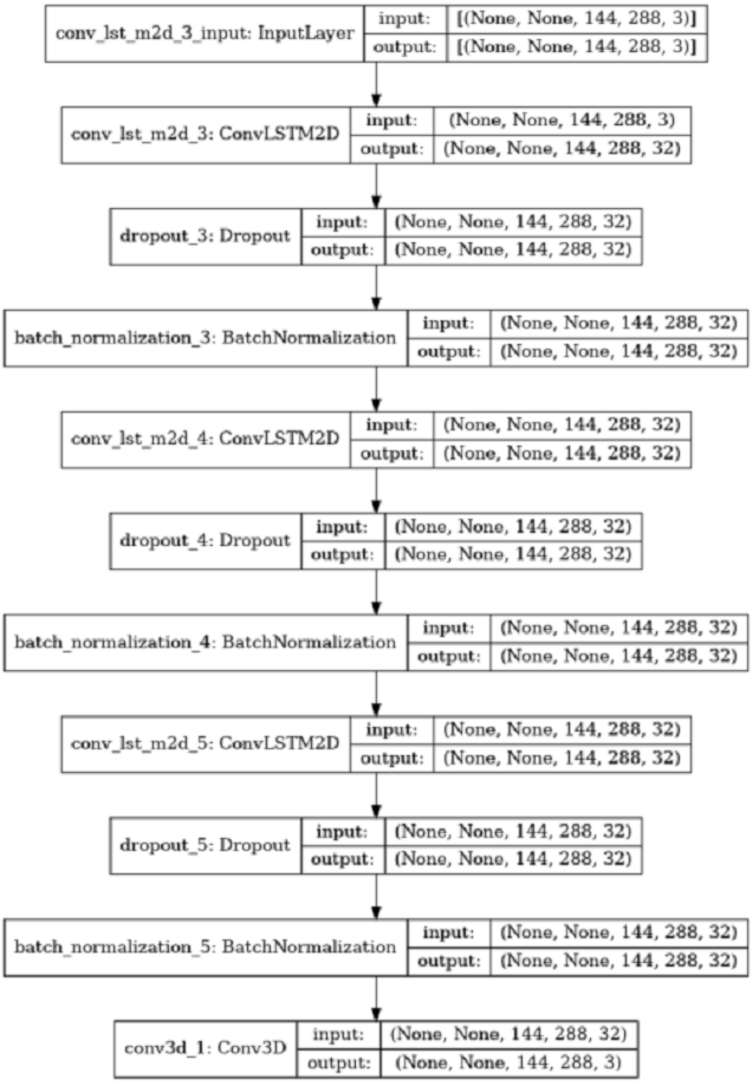

FIGURE 2
Plot of the ConvLSTM model graph
Рис. 2 – Сюжет модели конфликта Russian
Слика 2 – Приказ графа ConvLSTM модела

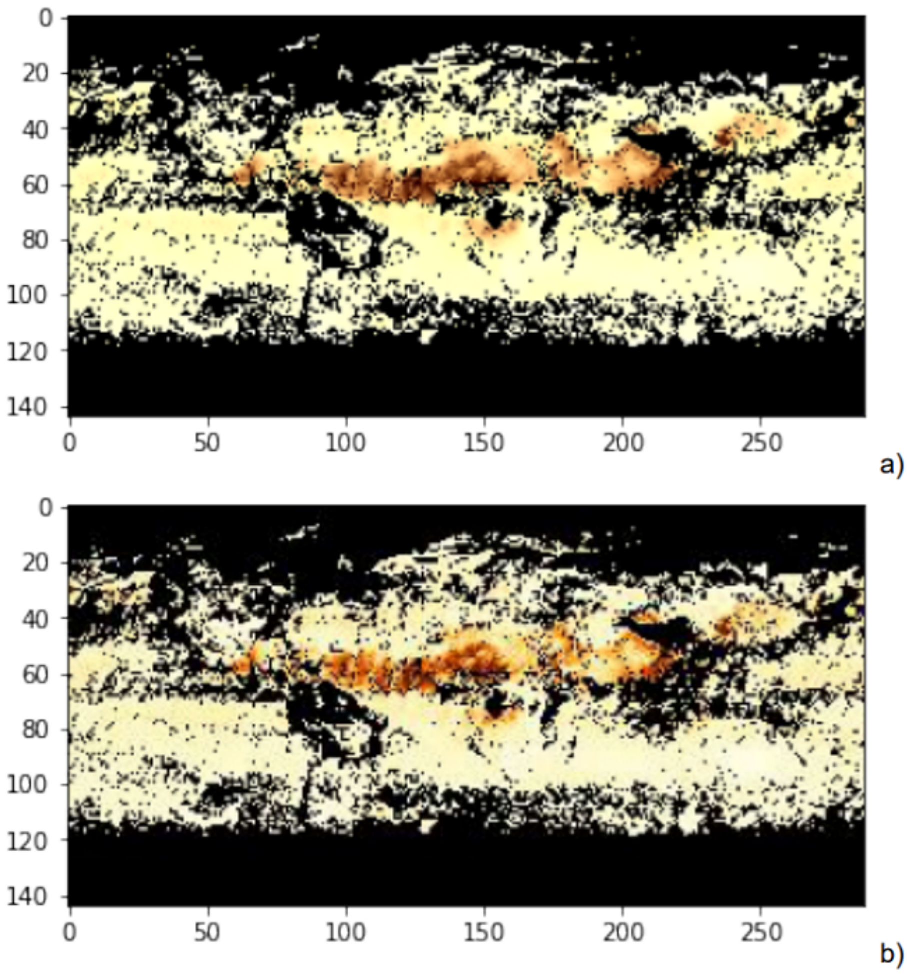

FIGURE 3
Global AOT a) predicted and b) actual (real)
Рис. 3 – Глобальный AOT а) прогнозируемый и б) фактический (реальный)
Слика 3 – Глобални AOT а) предвиђени и б) реални

For STP, as mentioned, it is common to use CNN + LSTM models (Ding et al., 2020). To compare ConvLSTM and CNN LSTM, the new CNN LSTM model has been developed. Figure 5 depicts the new CNN LSTM model. The evaluation metrics was for MSE 0.1117 and in comparison with the ConvLSTM model (MSE 0.0116) presents a higher value. Lower values of MSE indicate a better fit.

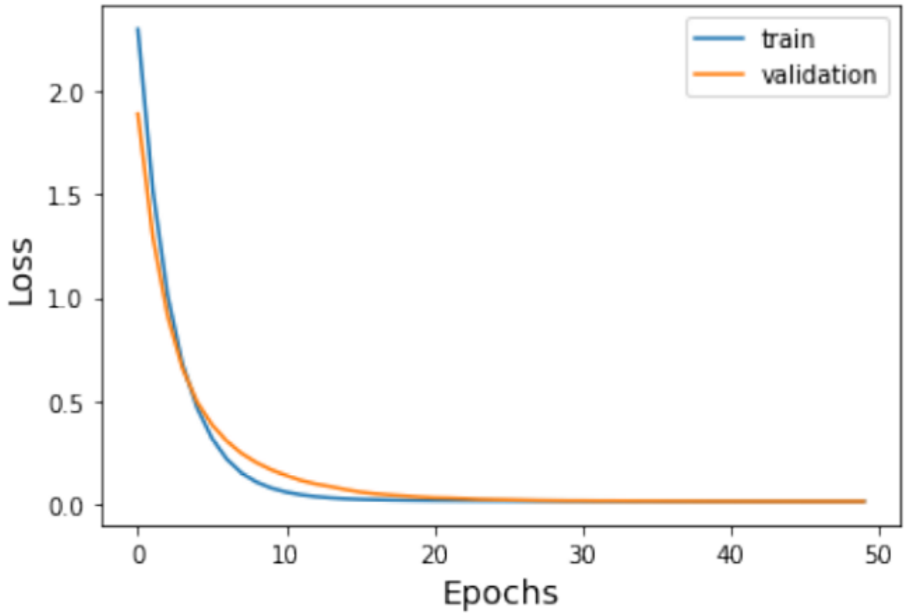

FIGURE 4
Line plots of loss over 50 training epochs
Рис. 4 – Линейное изображение потерь за 50 тренировочных периодов
Слика 4 – Губици током 50 епоха тренирања

For better comparison, the next statistics was done. The Mean Absolute Error (MAE) is a measure of errors between the paired observations expressing the same phenomenon and is used for predictions in a segment of 9 frames per image, Table 1.

The range for the MAE is from zero to infinity and lower values are better. From the obtained results, it can be concluded that the ConvLSTM model required well-structured input data, right selection and optimal tuned model hyperparameters before it could be utilized for reliable AOT predictions.

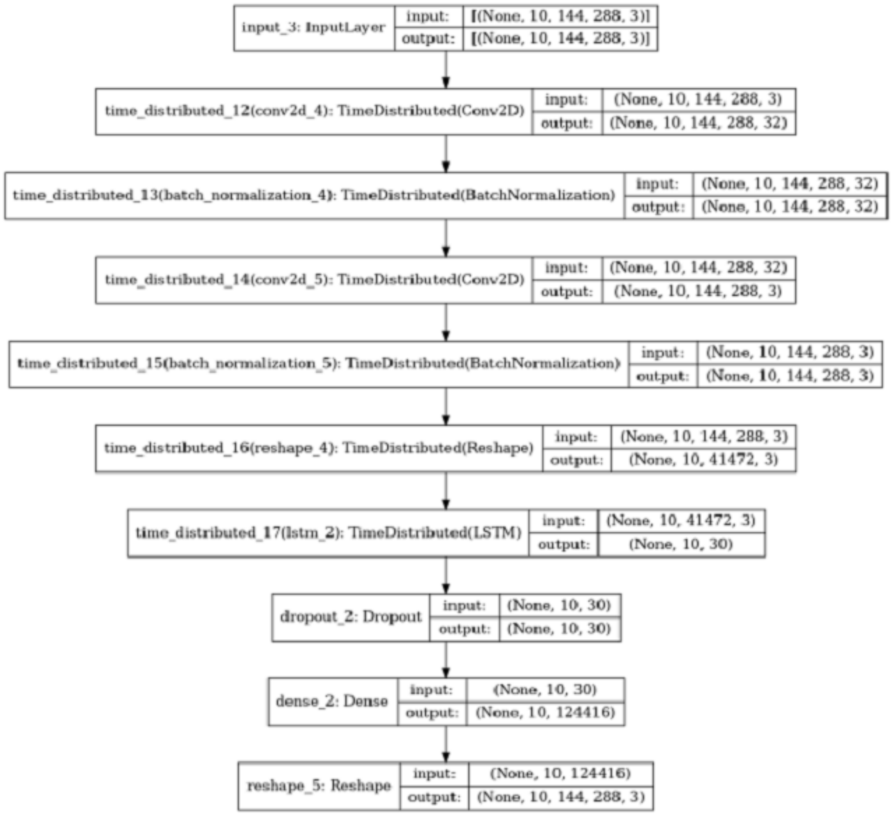

FIGURE 5
Plot of the CNN LSTM model graph
Рис. 5 – График модели CNN LSTM
Слика 5 – Приказ графа CNN LSTN модела

TABLE 1
MAE for predictions in a segment of 9 frames per image

ConvLSTM	CNN LSTM
0.02200718	0.24474642
0.02213584	0.2462145
0.02251104	0.24545886
0.02263835	0.2449535
0.0227564	0.24526556
0.02259156	0.24504275
0.02232519	0.24720876
0.02259231	0.2456902
0.02278301	0.24560421
0.23362	0.24605619

Conclusions and future research

Atmospheric aerosols play a major role in the Earth's radiation budget. Yet, aerosols are one of the greatest sources of uncertainty in climate modeling. Radiative forcing by aerosols may explain the difference between the observed and modeled trends in average global temperature. In fact, the interaction of aerosols with solar and terrestrial radiation perturbs the radiation budget via scattering and absorption of sunlight. Many recent studies show the importance of including aerosols in climate models to observe and measure human influence on atmospheric chemistry and climate change. Besides, some studies acknowledge that inhalation of aerosols is one way how COVID-19 spreads. Even when an infectious person is more than two meters away, aerosols have the ability to travel and infect others. These are some of the most important reasons why it is useful to predict global AOT.

The present study investigated the possibility of a new ConvLSTM model to forecast global AOT from MODIS satellite imagery. DL with big data is a new powerful tool which could help scientists in their research. A relatively new ConvLSTM2D layer in Keras merges spatial and temporal components and allows them to be used in STP.

Satellite images are helpful in seeing long-range transport of pollutants from other regions, but they do not give information about pollution levels on the ground. They see pollutants in the entire atmosphere, so the pollutants one sees in the satellite image could be kilometers above the ground. To find out whether the AOT in the satellite image is on the ground nearest to the surface, ground measurements need to be compared to satellite measurements. This can be done with AErosol RObotic NETwork (AERONET) like in the study (Beer et al., 2020). The AERONET project represents a federation of ground-based remote sensing aerosol networks established by NASA and PHOTONS (NASA Goddard Space Flight Center, 2022). Therefore, the next step in future research should be the validation of the ML model by comparing it with AERONET.

Another step for the developed ConvLSTM model should be to research how meteorological parameters such as wind speed, temperature, relative humidity, and rainfall improve AOT forecasting and accuracy. Further, deep neural networks showed to be very successful with time-stepped data (Radivojević et al., 2021) which should be concatenated with the input data of this study.

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