Fires Hotspot Forecasting in Indonesia Using Long Short-Term Memory Algorithm and MODIS Datasets

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Fires Hotspot Forecasting in Indonesia Using Long Short-Term Memory Algorithm and MODIS Datasets

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Abstract Vegetation fires are most common in South and Southeast Asian countries, including Indonesia. In addition to anthropogenic causes, climate change in the form of droughts is the biggest driver of fires in Indonesia. In particular, the peatlands in Indonesia are highly vulnerable to droughts with recurrent fires. In this study, we used a long short-term memory (LSTM) algorithm to predict the fire hotspots based on the 2010 to 2021 fire data. More than 700,000 fire hotspots from 2010 to 2021 have been collected and used as a training dataset to forecast fires for the year 2022. The LSTM algorithm successfully predicted 2022 fires with the minimum root mean squared error and high accuracy. Furthermore, the results of the 2022 prediction year matched the previous year's fire data seasonally, with increasing fires from August to November. The study highlights the potential use of the LSTM algorithm for forecasting fires in Indonesia.

Keywords Fires hotspot · Forecasting · Indonesia · LSTM · MODIS

1 Introduction

Fires are one of the biggest natural threats to forests, woodlands, and grasslands in many countries, including Indonesia (Albar et al. 2018; Akther and Hassan, 2011; Goldammer 2012; Hayasaka et al. 2014; Petropoulos et al. 2013; Justice et al. 2015; Kadir et al. 2019, 2020, 2021). In several South/Southeast Asian countries, fire is used to clear the forests for agriculture through slash and burn (Albar et al. 2018;

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Badarinath et al. 2007; 2008, 2009, 2015b; Badarinath and Prasad 2011; Biswas et al. 2015a); Biswas et al. 2021; Kant et al. 2000; Lasko and Vadrevu 2018; Petropoulos et al. 2013; Prasad et al. 2001a,b; Prasad et al. 2002a, 2002b;2003; 2004; Prasad and Badarinath 2004; Prasad et al. 2005; Prasad and Badarinth 2006; Vadrevu 2008; 2021a,b; Wooster et al. 2021; (Biswas et al. 2015a,b; Prasad et al. 2001a, b, 2002a, b;) agricultural residues after crop harvest to clear the land for the next crop (Lasko et al. 2017; 2018a,b; 2021; Vadrevu and Lasko 2015), to clear the forested lands for plantations (Albar et al. 2018), promoting the growth of grass in pasture lands for cattle (Thapa et al. 2022), etc., in addition to intentional or accidental human activities. While most of these fires are anthropogenic, the drivers of fires can also be natural such as lightning and extreme and prolonged drought conditions. Especially in tropical regions, there are usually two alternating rainy and dry seasons, and forests and grassland fires are highly vulnerable to fires during the dry season. Indonesia is one of the tropical countries with major fire issues, especially in Kalimantan and Sumatra Islands with recurrent fires (Hayasaka et al. 2014). Regardless of the ignition source, in forested areas, the fires can spread rapidly and become uncontrollable due to the local meteorological and environmental conditions. Further, fires are a major important source of air pollution which results in the release of greenhouse gas emissions and aerosols (Ito and Penner 2005; Gupta et al. 2001; Lasko and Vadrevu 2018; Vadrevu and Badarinath 2009; Vadrevu and Justice 2011; Kharol et al. 2012; Vadrevu and Lasko 2015; Vadrevu 2015; Vadrevu et al. 2008; 2013;). The smoke particles released from fires can interact with the cloud droplets and alter Earth's radiation budget (Martins and Dias 2009). The GHG emissions from biomass burning represent the largest source of inter-annual variability, in particular, CO_2 fluxes (Szopa et al. 2007; Kant et al. 2000;). Biomass burning is estimated to contribute to 7600 ± 359 Tg CO2eq year $- 1$ (FAOSTAT 2020). In addition, biomass burning has been shown to influence various land-atmospheric interactions at different scales, such as vegetation transpiration, soil erosion, albedo (Crutzen and Andreae 1990). Smoke-borne aerosols from fires disrupt normal hydrological processes and reduce rainfall, potentially contributing to regional drought. In addition to these effects on Earth's radiation, atmosphere, climate, and ecosystems, the pollutants released from the fires (Vadrevu et al. 2014a,b, 2017, 2018 2019) can impact health resulting in asthma, acute respiratory illness, eye irritation, cardiovascular mortality, thrombosis, etc. (Sigsgaard et al. 2015). Thus, fires can become a disaster for humans and the environment due to their severity and intensity. Considering these effects, mapping and monitoring of fires, including forecasting, can not only help in understanding land-atmospheric interactions useful for climate change studies but also protecting human lives, ecosystems, and related functions (Goldammer 2012; Eaturu and Vadrevu 2021; Vadrevu and Justice 2011; Vadrevu et al. 2020; 2021a,b, 2022a; b).

Several techniques have been proposed to forecast fires, such as fire danger indices combining climate data with site characteristics and fire data records (Akhter and Hassan 2011; Vadrevu et al. 2021a, b). In addition, multiple machine learning algorithms were also used to characterize fire patterns and predict fires. For most algorithms, previous fire data is essential for calibration and prediction (Liang et al. 2019;

Omar et al. 2021; Lamjiak et al. 2021; Abdul Kadir et al. 2022; Mohan et al. 2021). These studies considered both the climate and environmental factors in predicting the fires. Including meteorological factors in the prediction of fires is important as they can drive accuracy. A comprehensive data analysis of fire hotspot occurrences, their fire size, intensity, and how they can potentially spread into new areas, including forecasting methods, were given in earlier works (Khabarov et al. 2008; Han et al. 2019; Kadir et al. 2019; Kukuk and Kilimci 2021; Prapas et al. 2021). Recently, deep learning algorithms are gaining popularity in various fields, such as pattern recognition, including forecasting (Benzekri et al., 2020). In this study, we use the popular long short-term memory (LSTM) algorithm to forecast fires in Indonesia for 2022. We used the fire spots data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) from 2010 to 2021 and tested the algorithm's robustness in predicting the fires for 2022.

2 Datasets and Methodology

We used the NASA MODIS fire hotspots data from 2010–2021 for our study. Table 1 shows the sample fires dataset for Indonesia. The data has been normalized and grouped into a single date of fire occurrence. The data has been split into training and testing for fire forecasting. In the field of deep learning, the LSTM algorithm is an artificial recurrent neural network (RNN) architecture and was first introduced by Hochreiter and Schmidhuber (1997). LSTM is a special model of RNN that capable of learning in long-term dependencies and remembering information for prolonged periods as a default. Figure 1 shows the RNN-LSTM model's architecture, consisting of several main blocks called cells with input, output, and forget gates. The sigmoid activation function classifies the values in probabilities for the two predefined classes in the dense output layer.

The LSTM model can be explained as short-term memory, which acts when the information is being acquired, retains for a few seconds, and then destines it to be kept for more extended periods or discards it. Long-term memory permanently retains information, allowing its recovery or recall. It contains all our autobiographical data and all our knowledge. LSTM model can handle the problem with long-term dependencies of RNN in which the RNN algorithm cannot do in the prediction of the information stored in the long-term memory but can give more accurate prediction from the recent information. LSTM can use by default to retain the data for a long-term period. The algorithm can predict, process, and classify based on time series data (Le et al. 2019). The LSTM model has an incredible way of forecasting and works well in time series data. Furthermore, this model can organize in the form of a chain structure and has four interacting layers with a unique method of communication in data processing. Figure 2 shows an analysis block diagram of how the forecasting process of the fire hotspot is done in our study.

Table 1 Detail of fires hotspot dataset from year 2010 to 2021 (NASA 2021)

	Latitude	Longitude	Brightness	Scan	Track	acq_data	acq_time	Satellite	Instrument	Confidence	Version	Bright_t31	Frp	Daynight	Type
0	0.02110	116.87390	315.30	1.10	1.10	2010-01-01	251	terra	MODIS	42	6.2	295.60	8.70	D	0.0
1	0.48080	116.08060	312.30	1.00	1.00	2010-01-01	251	terra	MODIS	66	6.2	295.00	6.90	D	0.0
11	2.15090	117.49680	320.60	1.00	1.00	2010-01-01	550	Aqua	MODIS	0	6.2	297.50	10.60	D	0.0
10	– 8.10890	118.07430	319.30	1.00	1.00	2010-01-01	547	Aqua	MODIS	0	6.2	300.80	9.10	D	0.0
8	– 8.15960	117.58570	319.60	1.00	1.00	2010-01-01	547	Aqua	MODIS	43	6.2	297.70	9.10	D	0.0
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
14208	– 7.22331	110.42920	316.80	1.00	1.00	2021-12-31	300	terra	MODIS	67	6.1NRT	293.096	8.56	D	NaN
14209	– 6.96059	110.45844	318.84	1.00	1.00	2021-12-31	300	terra	MODIS	55	6.1NRT	291.66	6.42	D	NaN
14210	– 5.80178	139.61118	309.54	1.00	1.00	2021-12-31	418	Aqua	MODIS	65	6.1NRT	283.90	5.50	D	NaN
14211	– 4.51654	136.84802	313.68	1.21	1.09	2021-12-31	418	Aqua	MODIS	56	6.1NRT	291.74	7.84	D	NaN
14213	– 4.54666	136.77507	309.21	1.22	1.10	2021-12-31	418	Aqua	MODIS	52	6.1NRT	287.79	5.59	D	NaN

703116 rows × 15 columns

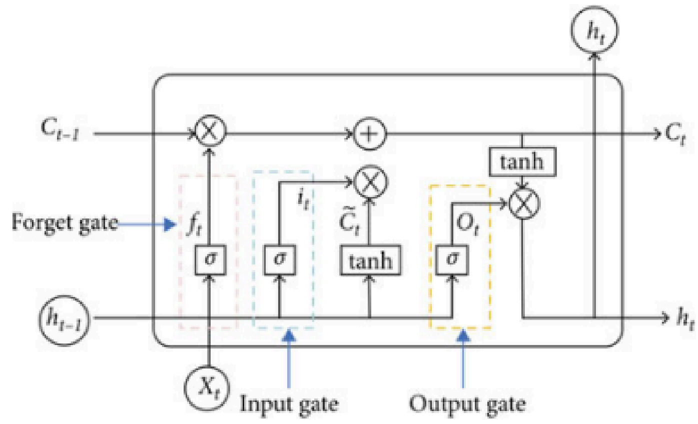

Fig. 1 Structure of RNN-LSTM algorithm

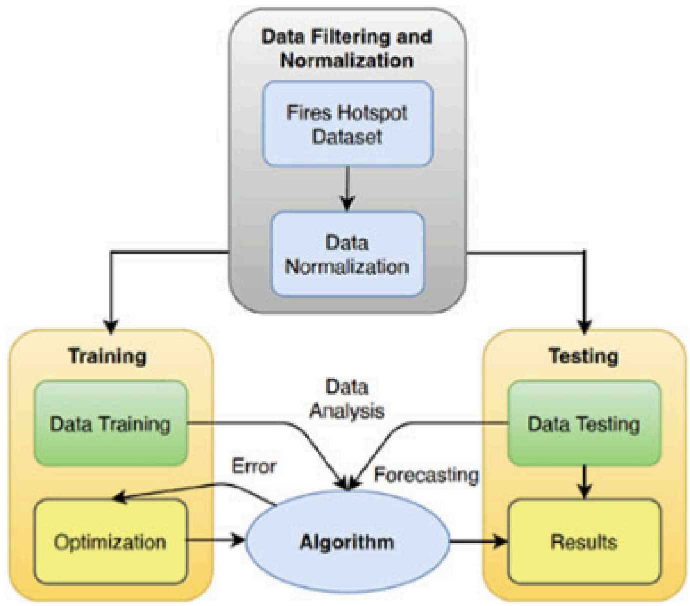

Fig. 2 Approach followed for fire forecasting using LSTM

The first step in data processing in forecasting is to construct an LSTM network model to identify the inputs and eliminate the information that is not necessary for the cell structure of LSTM (Fig. 1). The process of identifying and excluding data is governed by the sigmoid function, which takes the output of the last LSTM unit h_{t-1} at time $t-1$ and the current input X_t at time t. Additionally, the sigmoid function determines which part from the old output should be eliminated. This gate is called the forget gate f_t; where f is a vector with values ranging from 0 to 1, corresponding to each number in the cell state, C_{t-1}. . Our collected data had more than 700,000 fire hotspots within 12 years and, after normalization, became 4365 datasets of fires grouped in each day. The data was divided into training and testing data (Fig. 2). The optimization process was followed to evaluate results, increase the performance and enhance accuracy to minimize the error and final forecasting. The LSTM cell with sigmoid function W_f and b_f are the weight matrices and bias, respectively, of the forget gate. This step decides and stores the input data from the new information X_t

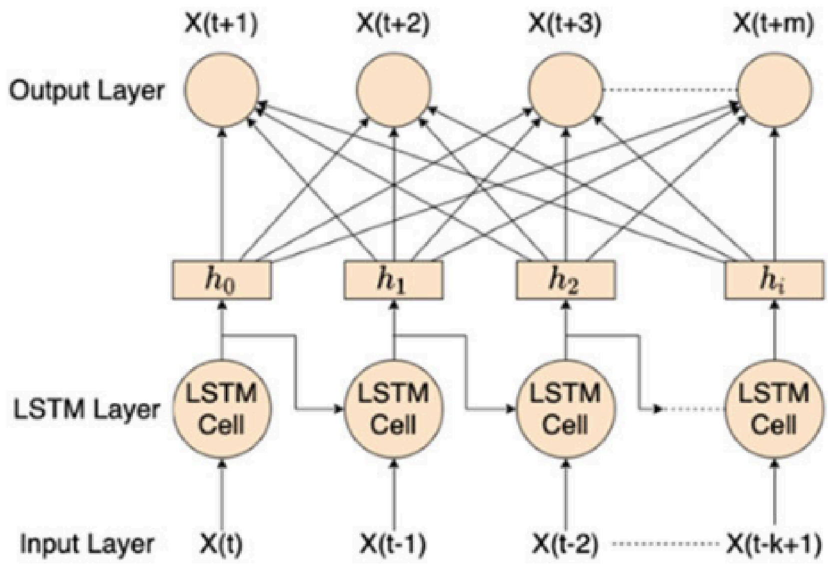

Fig. 3 Internal LSTM model process

in the cell state and updates the cell state. Then, the sigmoid layer decides whether the new data should be updated or ignored (0 or 1), and the tan *h* function gives weight to the values which is passed by deciding their level of importance (1 to 1). The two values are multiplied to update the new cell state. This new memory is then added to the old memory C_{t-1} resulting in C_t. Figure 3 depicts how the neuron process of the LSTM model works (Chen et al., 2021).

The next step is C_{t-1} and C_t are the cell states in the LSTM cell at time C_{t-1} and t while W and b are the weight matrices and bias of the cell state. In the last step, the value of h_t is based on the output cell state o_t, a sigmoid layer decides which parts of the cell state make it to the output. Next, the output of the sigmoid gate o_t is multiplied by the new values created by the *tanh* layer from the cell state C_t, with a value ranging between 1 and 1. Finally, the performance of the fire forecasting was done using the root mean square error (RMSE) with the prediction and actual data values using the below equation (1).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_i - \hat{X}_i\right)^2}{n}} \tag{1}$$

In the equation, X_i and X_i' are the actual fires hotspot data compared to forecasting fires data at the time t; X_i is the mean of actual values fires data and n is the total number of data. The smaller the RMSE values, the better the prediction.

3 Results and Discussion

Our fire dataset consisted of several parameters such as coordinate or location of fire occurrence, date and time, confidence level (probability of becoming a big fire and spreading out), brightness, day or nighttime, etc. (Table 1). In addition, we specifically used parameters that have a major impact and are essential to forecasting, which includes coordinates (latitude and longitude), acquisition date (acq_date), and confidence level. Figure 4a shows the mapping of fire hotspot distribution in Indonesia for 2021 and Fig. 4b for 2020. The fire hotspots were classified into five confidence levels, starting with the lowest from 0, low impact, and less potential to spread till 100, with high impact and high probability spread potential to become a big fire. The five-level classifications with confidence levels are shown in different colors (0–20 blue dot; level 21–40 green; 41–60 yellow; 61–80 as orange and 81–100 red with the highest).

The month-wise fire distribution is shown in Fig. 5a, b for the years 2021 and 2020, respectively. Classification based on confidence level and the distribution matched well with the total number of hotspots. Mostly, the map showed yellow and orange colors with confidence levels varying from 41–60 and 61–80, respectively. While red color is the highest potential of fire hotspots spread, they showed less in number in the predicted map.

Results from the LSTM suggested a similar pattern and number of daily fire hotspot incidents, with a maximum of 600 to 700 from the September to November dry or summer season. The daily average number of hotspots is 87. Although this number is insignificant for the entire of Indonesia, the number might increase drastically due to the prevailing weather and other fire-favorable factors. Another issue is the type of land that gets affected due to fires. For example, the Sumatra and Kalimantan Islands peatlands are easily ignited when dry land and fires are difficult to control. The LSTM algorithm for forecasting fire hotspots in Indonesia has been tested preliminarily to the 2121 data before 2022. Figure 6 compares actual fire hotspot data and forecasting results for the year 2021; the results showed a good agreement between the graphs. Preliminary forecasting suggested an RMSE error of 4.56%. We then fine-tuned the LSTM forecasting algorithm for 2022 by training more than 4000 datasets using the filtered data from 2010 to 2021; in essence, 30% of the total data was used for training and the rest 70% for testing.

Figure 7 shows a good agreement and similar normal distribution patterns for all the years, i.e., 2020, 2021, and 2022. The high occurrence of fire hotspots detected in the early part of the year, i.e., March, and lesser in the middle of the year, then increasing from September to November, is a typical pattern reflected in the figures. The spikes during the few days in late September are attributed to seasonal fires in Sumatra Island.

Overall, the LSTM RNN algorithm showed successful results with minimum error. The results of the 2022 prediction year matched the previous 2021-year fire data. Forecasting results in 2022 show good agreement and a similar pattern of fires with increasing fires from August to November. By comparing the predicted data

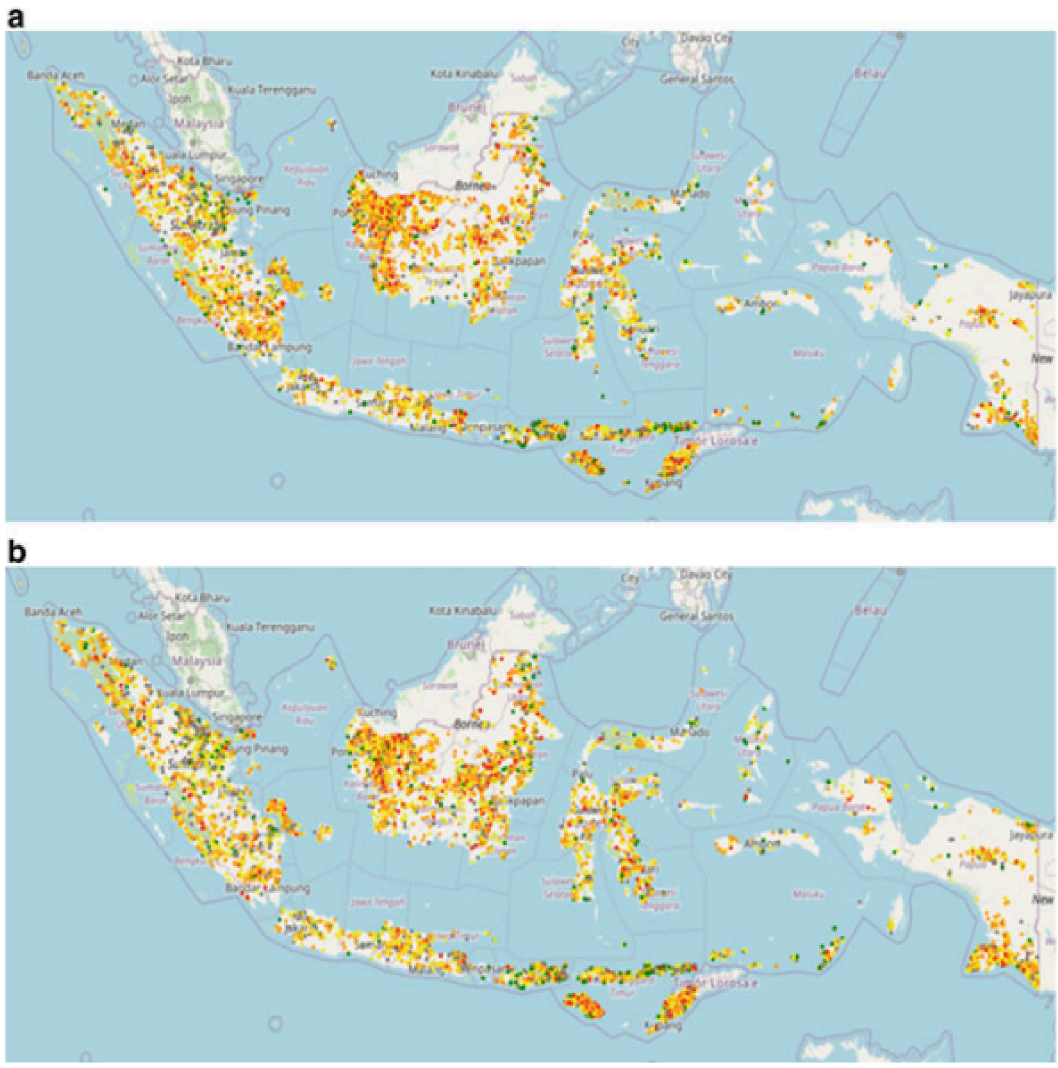

Fig. 4 Mapping of fires hotspots in Indonesia **a** year 2021 **b** year 2020

with the previous year's data, we could achieve an accuracy of up to 95% with an RMSE error of 4.56%. More robust data is required on the local conditions to achieve further high accuracy at specific locations. Our future studies will focus on the same, i.e., collecting and analyzing the data at a much higher spatial resolution for different regions in Indonesia.

4 Conclusion

We demonstrated the long short-term memory (LSTM) algorithm's potential in predicting and forecasting fire hotspots in Indonesia. A fire hotspots dataset from 2010 to 2021 obtained from the NASA MODIS data has been used to train and forecast fires for 2022. By comparing the predicted data with the previous year's

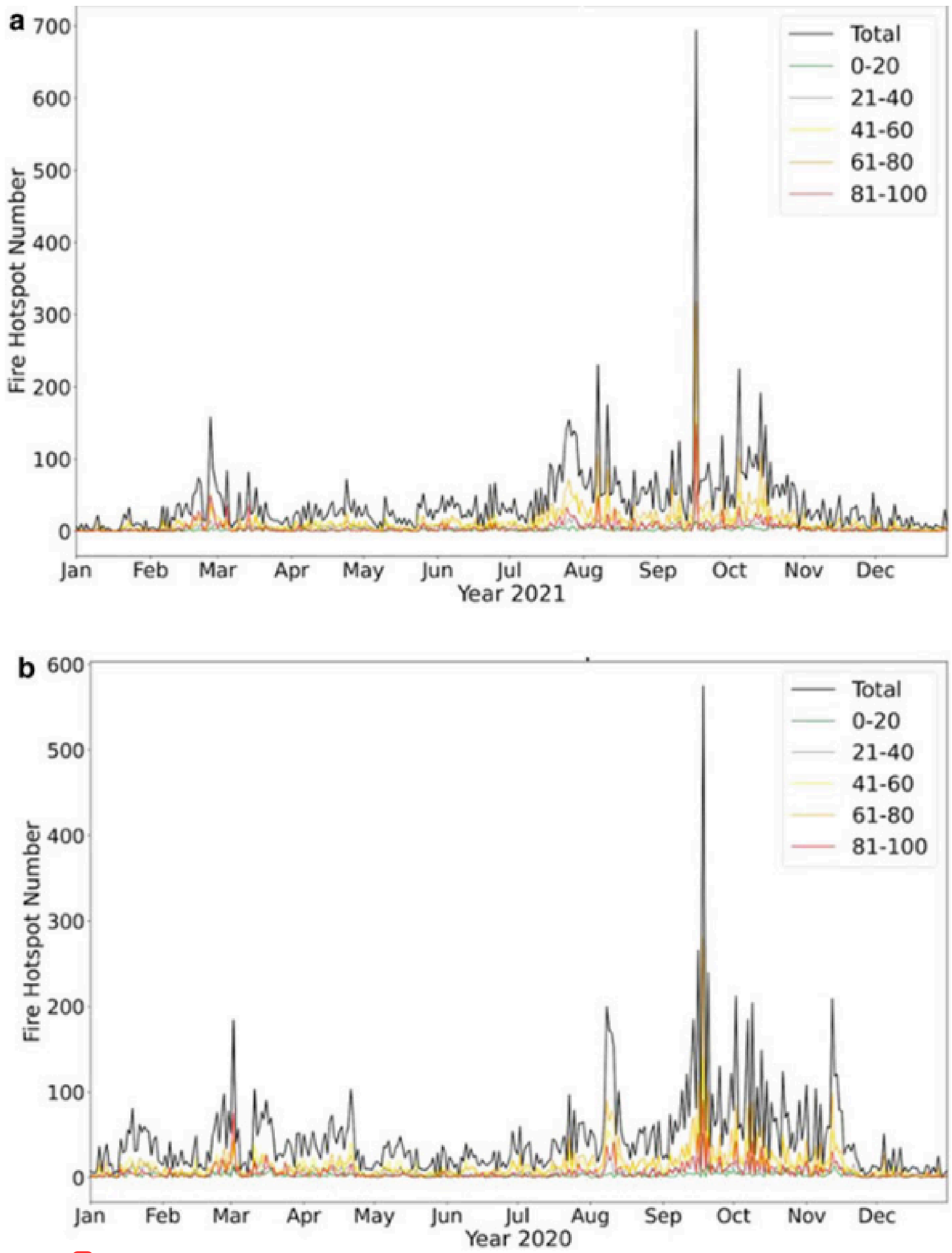

Fig. 5 Distribution of fires hotspots in Indonesia for the year from January to December **a** year 2021 **b** year 2020

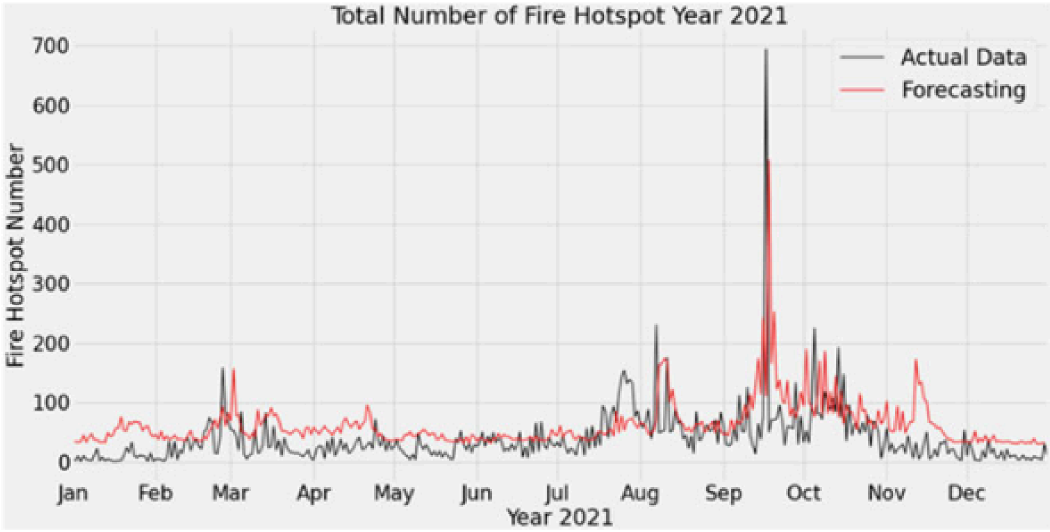

Fig. 6 Comparison of actual and fire forecasting data for year 2021

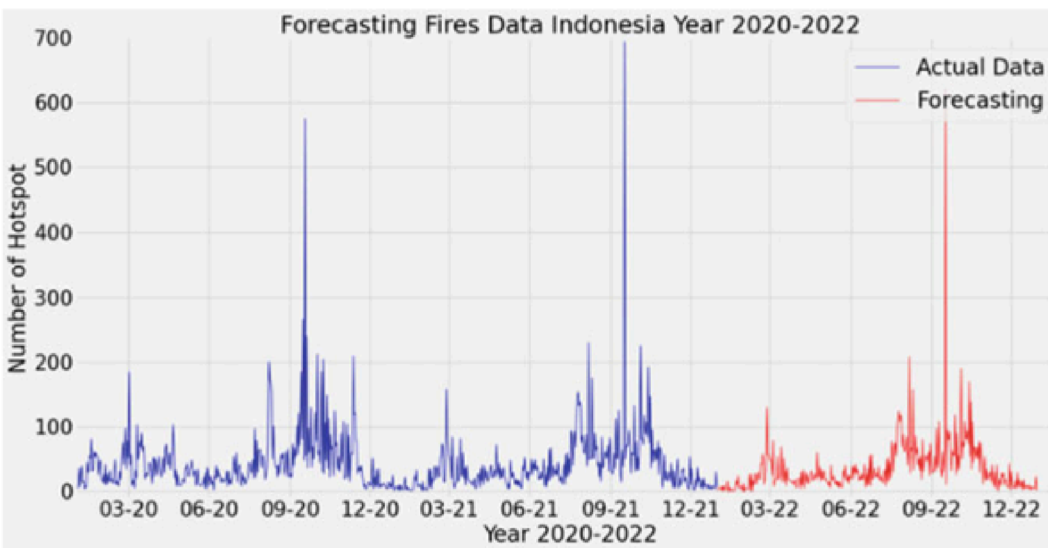

Fig. 7 Forecasting of fires hotspots in year 2022 and actual data of fires in year 2020–2021

data, we could achieve an accuracy of up to 95% with an RMSE error of 4.56%. The forecasted fire data patterns matched the previous year's data in seasonality from January to December. It is noted that the number of hotspots increase by the end of each year due to the dry season in Indonesia.

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