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Modeling the Impact of Climate Factors on COVID-19 Transmission in Nigeria

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Abstract: Due to spatial and temporal changes in climate, the incidences of COVID-19 is much more higher in some parts of America, Europe and Asia by comparing with Saharan and sub-Saharan Africa. Several studies show the link between climate factors (e.g., temperature rainfall and humidity) and COVID-19 occurrence will be used to aid intervention planning, prevention and control policies. Nigeria is a country that is sensitive to spatial and temporal variability in the occurrence of climate factors, and fully knowing it link with COVID-19 is crucial towards mitigation. In this study, we examined the link by firstly deployed convenience sampling to select three cities (Abuja, Kano and Lagos) where the international airports of Nigeria are situated and also the index case of the country came through Lagos. Secondly, we used the reported cases of COVID-19 from its onset in the country (22/02/2020) up to 21/05/2021. Thirdly, lagged regression was used to explore the link between weekly counts of COVID-19 cases and weekly recorded average of the climate data; including the google trend index as a measure of the populace health seeking behaviour. We found a significant influence of temperature, humidity and heath seeking trend, with a very negligible contributions of precipitation to the occurrence of the COVID-19 in the states investigated. This result will assist policy makers with a prior knowledge to plan for non-pharmaceutical interventions in anticipation of possible outbreak.

Keywords: COVID-19, Climate, Lagged, Regression, Trend

1. Introduction

Amid the first wave of COVID-19 pandemic, many countries including Nigeria have locked down cities as policy to block human-to-human transmission. Following the aftermath of the regime, successes were recorded across the board as reported [1], thus proving the policy effectiveness. Consequently, several socio-economic problems were unturned, particularly in the developing countries and to some extend had also mildly affected some developed countries. In Nigeria for instance, many jobs were lost, businesses stopped, health facilities overstretched, poverty increased and standard of living had fallen unprecedented. Furthermore, In United States of America alone, about seven million jobs were lost due to the impact of COVID-19 on their economy. Other strong economy like Great Britain, France, Italy, and Germany had suffered similar challenges [2].

The climate factors such as temperature, rainfall, humidity, wind speed among others driven COVID-19 transmission [3], and they changed significantly from place to place. In Italy, the first two cases were confirmed in January 2020 but before the end of February, the virus had taken over the northern parts of the country. Thereafter, in March 2020, the toll of new cases and deaths kept swelling, rapidly and overtook the number of registered cases in China [4]. In struggle to cope with the expanding threat, war-like measures were taking by the Government, but Italy was insufficiently prepared to face this unprecedented challenge, and on the brink of collapse, weaknesses were unveiled [5]. Revealing the impact of climate on the spread of COVID-19 virus will help to prepare for possible outbreak if the impending climate factor is predicted.

The goal of this research work is to provide scientific evidence regarding the future progression of COVID-19 under the changing circumstances of climate factors. However, it is imperative to explore novel approaches to monitoring and forecasting regional outbreaks as they happen or even before they do so [6]. Association of the COVID-19 pandemic in relation to Internet Search Volumes revealed that Worldwide public interest in Coronavirus was extended to its first peak end of January when numbers of newly infected patients started to rise exponentially in China [7]. The worldwide Google Trend index reached its peak on the 12th of March 2020 at a time when numbers of infected patients started to increase in Europe and COVID-19 was declared as pandemic. Therefore, it is crucial to study the dynamics of the infection, how it transmits and the insights into epidemics behaviour. This will enable understanding of the population where the total lockdown to be imposed and where to adopt partial lockdown, thus providing window or breathing space for economy to flourish.

The remaining sections is organised as follows. Section 2 presents some previous works on COVID-19 transmission and the methodologies used for modelling the transmission including the analysis of the data are presented in Section 3. In section 4, we presented the results and discussed our findings accordingly. We presented the conclusions and unravel an area for further study in Section 5.

2. Related Work

In an effort to mitigate COVID-19 spread worldwide, a great deal of researches have been carried out towards prevention, control and intervention policies. As such, various modelling techniques (e.g., statistical, mathematical and computational) were used to address wide range of issues. For instance, mathematical model was used to study severe acute respiratory syndrome corona virus 2 (SARS-CoV-2) [8] and estimated human-to-human transmission growth rate using reported cases. The estimate is used to determine how human-to-human transmission varies from cities when a typical case is introduced to a population. When cases of the SARS-CoV-2 are being underreported, the estimation of the reproduction will be difficult to determine [9–11]. An impact of non-pharmaceutical interventions (e.g., case isolation, school closure, social distancing, total lockdown among others) across 11 European countries was studied using Semi-Mechanistic Bayesian Model [12], and found that, in Italy the daily reported deaths is consistent with the interventions. A stochastic model for assessing case isolation and contact tracing was developed to control onwards transmission from imported cases of COVID-19 [13]. The results showed that likely outbreak could be controlled if the transmission is ended within 12 weeks or before 5000 cases is reached. A computational technique using Agent-based model (ABM) has extensively being used for investigating COVID-19 spread. In this approach, the agents involve are allowed to interact with each other according to some predefined rules, thus produce emergent pattern. The impact of non-pharmaceutical interventions to reduce COVID-19 mortality and healthcare demand was investigated using an individual based model [14] and found that social distancing is effective. Similarly, ABM was deployed to assess and compared several intervention strategies of COVID-19 spread in Australia [15]; thus the results obtained is consistent with the findings in [14]. Google Trends and Correlates are platforms created for generating an artificial data based on individual's internet searching [16]. These platforms have played a kay role in data analytics and modelling emerging phenomena with insufficient data [17]. For instance, COVID-19 predictability analysis was performed using Google Trends time series model [7]. The results found to be significant in terms of correlation between Google Trends pattern and COVID-19 cases. This finding is consistent with some previous studies [18] with the fact that online real-time data are ingredients that are valuable in the observing and forecasting of epidemics. Furthermore, can assist public health policy makers in addressing crucial issues. In another study by [19] which explored the potential use of Google Trends to monitor public restlessness toward COVID-19 infection in Taiwan. Deploying predictive time series models like autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) among other will assist in determining trend in the COVID-19 spread [20]. A predictive model of the confirmed cases of COVID-19 in Nigeria was studied by [21]. The researchers are of the views that, the virus affected all the nations of the world and triggered global economic crisis that will likely to last for years. This necessitates the need to monitor and predict COVID-19 occurrence for suitable control. A study was conducted by [22] using information on established cases of Hand, Foot, and Mouth Disease (HFMD), revealed the significance of climate parameters and search engine query logs. The data was analysed at aggregate level and no confidential information was involved. The outcome measures a seasonal Autoregressive Integrated Moving Average (ARIMA) model with external variables (ARIMAX) which was used to predict the HFMD incidence from 2011 to 2014 by considering temperature and search engine query data. Statistics of goodness-of-fit and precision of prediction were used to compare models on the ground of surveillance data only, and with the addition of temperature, the results showed a high correlation between HFMD incidence and temperature [23]. Numerical solutions of a simple epidemic model were investigated by [24] where the spatial extend of the system is taken into account. The research modelled the delayed onset outside China together with the early one in China within a single model with minimal assumptions. The initial condition of several hotspots was adopted, to find out which one reaches saturation much earlier than the others. Piecewise quadratic growth during the 2019 novel coronavirus epidemic during the first and second web was considered [24]. At each site, quadratic growth commences when the local number of infections has reached a certain saturation level. The total number of deaths does then indeed follow a piecewise quadratic behaviour. A study by [25] uses multiple linear regression modelling approach to predict new active cases of COVID-19 in India. The research specified a strong prediction model to forecast the next coming days active cases. Consequently, the Multiple Linear Regression model forecasts for July is 52,290 active cases are predicted towards 15th August in India and 9,358 active cases in Odisha and the situation continues in that manner. The models acquired remarkable accuracy in COVID-19 recognition. A valid global dataset was collected from World Health Organisation (WHO) daily statistics and correlation among the total confirmed, active, deceased, positive cases were stated. Regression model such as Linear and Multiple Linear Regression techniques were applied to the dataset to visualise the trend of the affected cases [26]. Similarly, a piece-wise linear regression model was developed by [27] to predict new cases of COVID-19. The goal of such predictions was to take strategic control of the disease. The predictions were deviated from the real COVID-19 dataset of several states of India using mathematical model which has not been explored earlier in the COVID-19 predictions. The research presented a variant of the linear regression model of piecewise linear regression and has performed relatively better compared to the other existing models. However, climate factors influence on COVID-19 transmission was examined by [28] using daily Average Temperature (AT) and Relative Humidity (ARH) together with the daily counts of COVID-19 cases recorded in 30 Chinese provinces. A Generalised Additive Model (GAM) was fitted to measure the province specific connotations existing amid meteorological variables and the daily cases of COVID-19 during the study periods. The model used a 14-day Exponential Moving Averages (EMAs) of AT and ARH, and their interaction were included with time trend and health-seeking behaviour as adjusted [28].

Their spatial distributions were visualised. AT and ARH showed significantly negative associations with COVID-19. Temperature and humidity showed negative associations with COVID-19 while a significant interaction between temperature and humidity existed. The study reveals that Countries and regions with low temperature and humidity should pay more attention. A successful government response to the pandemic: Contextualising national and urban responses to COVID19 outbreak in east and west was examined by [29]. The research described country cases from East, South East Asia, Europe and Asia-Pacific with overall impression that Asian cases reflect proactivity and diligence, while Western responses are reactive and more often than not slightly delayed. The findings of the study indicated that the country groups include successes, while the devastating prevalent of global benchmarks are Asian. The fact is that the management of COVID-19 crisis is basically, a multi-level authoritative issue, putting together dialogue about national strategies is improved.

3. Materials and Methods

In this section, we describe the methodologies adopted in this paper by fully explaining the sources of data collection, study area and a succinct overview of the statistical modelling technique to be used. The data handling software to be used is also presented.

3.1. Study Area

As reported, the COVID-19 index case of Nigeria came through Murtala Mohammed International Airport Lagos by a foreign national on 27th February 2020 [30]. Thus, this study is conducted in only three cities (Abuja, Kano and Lagos) of the country where the International Airports are located. The cities are chosen because they are the only entry points of the cases and assumed to have likelihood of high incidence as compared to the other cities in the country. Abuja is located just north of the confluence of the Niger River and Benue River. It is bordered by the states of Niger to the West and North, Kaduna to the northeast, Nasarawa to the east and south and Kogi to the southwest. Abuja lies between latitude 8.25° and 9.208.25° north of the equator and longitude 6.458.25° and 7.398.25° east of Greenwich Meridian, Abuja is geographically located in the canter of the country. The Federal Capital Territory has a landmass of approximately 7,315 km^2, and it is situated within the savannah region with moderate climatic conditions. Kano is bordered by the states of Jigawa to the north and east, Bauchi to the southeast, Kaduna to the southwest, and Katsina to the northwest. Kano consists of wooded savanna in the south and scrub vegetation in the north and is drained by the Kano-Chalawa-Hadejia river system. Lagos is dominated by its system of islands, sandbars, and lagoons. The islands are connected by bridges and the land is low-lying. Lagos's expansion took off during the oil boom in the 1970s and this industry is still key to Lagos and Nigeria's economic growth [31].

3.2. Data Source

Weekly counts of laboratory-confirmed cases of COVID-19 of the cities considered in this study is retrieved from the NCDC (National Center for Disease Control) official website http://COVID19.ncdc.gov.ng/. The data is covering periods from the unset of the index case in Nigeria to May 05, 2021. The climate factors data viz: weekly average temperature, weekly average humidity and weekly average rainfall are retrieved from the following link https://globalweather.tamu.edu/. Health seeking behaviour of individuals searching internet (e.g., COVID-19 Vaccine, COVID-19, Face Mask and Hand Sanitizer) to find information about COVID-19 prevention and control tips is considered to be among the important variables in the model. This data is collected through Google Trend index https://trends.google.com/ trends/ for the study period.

3.3. Statistical Technique and Software

A lagged regression technique is adopted to model the dependence of COVID-19 reported counts on climate factors and individual health seeking behaviour index. This technique is deployed because the data under consideration appeared to be time-dependent. We preprocessed the data using expository data analysis and summary statistics of the data is also explored to identify the distributional form of the COVID-19 reported cases. The R software (version 3.5.3, http://cran.r-project.org; R Foundation for Statistical Computing, Vienna, Austria) was used to perform statistical analyses. Gretl computational software https://gretl.en.softonic.com/was used to visualize the cases and prediction.

4. Presentation of Results and Discussion

The summary statistics and expository data analysis of the COVID-19 data and the independent variables (the climate factors and health seeking index mentioned in subsection 3.2) are presented in Table 1. Cross-correlation [32] of the COVID-19 cases and health seeking variables together with 95% confidence interval (CI) and established extreme probability of rejecting the null hypothesis.

The results are indicating that face mask use is highly demanding in the three states. Lagos being most affected state in Nigeria [33], our results also revealed a strong link of COVID-19 incidence and health seeking behaviour towards use of face mask compared to Abuja and Kano. Because of the strong association between face mask searches index as health seeking behaviours of individuals in the cities with COVID-19 series, the face mask is considered in the model among other regressors (i.e., COVD-19 Vaccine, COVID-19 and Hand Sanitizer). As presented in Table 1, the means of the COVID-19 series in the cities are greater than standard deviations, hence the distributional patterns are assumed negative binomial.

Where $\emptyset_{t-1}^{i}$ for i=1, 2 and 3 denoting the dependency of COVID-19 cases at lag 1 for Abuja, Kano and Lagos respectively.

Table 1. *Summary statistics of COVID-19 cases and Expository Analysis of the Google Trend Searches.*

.	Parameters	COVID-19 Vaccine	COVID-19	Face Mask	Hand Sanitizer	COVID-19 Summary Statistics
Abuja	Pvalue	0.1462	0.0920	0.2582	0.1633	-
	r	-0.1837	-0.1434	-0.1434	-0.1763	-
	95% CI	[-0.4110, 0.0650]	[-0.4355, 0.0352]	[-0.3760, -0.1061]	[-0.4046, 0.0726]	-
	$\bar{x}$	-	-	-	-	310.97
	S^2	-	-	-	-	379.27
	CoV	-	-	-	-	1.2196
	Skewness	-	-	-	-	1.8051
	Kurtosis	-	-	-	-	2.7347
Kano	Pvalue	0.1462	0.9572	0.0031	NA	-
	r	-0.1837	0.0068	0.3642	NA	-
	95% CI	[-0.4110, 0.0650]	[-0.2394, 0.2523]	[0.1300, 0.5599]	NA	-
	$\bar{x}$	-	-	-	-	68.4700
	S^2	-	-	-	-	84.9100
	CoV	-	-	-	-	1.2401
	Skewness	-	-	-	-	1.5946
	Kurtosis	-	-	-	-	2.1474
Lagos	Pvalue	0.1462	0.2922	0.3620	0.7465	-
	r	-0.1837	0.1337	-0.1159	0.0412	-
	95% CI	[-0.4110, 0.0650]	[-0.1159, 0.3674]	[-0.3516, -0.1338]	[-0.2067, 0.2841]	-
	$\bar{x}$	-	-	-	-	956.7500
	S^2	-	-	-	-	1094.8000
	CoV	-	-	-	-	1.1443
	Skewness	-	-	-	-	2.2888
	Kurtosis	-	-	-	-	5.6346

The results presented in Table 2, outlined the coefficients of the lagged regression model at lag 1 in COVID-19 series, lag 2 in temperature and precipitation series. The results show that temperature and precipitation have positive influence on COVID-19 incidence in Lagos than in Abuja and Kano. However, temperature and precipitation have negative influence on COVD-19 incidence in Kano and Abuja, and humidity which has dominant contributions in Lagos as compared to Abuja and Kano. The model shows face mask is effective for reducing the spread of COVID-19 in Lagos and Abuja, however, Kano is less restrictive. This indicating a significant compliance among the people of Abuja and Lagos to the guidelines set by NCDC towards use of face mask as preventive measures.

$$A_t=0.77A_{t-1}-6.48T_{t-2}-0.11P_{t-2}+0.36H_{t-2}-2.85GTI_t+296.16$$

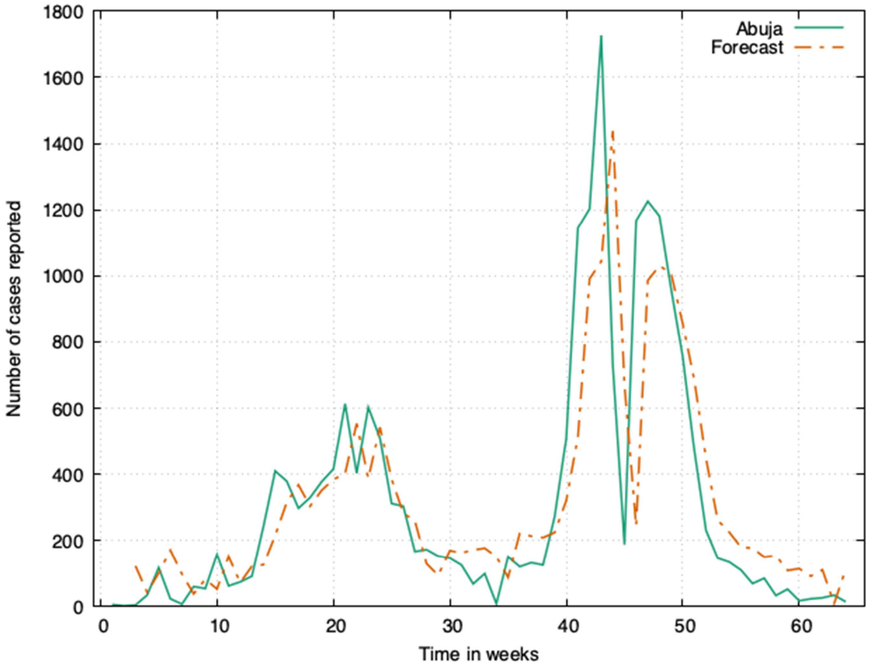
$$K_t=0.80K_{t-1}-2.91T_{t-2}-0.12P_{t-2}+0.37H_{t-2}+4.45GTI_t+112.24$$

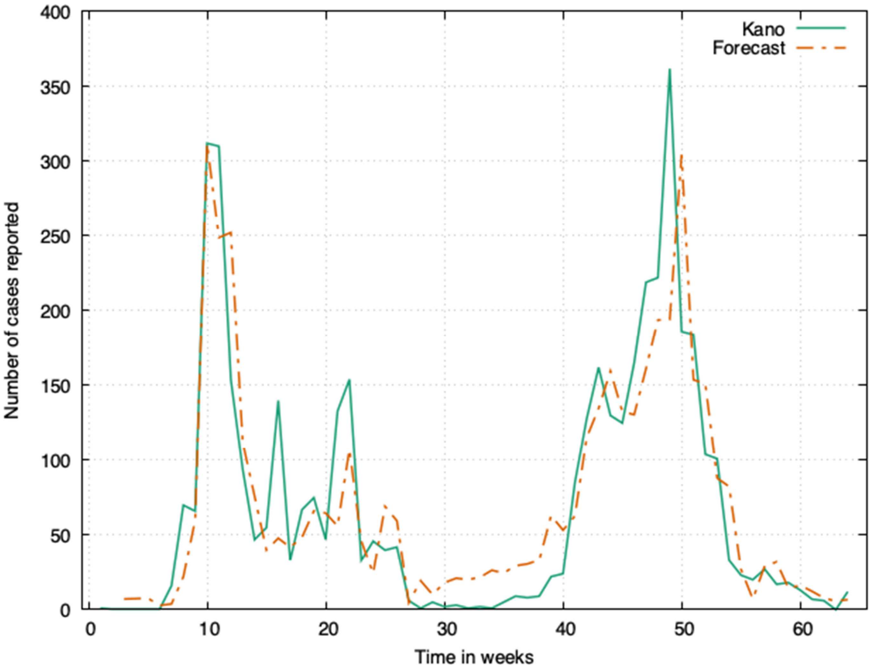
$$L_t=0.82L_{t-1}+84.48T_{t-2}+0.18P_{t-2}+1.32H_{t-2}-29.54GTI_t-2488.68$$

Table 2. *Lagged regression results summary of the three cities.*

	Abuja			Kano			Lagos		
	Coefficient	**t-Statistics**	**Pvalues**	**Coefficient**	**t-Statistics**	**Pvalues**	**Coefficient**	**t-Statistics**	**Pvalues**
Constants	296.1600	0.4758	0.6361	112.2420	2.7110	0.0089	-2488.6800	-1.7930	0.0781
β_1	-6.4756	-0.3642	0.7071	-2.9136	-2.8140	0.0067	84.4749	41.1114	0.0446
β_2	-0.1094	-0.9662	0.3381	-0.1216	-4.2970	0.0001	0.1831	0.7050	0.4837
β_3	0.3608	0.1818	0.8564	0.3721	1.0040	0.3199	1.3173	0.3008	0.7647
GTI	28.5440	-0.4595	0.6477	4.4495	41.8300	0.0000	-29.5444	-1.0920	0.2797
φ_{t-1}^{i}	0.7681	7.7640	0.0000	0.7945	9.0470	0.0000	0.8146	10.9900	0.0000

The lagged regression models (1) for the cities considered in this study are visualized in Figure 1 and the precision of the models accuracy using different statistic measures are outlined in Table 3. The model performed well in Kano (R^2=0.7763) as compared to Abuja (R^2=0.6458) and Lagos (R^2=0.7714). Although, on average the models are positively correlated and relatively similar in predicting the actual weekly counts of the cities.





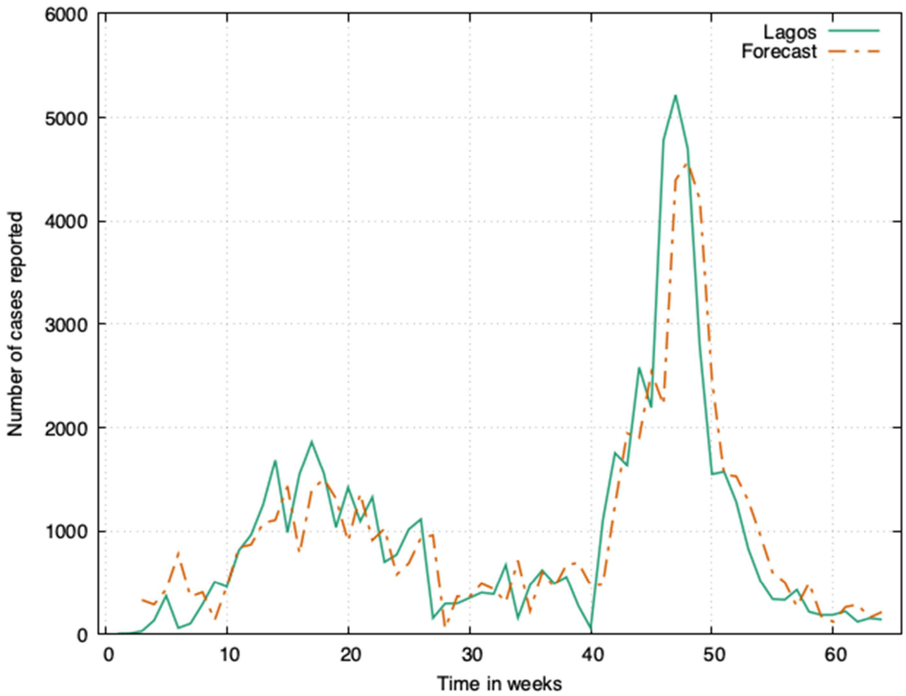


Figure 1. *Weekly counts of COVID-19 cases against the lagged regression models output of Abuja, Kano and Lagos respectively.*

Table 3. *Precision of the models accuracy.*

Statistics	Abuja	Kano	Lagos
	0.6458	*0.7763*	*0.7714*
AIC	*859.5921*	*645.5481*	*963.7030*
Durba in's h	*0.7928*	*-1.5829*	*0.8583*
Schwarz Criterion	*872.3549*	*658.3109*	*976.4648*
$\bar{\rho}$	*0.0631*	*-0.1452*	*0.8583*
Log-Likelihood	*-432.7960*	*-316.7740*	*-475.8510*
Hannan-Quinn	*864.6031*	*650.5591*	*968.7130*

5. Conclusion

Understanding the influence of climate factors on COVID-19 spread will assist policy makers with a prior knowledge to plan for possible non-pharmaceutical interventions in anticipation of outbreak. In this study, we investigated weekly counts of COVID-19 cases against climate variables, such as temperature, precipitation and humidity and google trend data on health seeking behaviour of individuals searching internet about COVID-19 vaccine, COVID-19, Hand sanitizer and Face mask. A lagged regression model was used to establish the relationship between the response and regressor variables. The result shows that temperature and humidity were correlated with the occurrence of COVID-19 incidence and negligible contributions of precipitation across the study areas. Furthermore, NCDC guidelines and particularly the use of face mask has been proven effective by decreasing the infection rate. This has evidenced by the significant compliance in Abuja and Lagos unlike Kano, in which restriction on use of the face mask is less. The interaction effect of the climate factors on COVID-19 transmission is reserved to be investigated in our future work.

Declaration

The authors declared to have no conflict of interest in this paper.

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References

[1] Melnick, E. R., & Ioannidis, J. P. (2020). Should governments continue lockdown to slow the spread of COVID-19. *BMJ*, 369.

[2] Costa Dias, M., Joyce, R., Postel-Vinay, F., & Xu, X. (2020). The challenges for labour market policy during the COVID-19 pandemic. *Fiscal Studies*, 41 (2), 371-382.

[3] Alam, M. S., & Sultana, R. (2021). Influences of Climatic and non-climatic factors on COVID-19 outbreak: a review of existing literature. *Environmental Challenges*, 100255.

[4] Zhu, H., Wei, L., & Niu, P. (2020). The novel coronavirus outbreak in Wuhan, China. *Global health research and policy*, *5* (1), 1-3.

[5] Ciaffi, J., Meliconi, R., Landini, M. P., & Ursini, F. (2020). Google trends and COVID-19 in Italy: could we brace for impact. *Internal and Emergency Medicine*, 15, 1555-1559.

[6] Mavragani, A., & Gkillas, K. (2020). COVID-19 predictability in the United States using Google Trends time series. *Scientific reports*, 10 (1), 1-12.

[7] Effenberger, M., Kronbichler, A., Shin, J. I., Mayer, G., Tilg, H., & Perco, P. (2020). Association of the COVID-19 pandemic with internet search volumes: a Google TrendsTM analysis. *International Journal of Infectious Diseases*, *95*, 192-197.

[8] Kucharski, A. J., Russell, T. W., Diamond, C., Liu, Y., Edmunds, J., Funk, S., & Flasche, S. (2020). Early dynamics of transmission and control of COVID-19: a mathematical modelling study. *The lancet infectious diseases*, 20 (5), 553-558.

[9] Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., & Shaman, J. (2020). Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2). *Science*, 368 (6490), 489-493.

[10] Zhao, J., Yuan, Q., Wang, H., Liu, W., Liao, X., Su, Y., & Zhang, Z. (2020). Antibody responses to SARS-CoV-2 in patients with novel coronavirus disease 2019. *Clinical infectious diseases*, 71 (16), 2027-2034.

[11] Jombart, T., Van Zandvoort, K., Russell, T. W., Jarvis, C. I., Gimma, A., Abbott, S., & Bosse, N. I. (2020). Inferring the number of COVID-19 cases from recently reported deaths. *Wellcome Open Research*, 5.

[12] Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., & Bhatt, S. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, 584 (7820), 257-261.

[13] Hellewell, J., Abbott, S., Gimma, A., Bosse, N. I., Jarvis, C. I., Russell, T. W., & Eggo, R. M. (2020). Feasibility of controlling COVID-19 outbreaks by isolation of cases and contacts. *The Lancet Global Health*, 8 (4), e488-e496.

[14] Ferguson, N. M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., & Hinsley, W. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. Imperial College COVID-19 Response Team. *Imperial College COVID-19 Response Team*, 20.

[15] Blakely, T., Thompson, J., Bablani, L., Andersen, P., Ouakrim, D. A., Carvalho, N., & Stevenson, M. (2021). Determining the optimal COVID-19 policy response using agentbased modelling linked to health and cost modelling: Case study for Victoria, Australia. *Medrxiv*.

[16] Jun, S. P., Yoo, H. S., & Choi, S. (2018). Ten years of research change using Google Trends: From the perspective of big data utilizations and applications. *Technological forecasting and social change*, 130, 69-87.

[17] Akay, A., & Hess, H. (2019). Deep learning: current and emerging applications in medicine and technology. *IEEE journal of biomedical and health informatics*, 23 (3), 906-920.

[18] Lu, F. S., Hou, S., Baltrusaitis, K., Shah, M., Leskovec, J., Hawkins, J., & Santillana, M. (2018). Accurate influenza monitoring and forecasting using novel internet data streams: a case study in the Boston Metropolis. *JMIR public health and surveillance*, 4 (1), e4.

[19] Husnayain, A., Fuad, A., & Su, E. C. Y. (2020). Applications of Google Search Trends for risk communication in infectious disease management: A case study of the COVID-19 outbreak in Taiwan. *International Journal of Infectious Diseases*, 95, 221-223.

[20] Alzahrani, S. I., Aljamaan, I. A., & Al-Fakih, E. A. (2020). Forecasting the spread of the COVID-19 pandemic in Saudi Arabia using ARIMA prediction model under current public health interventions. *Journal of infection and public health*, *13* (7), 914-919.

[21] Ogundokun, R. O., Lukman, A. F., Kibria, G. B., Awotunde, J. B., & Aladeitan, B. B. (2020). Predictive modelling of COVID-19 confirmed cases in Nigeria. *Infectious Disease Modelling*, 5, 543-548.

[22] Du, Z., Xu, L., Zhang, W., Zhang, D., Yu, S., & Hao, Y. (2017). Predicting the hand, foot, and mouth disease incidence using search engine query data and climate variables: an ecological study in Guangdong, China. *BMJ open*, 7 (10), e016263.

[23] Zhao, D., Wang, L., Cheng, J., Xu, J., Xu, Z., Xie, M., & Su, H. (2017). Impact of weather factors on hand, foot and mouth disease, and its role in short-term incidence trend forecast in Huainan City, Anhui Province. International journal of biometeorology, 61 (3), 453-461.

[24] Brandenburg, A. (2020). Piecewise quadratic growth during the 2019 novel coronavirus epidemic. *Infectious Disease Modelling,* 5, 681-690.

[25] Rath, S., Tripathy, A., & Tripathy, A. R. (2020). Prediction of new active cases of coronavirus disease (COVID-19) pandemic using multiple linear regression model. Diabetes & Metabolic Syndrome: *Clinical Research & Reviews*, 14 (5), 1467-1474.

[26] Forstmeier, W., & Schielzeth, H. (2011). Cryptic multiple hypotheses testing in linear models: overestimated effect sizes and the winner's curse. *Behavioral ecology and sociobiology*, 65 (1), 47-55.

[27] Senapati, A., Maji, S., & Mondal, A. (2021). Piece-wise linear regression: A new approach to predict COVID-19 spreading. *In IOP Conference Series: Materials Science and Engineering* (Vol. 1020, No. 1, p. 012017). IOP Publishing.

[28] Qi, H., Xiao, S., Shi, R., Ward, M. P., Chen, Y., Tu, W., & Zhang, Z. (2020). COVID-19 transmission in Mainland China is associated with temperature and humidity: a time-series analysis. *Science of the total environment*, 728, 138778.

[29] Anttiroiko, A. V. (2021). Successful government responses to the pandemic: Contextualizing national and urban responses to the COVID-19 outbreak in east and west. *International Journal of E-Planning Research (IJEPR)*, 10 (2), 1-17.

[30] Ohia, C., Bakarey, A. S., & Ahmad, T. (2020). COVID-19 and Nigeria: putting the realities in context. *International Journal of Infectious Diseases*, 95, 279-281.

[31] Taiwo, J. N., & Falohun, T. O. (2016). SMEs financing and its effects on Nigerian economic growth. *European Journal of Business, Economics and Accountancy*, 4 (4).

[32] Modu, B., Asyhari, A. T., & Peng, Y. (2016, December). Data Analytics of climatic factor influence on the impact of malaria incidence. In 2016 IEEE Symposium Series on Computational Intelligence (SSCI) (pp. 1-8). *IEEE*.

[33] Osikomaiya, B., Erinoso, O., Wright, K. O., Odusola, A. O., Thomas, B., Adeyemi, O., & Abayomi, A. (2021). 'Long COVID': persistent COVID-19 symptoms in survivors managed in Lagos State, Nigeria. *BMC Infectious Diseases*, 21 (1), 1-7.