Science of the Total Environment 768 (2021) 145187

Contents lists available at ScienceDirect

Science of the Total Environment

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

Season, not lockdown, improved air quality during COVID-19 State of Emergency in Nigeria

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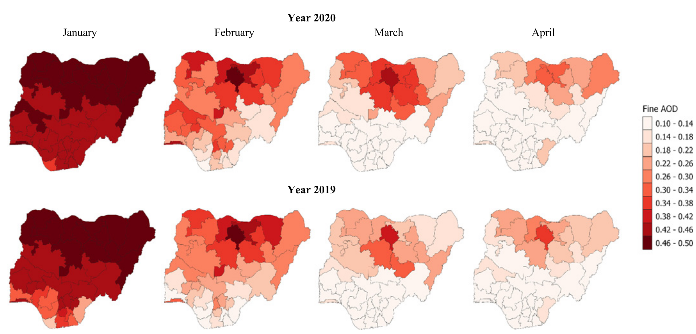
HIGHLIGHTS

- Substantial decline (21%) in fine aerosols is observed during COVID lockdown than pre-lockdown in 2020.
- A small decline (1%) in fine aerosol levels occured in 2020 lockdown compare to same period in 2019.
- Analyses of long-term changes reveal no difference ($\alpha = 0.05$) in aerosol levels between 2020 and 2002–2019.
- Changes in air quality during lockdown is not due to COVID intervention, but season.

GRAPHICAL ABSTRACT



Monthly average fine model aerosol optical depth (fine AOD) across Nigerian States in January to April, 2020 and 2019.

ARTICLE INFO

Article history:
Received 11 September 2020
Received in revised form 9 January 2021
Accepted 10 January 2021
Available online 21 January 2021

Editor: Philip K. Hopke

Keywords:
$PM_{2.5}$ in Nigeria
Linear time-lag model for trend analysis
Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) satellites
Artificial Neural Network (ANN)
Multi-angle Implementation of Atmospheric Correction of Aerosol Optical Depth (AOD) (MAIAC-AOD)

ABSTRACT

Globally, ambient air pollution claims ~9 million lives yearly, prompting researchers to investigate changes in air quality. Of special interest is the impact of COVID-19 lockdown. Many studies reported substantial improvements in air quality during lockdowns compared with pre-lockdown or as compared with baseline values. Since the lockdown period coincided with the onset of the rainy season in some tropical countries such as Nigeria, it is unclear if such improvements can be fully attributed to the lockdown. We investigate whether significant changes in air quality in Nigeria occurred primarily due to statewide COVID-19 lockdown. We applied a neural network approach to derive monthly average ground-level fine aerosol optical depth (AOD_f) across Nigeria from year 2001–2020, using the Multi-angle Implementation of Atmospheric Correction (MAIAC) AODs from Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) satellites, AERONET aerosol optical properties, meteorological and spatial parameters. During the year 2020, we found a 21% or 26% decline in average AOD_f level across Nigeria during lockdown (April) as compared to pre-lockdown (March), or during the easing phase-1 (May) as compared to lockdown, respectively. Throughout the 20-year period, AOD_f levels were highest in January and lowest in May or June, but not April. Comparison of AOD_f levels between 2020 and 2019 shows a small decline (1%) in pollution level in April of 2020 compare to 2019. Using a linear time-lag model to compare changes in AOD_f levels for similar months from 2002 to 2020, we found no significant difference (Levene's test and ANCOVA; $\alpha = 0.05$) in the pollution levels by year, which indicates that the lockdown did not significantly

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https://doi.org/10.1016/j.scitotenv.2021.145187
0048-9697/

improve air quality in Nigeria. Impact analysis using multiple linear regression revealed that favorable meteorological conditions due to seasonal change in temperature, relative humidity, planetary boundary layer height, wind speed and rainfall improved air quality during the lockdown.

1. Introduction

Following the declaration of World Health Organization on March 11, 2020 that the novel coronavirus (COVID-19) is a global pandemic (Cucinotta and Vanelli, 2020), many countries took some form of actions to prevent or reduce this virus spread. Among others, these actions involved mandatory shutdown of economic activities and restriction of non-essential travel. The global response to COVID-19 provided researchers a unique opportunity to assess the short-term impact of intervention measures on ambient air quality. Such studies are critically important considering that about nine million people, worldwide, die every year from stroke, heart disease, respiratory infections, chronic obstructive pulmonary disease and lung cancer caused by exposures to ambient fine particulate matter ($PM_{2.5}$) pollution (Cohen et al., 2005; Burnett et al., 2018; Yin et al., 2020). Exposure to $PM_{2.5}$ pollution has also been linked to increased deaths from diabetes mellitus (Meo et al., 2015; Weinmayr et al., 2015) and more recently, COVID-19 (Hendryx and Luo, 2020; Setti et al., 2020; Wu et al., 2020).

Several studies reported substantial improvements in air quality during COVID-19 lockdown compared to pre-lockdown (Abdullah et al., 2020; Chen et al., 2020; Li et al., 2020; Menut et al., 2020; Rodríguez-Urrego and Rodríguez-Urrego, 2020; Tobías et al., 2020; Wang et al., 2020; Zambrano-Monserrate et al., 2020; Zheng et al., 2020). Other studies comparing $PM_{2.5}$ pollution levels during lockdown with baseline average also found substantial declines in $PM_{2.5}$ pollution levels during the lockdown period. For example, between 10% and 54% reductions in $PM_{2.5}$ pollution levels were reported for different localities in India during lockdown compared to baseline averages (Chauhan and Singh, 2020; Kumar et al., 2020; Mahato et al., 2020; Ranjan et al., 2020; Sharma et al., 2020). Similar or lower reductions in $PM_{2.5}$ pollution levels were also reported for localities in China (Pei et al., 2020; Zheng et al., 2020), Brazil (Dantas et al., 2020; Nakada and Urban, 2020), United States and Canada (Adams, 2020; Berman and Ebisu, 2020), and in many parts of the world (Baldasano, 2020; Chauhan and Singh, 2020; Muhammad et al., 2020).

Except for China, many countries began lockdown between mid-March and early April. During this period, most countries transitioned from one weather season to the next. For example, India transitioned from winter to summer, while Nigeria moved from dry to rainy season. Some seasons such as winter are known to aggravate air pollution, while others such as rainy seasons reduce pollution level. Indeed, air pollution levels were found to be strongly influenced by season (Etchie et al., 2018a). For instance, studies conducted in India observed higher levels of $PM_{2.5}$ pollution during winter compared with summer (Pandey et al., 2013; Singla et al., 2012; Tiwari et al., 2012), or during dry (summer) compared to rainy (monsoon) season (Etchie et al., 2017). Recently, Chauhan and Singh (2020) attributed about 20% and 30% reduction in $PM_{2.5}$ pollution level during COVID-19 lockdown period in New York and Los Angeles, respectively, to rainfall. Likewise, the analysis of long-term trends (2015–2020) in $PM_{2.5}$ pollution during the months of January to May in New York did not find a significant change in air pollution resulting from COVID-19 lockdown (Zangari et al., 2020). Improvement in air quality during the lockdown months in New York was attributed to seasonal change and previous environmental interventions (Zangari et al., 2020). To the best of our knowledge, no study has examined the long-term seasonal changes in air quality in tropical countries (such as a transition from dry to rainy season) in the months of COVID lockdown. This study aims to shed light on the changes in $PM_{2.5}$ pollution level in a tropical country and its relation on COVID lockdown.

Satellite-based aerosol optical depths (AODs), which represent the extinction capability of total atmospheric column content were found to correlate with ground-level (ambient) $PM_{2.5}$ measurements (Wang and Christopher, 2003; Gupta et al., 2006; Guo et al., 2009; Jiang et al., 2021). Thus, satellite AODs have been widely used to derive ambient $PM_{2.5}$ concentrations due to their high spatial (global) and temporal (~20 years of daily observations) coverages. Several methods have been utilized to derive ambient $PM_{2.5}$ concentrations at a high spatiotemporal resolution using satellite AOD products (Wei et al., 2019). The methods include: semi empirical models (Lin et al., 2015; Zhang and Li, 2015); chemical transport models (van Donkelaar et al., 2019); and statistical models such as linear model (Chudnovsky et al., 2013), mixed-effect model (Chudnovsky et al., 2014; Kloog et al., 2015; Xiao et al., 2017; Zhang et al., 2019), generalized additive model (Ma et al., 2016) and geographically and/or temporally weighted regression models (Hu et al., 2013; He and Huang, 2018).

Recently, machine learning algorithms have been used to predict ambient $PM_{2.5}$ levels from satellite AODs. This is due to their flexibility in solving large, complex and non-linear relationships among environmental, meteorological and geographical predictors. Thus, overcoming the inherent limitations of the statistical model assumptions such as normality, homoscedasticity, multicollinearity and independence (Z.Y. Chen et al., 2019; Li and Zhang, 2019). The machine learning algorithms frequently used for $PM_{2.5}$ predictions from satellite AODs include: neural network (NN) (Gupta and Christopher, 2009; Wu et al., 2012; Zou et al., 2015; Li et al., 2017a), deep belief network (Li et al., 2017b), extreme gradient boosting (J. Chen et al., 2019), support vector machines (Liu et al., 2017; Wang et al., 2017), decision tree (Reid et al., 2015; Zhan et al., 2017), random forest (Brokamp et al., 2018; Park et al., 2019, 2020; Yang et al., 2020; Jiang et al., 2021) and extremely randomized tree (Wei et al., 2019, 2020, 2021).

The lack of ground-level monitoring network for $PM_{2.5}$ in Nigeria makes it difficult to derive spatial and temporal datasets for $PM_{2.5}$. Consequently, AERONET's (Aerosol Robotic Network) measurements have been utilized to assess local aerosol pollution levels in Nigeria (Nwofor et al., 2018; Ogunjobi and Awoleye, 2019). Satellite AODs have also been utilized to assessed long-term trends in aerosol pollution levels in China (Guo et al., 2011; Cheng et al., 2013), South Africa (Kumar et al., 2014), United States (Tang et al., 2017) and India (Mahato et al., 2020; Ranjan et al., 2020). Satellite AODs however represent both natural and anthropogenic aerosol pollution level, and may have high measurements error compared to ground-level fine mode AODs (AOD_f), which have radii between 0.1 and 0.25 (Park et al., 2019) and are mainly anthropogenic.

In this study, we utilized NN to derive monthly average ground-level AOD_f across localities in Nigeria from the year 2001 to 2020 using satellites AOD products, AERONET aerosol optical properties, meteorological parameters and spatial predictors. We statistically assessed the long-term trends (2001 to 2020) in AOD_f in order to ascertain whether changes in air quality occurred in Nigeria due to COVID-19 lockdown or not. We believe that ours is a first study to statistically examine the long-term trends in air quality in a tropical country with high baseline air pollution level, high frequency of rainfall and no environmental intervention measures prior to 2020.

2. Materials and methods

2.1. Overview of the COVID-19 State of Emergency in Nigeria

Nigeria detected the first COVID case in Ogun State on February 28, 2020 traced to an Italian visitor to Nigeria through the Murtala Muhammed International Airport in Lagos. On 26th March 2020, the first COVID fatality was recorded in Nigeria, prompting the Federal Government to declare a nationwide lockdown in effect from 11 pm on 30th March 2020. The lockdown, spanning from 30th March to 3rd May 2020, banned all non-essential international and domestic travels, and shutdown economic activities including schools.

Between 4th May and June 1st of 2020, the first phase of easing of the lockdown (easing phase-1) took place. During this period, intrastate movement resumed but commercial drivers were allowed to take only 60% of their normal carriage capacities. Also, overnight curfew from 8 pm to 6 am was exercised but was later shortened from 10 pm to 4 am in most States of Nigeria. Senior public offices and private businesses were allowed to work only on Mondays, Wednesdays and Fridays. In the second phase of easing (easing phase-2), which was from 2nd June to 29th June 2020, banks resumed normal working hours. Religious gatherings less than 20 persons were allowed to hold just one service per week. Government offices opened from Monday to Friday but working hours were from 9 am to 2 pm. This second phase was later extended to September 03, 2020. During this extension, domestic travels resumed followed by international flights. Vehicles were mandated to travel with 50% of their carriage capacities, with compulsory use of face mask.

2.2. Data acquisition and processing

2.2.1. Satellites AOD products

We obtained daily Multi-angle Implementation of Atmospheric Correction (MAIAC) AOD products (green band at 550 nm) (MCD19A2) over land from the Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) satellites. The MAIAC processed AOD products are level-2 gridded datasets with spatial resolution of 1 km $\times$ 1 km (Lyapustin and Wang, 2018a, 2018b). We acquired and processed monthly average AODs for all pixels covering Nigeria, as well as the average values for pre-lockdown (January 01–March 30), lockdown (March 31–May 03), easing phase-1 (May 04–June 01), and easing phase-2 (June 02–August 25) for each year from 2001 to 2020 using codes in Google Earth Engine (GEE) cloud platform (https://code.earthengine.google.com/). We used the GEE's built-in country boundary feature (USDOS/LSIB_SIMPLE/2017) to specify Nigeria using the FIPS country code. The monthly average and phase-wise means of AOD over Nigeria were exported and processed in QGIS 3.12.3. Zonal statistics were computed using Nigeria's administrative unit layers for States (Etchie et al., 2018b, 2019).

2.2.2. AERONET aerosol optical properties

AERONET, developed by the United States National Aeronautics and Space Administration (NASA), is a global network of ground-level sun photometers. The sun photometers measure aerosol optical properties such as AOD, AOD_f and fine mode fraction (FMF) at multiple wavelengths ranging from 340 to 1020 nm (Tian and Gao, 2019; Aldabash et al., 2020). The instruments are well-calibrated and have high temporal resolution taking measurements for every 15 min. AERONET has only one ground-monitoring station in Nigeria, which is at Ilorin (8.48° N, 4.67° E, at elevation of 400 m). We downloaded version 3, level 2 (cloud screened and quality controlled with pre-field and post-field calibration applied), monthly aerosol optical properties (AOD and AOD_f at 500 nm and the Angstrőm exponents at 440–870 nm and 500 nm, respectively) from 2001 to 2019 (the most recent year) from https://aeronet.gsfc.nasa.gov/. Since the satellite AODs were at 550 nm wavelength, we converted the AERONET AODs and AOD_f to 550 nm following a standard algorithm (Holben et al., 2001; Bibi et al., 2015; Ogunjobi and Awoleye, 2019).

2.2.3. Meteorological and spatial predictors of AOD_f

We downloaded different monthly average meteorological predictors over Nigeria: rainfall (RF) (mm), relative humidity (RH) (%), air temperature at 2 m above the ground (T) (K), wind speed at 10 m above ground (WS) (m/s), and planetary boundary layer height (PBLH) (m), for each year from 2001 to 2020 from the second Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) site (https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/). Additional downloaded predictors were monthly averages of normalized difference vegetation index (NDVI) for each year from 2001 to 2020 from Terra MODIS (https://modis.gsfc.nasa.gov/data/dataprod/mod13.php); and yearly average gridded population density (PD) (number of persons per square kilometer) for the year 2000, 2005, 2015 and 2020 from the Socioeconomic Data and Application Center (SEDAC) (https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11). The datasets were processed and downloaded using GEE cloud platform with its built-in country boundary feature for Nigeria.

2.3. Spatiotemporal modeling of AOD_f across Nigeria

First, we evaluated the satellite MAIAC AODs (AOD_{MAIAC}) against the corresponding ground-level AERONET AOD datasets at 550 nm ($AOD_{AERONET}$) at Ilorin using simple linear regression, after removing outliers ($n = 9$). The validation result is shown in Eq. (1):

$$AOD_{MAIAC} = 0.54 \times AOD_{AERONET} + 0.04 \tag{1}$$

The correlation coefficient (r) is 0.84, and the root mean squared error (RMSE) is 0.10. The regression intercept is 0.04. The small value of intercept suggests that the MAIAC algorithm greatly reduced measurement error due to surface reflectance. However, a slope of 0.54 shows that the monthly average MAIAC AODs underestimate the actual ground-level measurements from AERONET. This suggests that the Terra and Aqua MODIS AOD measurements at Ilorin at 10:30 am and 1:30 pm local time underrepresent AERONET's measurements taken every 15 min, by approximately half, at the monthly time scale. A previous study that also utilized monthly AODs from AERONET at Ilorin, but over shorter period of time (2004–2014) to validate monthly AODs from the MODIS Deep Blue algorithm reported a relatively weaker correlation coefficient ($r = 0.58$), larger intercept (0.09), but comparable slope value of 0.51 (Ogunjobi and Awoleye, 2019).

We utilized the multilayer perceptron, neural network (MLP-NN) procedure, which is a feedforward architecture from the input layer through the hidden layer to the output layer. The input parameters were location, year, month, AOD_{MAIAC}, RF, RH, T, WS, PBLH, NDVI and PD, while the output parameter was ground-level AOD_f. We obtained the number of nodes in the hidden layer from training without external interference. The main function of the NN model was to estimate the nonlinear monthly average values of AOD_f from 2001 to 2020 across Nigerian localities using MAIAC AODs, meteorological and spatial predictors. The analysis was performed using IBM SPSS 23 statistics package.

2.4. Statistical analyses

2.4.1. Time-lag modeling

We used a quantitative method to assess and compare the monthly average AOD_f (from January to August) in 2020 with the corresponding values for the previous eighteen years (2002–2019). In other words, we took into account any potential decline in air pollution going from year 2002 to 2020, while testing if there has been a significant short-term decrease in air pollution levels in 2020 as a result of COVID lockdown. We utilized a linear time-lagged regression model (Eq. (2)) and analysis of covariate (ANCOVA) to test for statistically significant difference in pollution level for the same period by year (Zangari et al., 2020). The time-lagged regression is given by:

$$y = \beta_0 + \beta_1 X + \beta_n Z_n + XZ_n + t_n + \varepsilon \quad (2)$$

where: β_0 is intercept for year 2020, β_1 is coefficient for time, X. Here, X is covariate for month of the year (January–August). $\beta_1 X$ is slope for 2020, while $\beta_n Z_n$ and XZ_n are the intercept and slope, respectively, for each nth year (2002–2019). t_n is time lag for each year (2002−2020) and ε is error term (Zangari et al., 2020).

We performed ANCOVA using F-test for type III sums of squares, testing for homogeneity of the regression intercepts (change in air pollution levels) and homogeneity of the regression slopes for time, X (rate of change of air pollution) for each previous year relative to 2020, using a dummy covariate for year (2002–2019 = 0; and 2020 = 1). The analyses were performed using IBM SPSS 23 statistics package.

2.4.2. Impact analysis

We investigated the impact of local meteorological conditions on the AOD_f, using multiple linear regression, of the form:

$$y = \beta_0 + \beta_1 X + \beta_2 S + \beta_3 RH + \beta_4 RF + \beta_5 T + \beta_6 WS + \beta_7 PBLH + \beta_8 Z + \varepsilon \quad (3)$$

where y is AOD_f, β_0 is intercept, β_1 to β_8 are the coefficients for time (X, is month of the year from January to August), season (S: dry season is January–February, while rainy season is March–August.), relative humidity (RH), rainfall (RF), temperature (T), wind speed (WS), planetary boundary layer height (PBLH) and year (Z, is 2001–2020), respectively. ε is error term.

3. Results and discussion

3.1. Spatiotemporal trend of satellite aerosols (AODs) across Nigeria

The period average AODs across Nigeria during pre-lockdown, lockdown and easing phases in the year 2020 are shown in Fig. 1. There were substantial reductions in AOD levels across the States in Nigeria during the period of lockdown or easing phases compared to pre-lockdown in year 2020 (Fig. 1). During lockdown, the average air pollution level in Nigeria fell by about 69% in comparison to the pre-lockdown value, with further reduction of about 23% during easing phase-1. In Lagos, the pollution levels changed by about 81% and 6% respectively for the above two phases, and the reduction was observed to be about 50% and 56% respectively for these phases in FCT area. Generally, air pollution reductions during lockdown appeared to be greater in the Southern States than in the Northern States. Also, the lowest pollution levels were observed during easing phase-1, but not during lockdown. The pollution levels increased considerably, particularly in the Central States, during easing phase-2. The percentage increase in pollution levels in Nigeria as a whole, Lagos or FCT during easing phase-2 compared with easing phase-1 was approximately 44%, 11% or 381% respectively.

A time-series analysis of historical changes in AOD levels from 2010 to 2020 (Fig. 2) did not reveal a considerable change during lockdown or phase easing in 2020 compared to the past ten years. Seasonal influence and local meteorological conditions, rather than lockdown, appear to account for the reduction in air pollution level during lockdown or phase easing. For example, the mean pollution level during lockdown in 2020 in Nigeria of 0.22 was greater than the corresponding period in 2013 or 2014, which is 0.19 or 0.21, respectively. Similarly, the AOD levels during easing phase-2 in 2020 of 0.25 exceeded the value for similar period in year 2016, 2018 or 2019, which is 0.22, 0.23 or 0.22, respectively. The mean AOD level during easing phase-1 in the years 2020 and 2012 are similar i.e. 0.17.

Two distinct AOD spikes could be seen in the period corresponding to the COVID lockdown in the year 2015 and 2018 (Fig. 2). We attempted to unravel the cause of the spike by examining the long-term trends (2001−2020) of AOD, surface temperature and rainfall for the month of April, which is the dominant month of the lockdown. The result (Fig. 3) shows that throughout the 20-year period, the air temperature was almost stable, but rainfall showed considerable fluctuations. The amount of rainfall dropped considerably in year 2015, which probably caused the spike in AOD level. However, this was not the case in year 2018 where both the AOD level and the amount of rainfall were high. Thus, while we could attribute the spike in AOD in the period corresponding to the COVID lockdown in year 2015 to reduced (or delayed) rainfall, we could not suggest the same for the AOD spike for the same period in 2018.

3.2. Spatiotemporal trend of ground-level fine mode aerosols (AOD_f) across Nigeria

The COVID lockdown measures in Nigeria are expected to impact mainly anthropogenic pollution sources. Therefore, we statistically assessed the long-term trends (2001–2020) in ground-level fine mode aerosols (AOD_f) across localities in Nigeria. The MLP-NN validation result for the prediction is shown in Fig. 4. About 65% of the datasets were used for training, while 35% was used for testing. The relative error for training and testing was 0.08 and 0.05, respectively. The model R^2 and RMSE was 0.93 and 0.034, respectively.

The spread of fine aerosol pollution across localities in Nigeria from January to April in years 2020 and 2019 are shown in Fig. 5. There were substantial reductions in the pollution levels across the localities during COVID lockdown (April) compared to pre-lockdown months (January to March) in both year 2020 and 2019. The trends of fine aerosols from year 2001 to 2020 using monthly means are shown in Fig. 6. In year 2020 the average level of fine aerosols fell by about 21% during the lockdown month of April compared to March, with further reduction of about 26% in May (easing phase-1). Similar pattern of decline in fine aerosol levels of 7% or 28% was observed during the month of lockdown or easing phase-1 in 2019. The pollution levels however increased in June, July or August by 7%, 46% and 25% in 2020 or by 7%, 41% and 19% in 2019, compared to the preceding month. Comparison of the average pollution level in Nigeria between lockdown month (April) of 2020 and 2019 shows a decline in the pollution level by 1% in 2020 compared to 2019. Furthermore, fine aerosol pollution levels were generally higher in the Northern States compared to the Southern States. During the lockdown month of April 2020, the level of fine aerosol pollution declined by about 10% and 48% in Lagos and FCT, respectively, compared to the pre-lockdown month of March 2020. Comparison of the lockdown month in 2020 and 2019 however showed that fine aerosol pollution levels increased by about 28% in Lagos, but decreased by 3% in FCT in 2020 lockdown compared to 2019.

Throughout the 20-year period, the levels of fine aerosol pollution were highest in January, and lowest in May or June, but not April, which is the lockdown month. Both Levene's test and ANCOVA did not detect a statistically significant difference ($\alpha = 0.05$) between the pollution levels (intercepts of the time-lag model) or the change in pollution levels (slopes of the time-lag model) in Nigeria by year (see the Supplemental Materials Tables S1 and S2). This indicates that both the pollution level and the rate of change of pollution in 2020 are similar to the values for the previous eighteen years (2002–2019).

The impact analysis using multiple linear regression shows that seasonal change and variations in local meteorological conditions are significant ($\alpha = 0.05$) factors influencing fine mode aerosol levels across Nigeria (Table 1). The prevailing temperature has the greatest effect on fine aerosols pollution in Nigeria, followed in a decreasing order by month of the year, relative humidity, PBLH, season and wind speed.

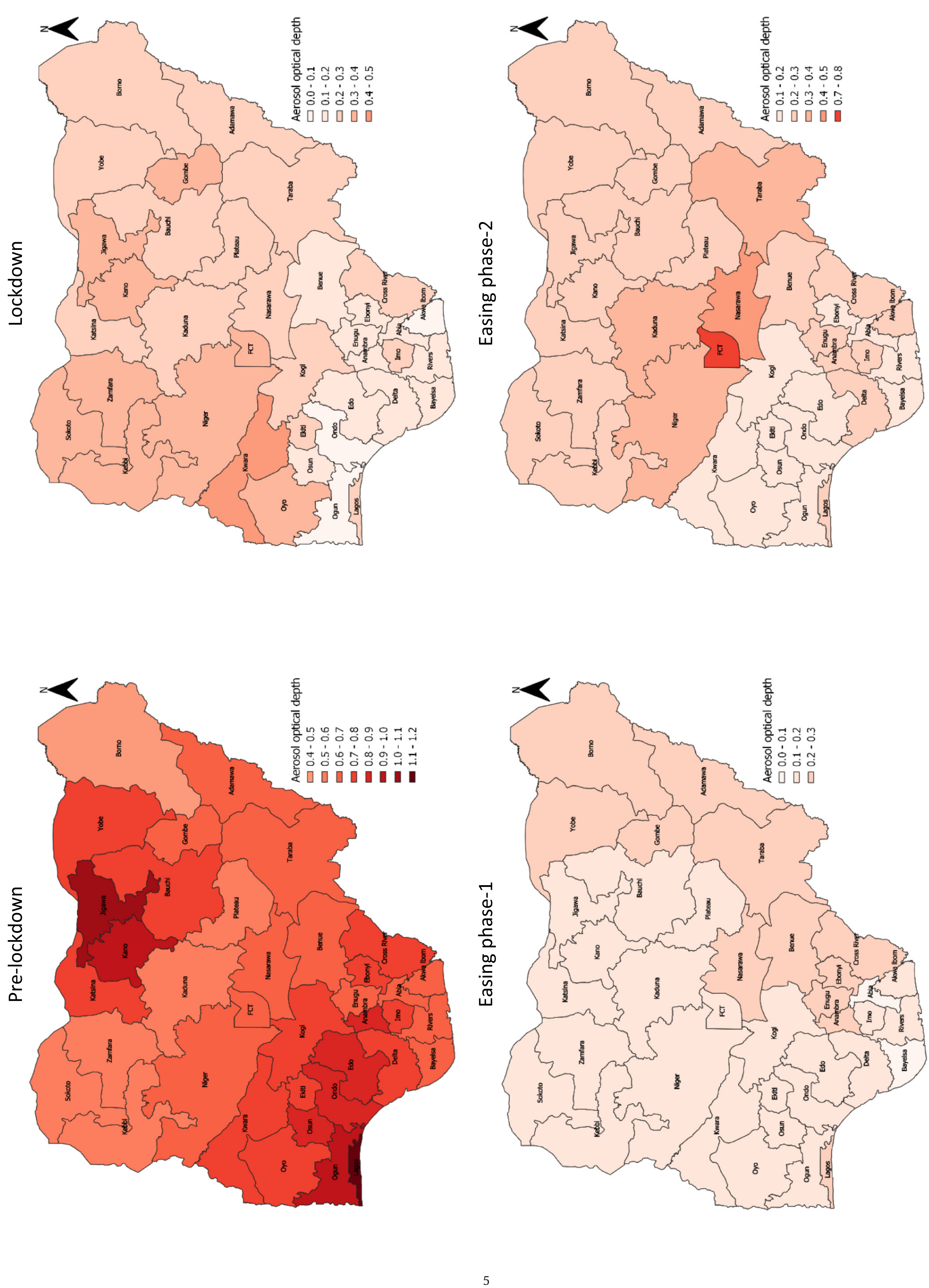

Fig. 1. Phase-wise mean MAIAC AOD across Nigerian States and FCT (Federal Capital Territory) in 2020.

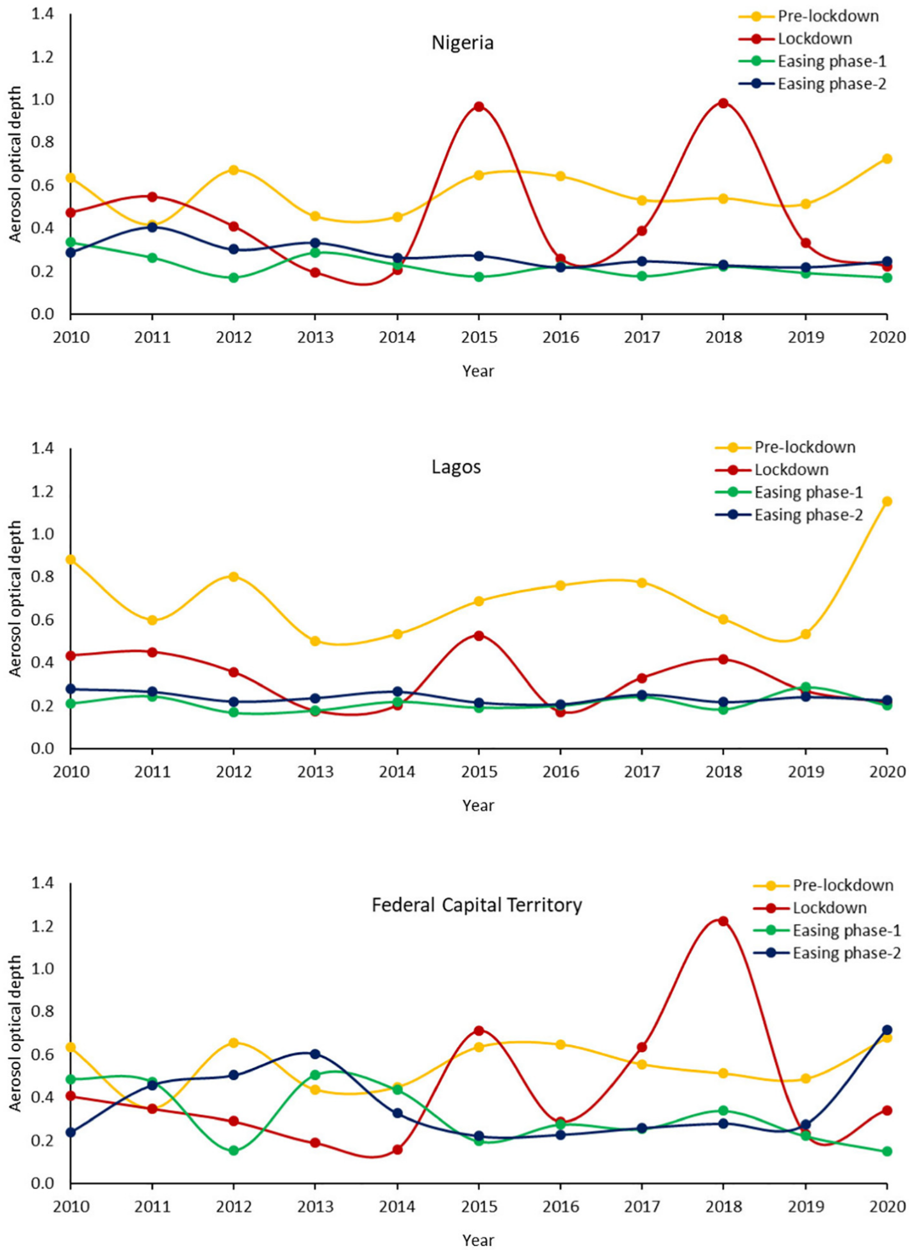

Fig. 2. Phase-wise mean MAIAC AOD in Nigeria as a whole, Lagos and the Federal Capital Territory from 2010 to 2020.

The negative sign in Table 1 indicates negative correlation between the parameter of interest and AOD_f. For example, when the surface temperature increases, the convective currents become stronger dispersing ground level aerosols leading to a decrease in AOD_f levels. Similarly, increase in surface relative humidity favors the hygroscopic size growth and accumulation of fine mode aerosols into coarse mode aerosols (Hu et al., 2010) resulting in lower AOD_f levels. High wind speed reduces AOD_f levels by dispersion. Aerosols interact strongly with meteorological parameters within the PBLH. PBLH characterize the convective and turbulent processes, entrainment and dispersion of aerosols and was found to correlate negatively with surface relative humidity (Zhang et al., 2013; Miao et al., 2019), except over desert region dominated with stable PBL regime (Zhang et al., 2018). Therefore, a decrease in PBLH (i.e. increase in surface relative humidity) may lead to the growth/accumulation of coarse mode aerosols from fine mode aerosols, leading to a reduction in AOD_f levels.

For the coastal state of Lagos, the effect was greatest for temperature followed in a decreasing order by month of the year, rainfall, wind speed, season, year and PBLH. The result for Lagos suggests that rainfall may also have statistically significant effects on aerosol pollution levels in other southern States of Nigeria where the intensity of rainfall is high. Heavy rainfall can reduce aerosol pollution levels by directly scavenging the pollutants or indirectly, by limiting outdoor activities that cause the pollution. For instance, both economic and commercial activities are affected by heavy rainfall. Rainfall also reduces household burning of solid fuels and wastes. In periods of heavy downpour, rainfall degrades roads and causes flood, leading to reductions in non-essential movements. Floods also pollute drinking water resources considerably (Adewuyi et al., 2014; Etchie et al., 2013, 2014, 2020).

Very few investigations are available on the impact of seasonal change on air quality in Nigeria. A study that assessed ground-level concentrations of $PM_{2.5}$ in residential, commercial and industrial areas in Ibadan, Nigeria reported substantially lower concentrations of $PM_{2.5}$ in rainy season (July to October) of 8–30 μg/m^3 compared to dry season (November to February) of 25–60 μg/m^3 (Akinlade et al., 2015). Owoade et al. (2013) assessed concentrations of ambient $PM_{2.5}$ in

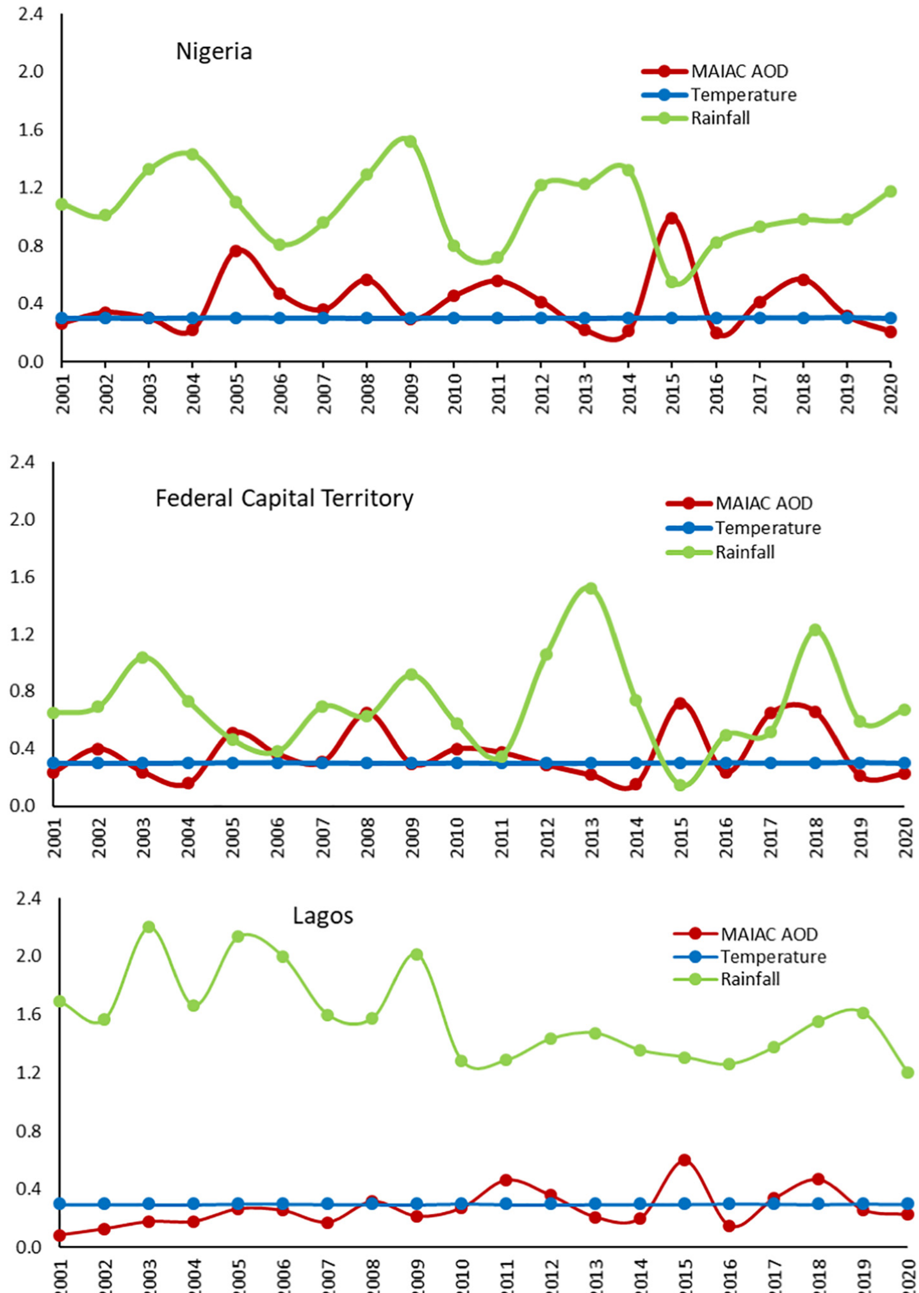

Fig. 3. Comparison of MAIAC AOD with temperature [K (×1000)] and rainfall [mm (×100)] in April (lockdown period) from 2001 to 2020.

residential, commercial and industrial areas of Lagos from February to October 2010, and reported $PM_{2.5}$ concentrations ranging from 2 μg/m^3 to 67 μg/m^3. However, no comparison was made between $PM_{2.5}$ levels in rainy and dry seasons. Another study that assessed concentrations of PM_{10} and $PM_{2.5}$ outside a scrap iron and steel smelting facility in Osun State, Nigeria reported a statistically significant decline in concentrations of PM_{10}, but not $PM_{2.5}$, during rainy season compare to dry season (Owoade et al., 2015). Ogundele et al. (2017) assessed heavy metal concentrations in $PM_{2.5}$ outside the steel smelting facility, but did not report the impact of seasonal change on metal concentrations.

Our statistical analyses show that favorable seasonal change and local meteorological conditions, rather than COVID-19 intervention measures, accounted for the reductions in aerosol pollution levels in Nigeria during the period of lockdown or phase easing compared to pre-lockdown in 2020. Local meteorological condition have been implicated to significantly impact both the $PM_{2.5}$ level and its composition (Cui et al., 2020). Our studies (Etchie et al., 2017, 2018b) found significantly lower concentrations of $PM_{2.5}$ and airborne polycyclic aromatic hydrocarbons in an Indian district (Nagpur) during rainy (monsoon) season compared to summer, winter or post-monsoon season. Recently, Chauhan and Singh (2020) attributed about 20% and 30% reductions in $PM_{2.5}$ pollution levels during COVID-19 lockdown in New York and Los Angeles, respectively, to rainfall.

Recent studies in different parts of the world have reported significant improvements in air quality during COVID-19 lockdown (Berman and Ebisu, 2020; Chen et al., 2020; Kumar, 2020; Kumar et al., 2020; Mahato et al., 2020; Muhammad et al., 2020; Ranjan et al., 2020; Rodríguez-Urrego and Rodríguez-Urrego, 2020). However, studies that analyzed the long-term changes in air pollution in temperate localities found no significant improvement resulting from the lockdown measures (Adams, 2020; Zangari et al., 2020). Using ground-level fine mode aerosol levels across Nigeria from 2001 to 2020, we have, for

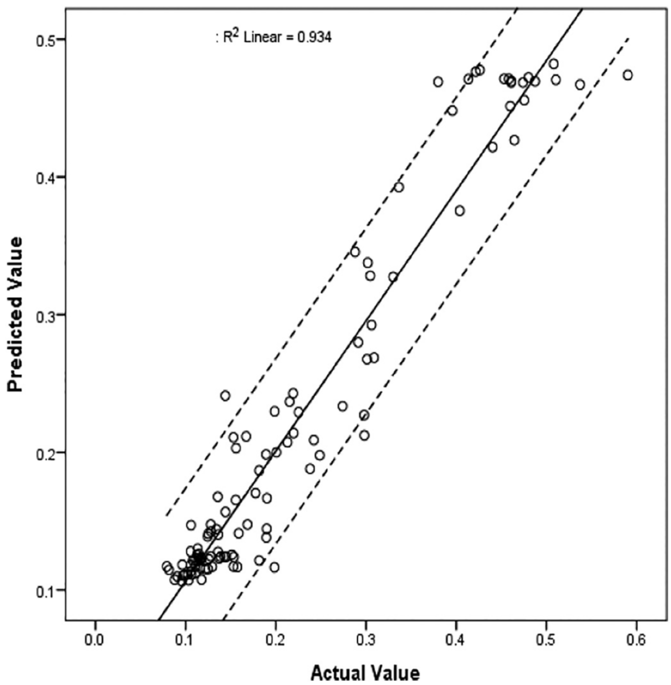

Fig. 4. Predicted versus actual AOD_f, based on multilayer perceptron neural network. Broken lines indicate 95% confidence interval.

the very first time, shown that the COVID-19 shutdown measures did not contribute significantly to air quality improvement in Nigeria. Although there was substantial decline in the pollution levels during the COVID lockdown and phasing easing months (April–August 2020) compared with pre-lockdown months (January–March 2020), the change in pollution was similar in magnitude to reductions occurring during the same period in past years (2001 to 2019). The impact analysis revealed that seasonal change to favorable meteorological conditions in Nigeria is responsible for the decline in air pollution during the COVID lockdown period.

We note some limitations of this study. First, we derived the levels of fine aerosols across Nigeria using AERONET's ground-level measurements due to the lack of ground-level monitoring stations for $PM_{2.5}$ or gaseous pollutants such as NO_x and SO_2 in Nigeria. Thus we could not interpret the magnitude of the changes in fine aerosols in terms of actual concentrations or risk to human health in Nigeria. Secondly, our estimates of fine aerosols were based on datasets from the only AERONET monitoring station in Nigeria, which is at Ilorin. Therefore, the spatio-temporal variability of fine aerosols across Nigeria is dependent on the variability in MAIAC AODs, spatial predictors and meteorological parameters utilized.

4. Conclusion

From this study, we conclude that there were significant improvements in air quality across Nigerian localities during the COVID-19 lockdown and easing phases, compared with pre-lockdown period in year 2020. However, the air quality improvements were not due to the lockdown measures, but seasonal change of favorable meteorological conditions. Namely, improvement in air quality resulting from the 2020 COVID lockdown measures in Nigeria was not statistically significant because of the strong effects of seasonal weather changes. Possibly, this conclusion may also be applicable to other tropical countries that transitioned into a season characterized by low pollution levels at the time of COVID shutdown, and should be investigated in future studies. To our knowledge, ours is the first study that has statistically assessed the effect of COVID-19 lockdown intervention on air quality in a tropical country with high baseline pollution level, strong seasonality and no environmental intervention history before 2020.

CRediT authorship contribution statement

Tunde Ogbemi Etchie: Conceptualization, Methodology, Validation, Project administration, Funding acquisition, Writing – original draft. **Ayotunde Titilayo Etchie:** Conceptualization, Data curation, Validation, Software, Formal analysis, Writing – review & editing. **Aliyu Jauro:** Visualization, Writing – review & editing. **Rachel T. Pinker:** Resources, Visualization, Supervision, Writing – review & editing. **Nedunchezhian Swaminathan:** Conceptualization, Visualization, Supervision, Writing – review & editing.

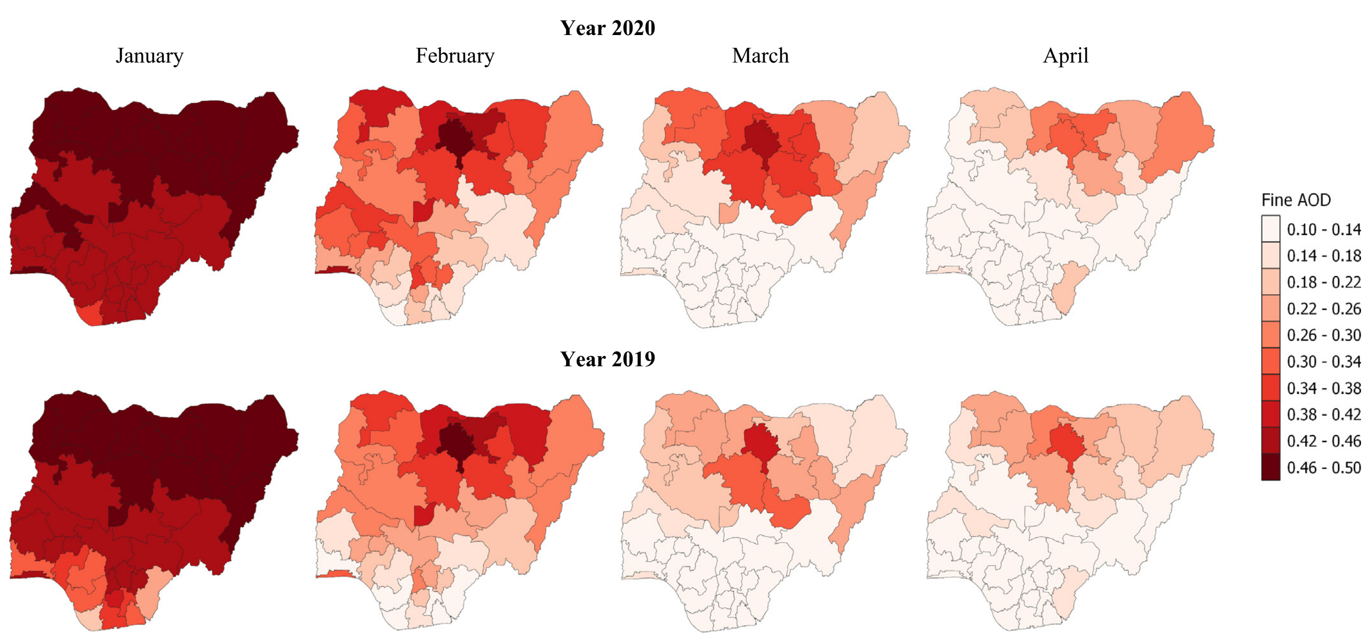

Fig. 5. Monthly average AOD_f across Nigerian States and Federal Capital Territory in 2020.

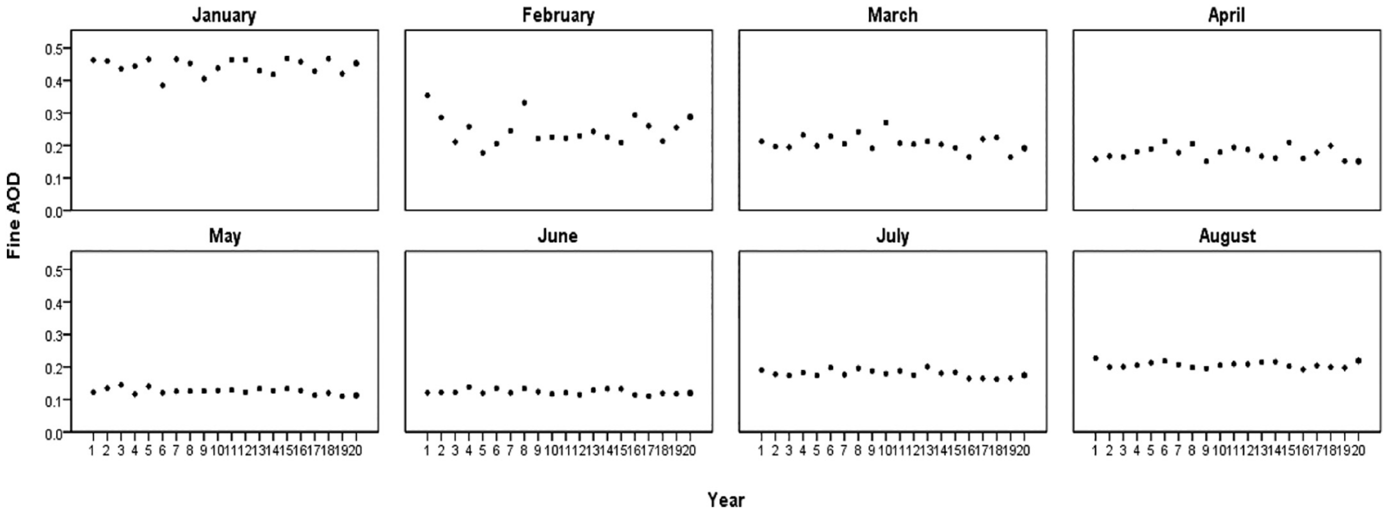

Fig. 6. Monthly average levels of fine mode AOD from year 2001 to 2020 in Nigeria.

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.

Acknowledgement

This study was made possible by the efforts of numerous persons over many years that collectively developed and maintained high quality datasets that enabled the analyses presented here. Our thanks to Dr. Alexei Lyapustin and his staff for their effort in establishing and maintaining the MAIAC MODIS AOD products used in this study. We thank the staff of AERONET at NASA and at the Ilorin site for maintaining high quality aerosol optical properties datasets. We are grateful to the NASA's Goddard Space Flight Center, Global Modeling and Assimilation Office for providing the meteorological datasets (MERRA-2) used in this study. The NASA's Socioeconomic Data and Application Center (SEDAC) and Center for International Earth Science Information Network (CIESIN) at Columbia University are acknowledged for providing gridded population density datasets (GPWv4) used in this study. We acknowledge Meteorology, Environment & Demographic Surveillance (MEDsurveillance) Ltd., Port Harcourt, Nigeria, for support under grant (19-20-A0001).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.145187.

Table 1
Factors that significantly ($\alpha = 0.05$) influenced fine mode aerosol optical depths (AOD_f) in Nigeria and Lagos.

S/N	Nigeria		Lagos	
	Parameter	Coefficient (β): $r = 0.95$, $R^2 = 0.90$	Parameter	Coefficient (β): $r = 0.92$, $R^2 = 0.84$
1	Temperature	−0.984	Temperature	−0.678
2	Month	−0.699	Month	−0.394
3	Relative humidity	−0.361	Rainfall	−0.278
4	PBLH	0.267	Wind speed	−0.206
5	Season	0.224	Season	−0.181
6	Wind speed	−0.127	Year	0.179
7	–	–	PBLH	0.087

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