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Impact of Temperature and Population Size on the Spread of COVID-19 in Nigeria: A Robust Regression Approach.

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ABSTRACT

Background: COVID-19, a global pandemic ravaging many countries, shares some semblances with influenza, whose transmission can be affected by many factors. Atmospheric temperature and population density have been identified as two key factors influencing the spread of viruses. Nigerian states with different weather patterns and varying populations across her states have recorded about 173,908 COVID-19 cumulative confirmed cases between March 2020 and July 2021.

Methods: Data sets of confirmed Covid-19 cases, average monthly temperature and population of each State, and Nigeria's Federal Capital Territory were obtained. A test of assumptions of linear regression was carried out and there is the presence of outliers in the dataset. M-estimator as an alternative to Ordinary Least Square (O.L.S.) estimator for regression analysis was used to investigate the impacts of each State's population size and atmospheric temperature on the rate of COVID-19 cases confirmed. The spearman rank correlation coefficient was also used to investigate the strength of the relationship between the confirmed cases, the population and temperature.

Results: Results show no multicollinearity (VIF=1.041) between the independent variables, and there is no autocorrelation as the Durbin-Watson test value gives 2.113 (approximately 2). There is a weak positive correlation between cumulative confirmed cases and population (r = 0.281), but a weak negative correlation exists between COVID-19 cumulative confirmed cases and atmospheric temperature (r = -0.341). For OLS estimation method, only population is significant (β_1= 0.002, p < 0.002) but the population (β_1= 0.0006, p < 0.05) and the atmospheric temperature (β_2= -683, p < 0.05) are both significant when M-estimation method was applied.

Conclusion: The findings in this study show that population size and temperature are important factors in the spread of Covid-19. The spread of the pandemic may be partially suppressed with higher temperatures but increases with an increased population.

Keywords: Covid-19, Temperature, Population size, O.L.S., M-Estimation, Nigeria.

1. INTRODUCTION

Antecedent to the eruption of Coronavirus 2019 (COVID -19) was the outbreak of two other β-coronaviruses; Severe Acute Respiratory Syndrome Coronavirus, SARS CoV-1 in 2003 [1] and the Middle East Respiratory Syndrome Coronavirus, MERS-CoV in 2012 [2]. COVID-19 is a malignant respiratory disease with almost ascertained background from a bat. SARS-CoV-2, the carrier of COVID-19, has its origin from SARS-like corona species appearing larger than SARS, MERS, and Influenza at 125 nm. [3]. COVID-19, an infectious respiratory disease with symptoms like fever, dry cough, and fatigue, gained its transmission power in Wuhan, Hubei Province of China, with the first case reported in December 2019 [4, 5, 6]. Since the first record in China, almost all edges of the world, including Nigeria, have been assailed by virulence, and since then, its ravaging force has gained total dominance [7, 8]. The World Health Organization (W.H.O.) first declared COVID-19 as a disease of international concern on the 30th of January, 2020 [9]. On the 12th of March, 2020, W.H.O. announced COVID-19 disease as a pandemic. Economically buoyant countries such as the U.K., Italy, and the U.S., surprisingly, despite their diverse growth and advancement in healthcare systems, suffered the hugest transmission rates and deaths among their people. In these countries, innumerable factors like limited testing, inadequate contact tracing, quarantine measures, delayed public health responses, and population demographics and disease comorbidities contributed to the high burden [10, 11]. Nigeria reported her first case, an Italian citizen in Lagos, on the 27th of February 2020. In the second case, a Nigerian citizen traced to have had contact with the Italian confirmed in Ogun State on 09th March 2020 [12]. The former makes Nigeria the third African country to report her first case after Egypt with the first case on the 14th of February 2020 and Algeria with her first case on the 25th of February 2020. By the 30th of November, 2020, Nigeria's COVID-19 confirmed cases had risen to 67,557 [13]. However, many have wondered why the number of confirmed cases of covid-19 in Africa has remained low compared to other continents despite significantly weaker health systems and a lower standard of living. Many researchers have tried to investigate the reasons for this. The youthful population of Africa, with a median age of fewer than 20 years when compared with Europe and the United States (with median age greater than 38 years), has been suggested as one of the factors contributing to the low numbers of severe COVID-19 cases and deaths in Africa [14, 15]. Another factor suggested is warmer weather in Africa with a low level of sunlight enhancing the spread [16, 17].

The spread of respiratory viral infections is influenced by the change in weather factors, as human coronaviruses have been discovered to be prevalent during winter [18]. Another author affirms that severe acute respiratory syndrome (SARS), caused by the coronavirus SARS-CoV, is affected by temperature [19]. Dowell opined that host behavioural patterns, pathogen prevalence, and climatic factors have a high propensity to contribute to infectious disease susceptibility [20]. It has also been established that the coronavirus can retain its infectivity for up to two weeks in a low temperature and low humidity environment, which might aid the virus transmission in a community located in a subtropical climate [21]. The underlying mechanism patterns of climate determination that lead to infection and possible disease transmission are etiological factors such as the ability of the virus to survive external environmental conditions before staying in a host, changes in the host's physiological susceptibility, immune system function, social behaviour, and weather conditions [22, 23]. Temperature and rainfall were also identified as some of the weather conditions that predominately influence outbreaks of these diseases [24]. A study considering about 429 cities in China reveals that temperature impacts the spread of COVID-19 [25]. Another study in Indonesia, however, invalidates this as it was found that there is no correlation between temperature and COVID-19 spread [26].

In a research carried out in the United States trying to study the effect of climate on COVID-19 spread rate, it was discovered that the mean COVID-19 replication rates (R.R.) were significantly lower in warm climate countries compared with cold countries. Similarly, the rate of spread (R.O.S.) was considerably lower in warm climate countries than in cold countries. Both R.R. and R.O.S. displayed a moderate negative correlation with temperature [27]. Another research reported that temperature was positively linked with mortality in Wuhan, China [28]. Adequate synthesis of 7-de-hydrocholesterol by human skin has been linked to sufficient exposure, reducing susceptibility to COVID-19 infection [29, 30].

In Nigeria, seasons range from harmattan (dry) to rainy (wet), with rainy seasons spanning from April to October and dry seasons from November to March [31, 32]. Changes in the temperature level across all-state in Nigeria might affect susceptibility via immune response rather than the virus among various populations with different weather temperature levels, thus suggesting that transmission dynamics could be independent of weather [7]. In Lagos state, the economic capital of Nigeria, research shows that atmospheric temperature has a significant weak negative correlation with COVID-19 transmission. Similarly, temperature and cumulative mortality have a significant weak negative correlation [33]. On the other hand, several researchers have tried to establish the relationship between population densities and COVID-19 spread. Some of this work concluded that these two factors positively correlate [34]. At the same time, some research presumes that population density has no impact on the spread of the disease [35, 36]. Another finding involving 81 provinces in Turkey shows that population density effectively spreads the virus [37]. Nigeria's first dozen cases of COVID-19 had their roots in crowded places with people. This led to a suspension of several social activities, disallowance from religious and other highly-crowded gatherings, and implementation of a social distancing rule was agreed to have minimally settled this [38].

Since it is a general assumption that density is associated with higher rates of transmission, infection, and mortality from highly contagious diseases such as COVID-19 [39, 40], this study investigates the influence of weather temperature and population on the record of COVID-19 confirmed cases in Nigeria.

2. METHODS

2.1 Study Location

Nigeria is located on the western coast of Africa, bordered to the north by Niger, to the east by Chad and Cameroon, to the south by the Gulf of Guinea of the Atlantic Ocean, and on the west by the Benin Republic. Nigeria is divided into six geo-political zones, with thirty-six states and the Federal Capital Territory. Nigeria is the most populous African country, with an estimated population of about 200 million people.

2.2 Data extraction:

The data for a daily number of confirmed cases from March 2020 to July 2021 for each of thirty-six states and Nigeria's federal capital territory were extracted from the Nigeria Centre for Disease Control (NCDC) [31]. Nigeria states' monthly averaged temperature data from the same time interval were retrieved from the Weather spark official website [41]. Nigeria's most recent population by state data were extracted from the National Bureau of Statistics [42].

2.3 Analysis of Data: All the acquired data are exported to excel with each State with their corresponding confirmed cases and temperature for each of the months considered (March 2020 – July 2021), and then the population values. This study carefully investigates the impact of the independent variables (average temperature and population size) on the dependent variable (covid-19 confirmed cases). The equation for multiple linear regression is given as:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (1)$$

where y is the confirmed cases, X_1 is the temperature, X_2 is the population, and εis the error term. Hence, the multiple linear regression in this study is given as:

$$\text{confirmed cases} = \beta_0 + \beta_1 \text{ temperature} + \beta_2 \text{ population} \quad (2)$$

The descriptive statistics of the data set were obtained. The Ordinary Least Square Estimator (O.L.S.E.) is Best Linear Unbiased Estimator (BLUE) if all of the assumptions of the classical linear regression are satisfied. However, this is not true if one or more assumptions of the classical linear regression are violated. One of the assumptions that must be satisfied is that the two independent variables used in this study (temperature and population) are not related. If there is a high correlation between the independent variables (multicollinearity) and the O.L.S.E. is used to estimate the parameters, then the variance of the regression estimates becomes inflated [43]. Outliers in a dataset render the O.L.S.E. unreliable and inefficient [44]. However, some robust regression estimators have been proposed to handle the problem of outliers in a dataset. One of the most common general robust regression methods is M-estimation, introduced by Huber [45]. Robust Regression is an essential statistical method used to handle datasets that contain outliers.

3. RESULTS AND DISCUSSION

During this study (27th of February 2020 to 31st of July 2021), Nigeria recorded a maximum cumulative incidence of 63,782 COVID-19 confirmed cases from one of her states (Table 1; Figure 2a). There were Nigerian states with very few confirmed cases records, with less than 0.5% of total cases (Table 2, Figure 2b). An observed growing pattern in the number of COVID-19 cases monthly and across the two seasons (dry and wet) in Nigeria is likely to be associated with meteorological factors like atmospheric temperature and demographic factors like the population size of the states. The minimum and maximum atmospheric temperatures across all Nigerian states within this period are 25.18°C and 32.31°C, respectively, whereas the minimum and maximum

population of the State are 2,277,961 and 15,076,892, respectively (Table 1). The minimum and maximum Covid-19 confirmed cases by states are 5 and 63,782, respectively. There was an average cumulative incidence of 4,700 ± 10,646 confirmed cases.

Table 1: Summary of COVID-19 confirmed cases and other meteorological and demographic factors

Variables	Mean ± SD	Minimum	Maximum
Confirmed cases	4,700 ±10,646	5	63,782
Population	5,268,934 ± 2,515,299	2,277,961	15,076,892
Temperature	28.69±1.797	25.18	32.31

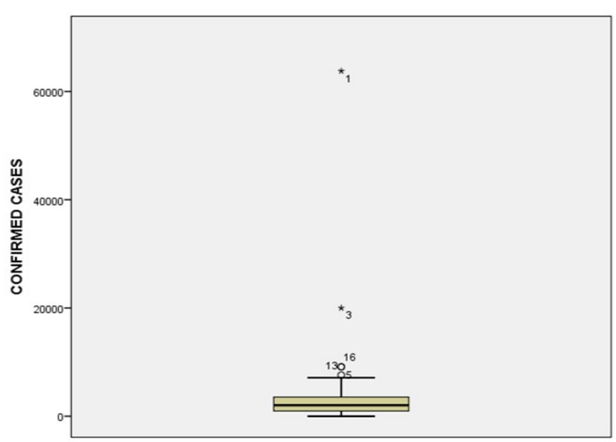

Figure 1: Box plot showing States with inconsistent observations of cumulative confirmed cases.

The diagnostics test of multicollinearity to confirm if the independent variables (atmospheric temperature and population by states) exhibit a very high or perfect linear relationship was carried out (see Table 3) with the Variance Inflation Factor (V.I.F.) estimated to be 1.041 (V.I.F. < 10). This shows that there is no multicollinearity between

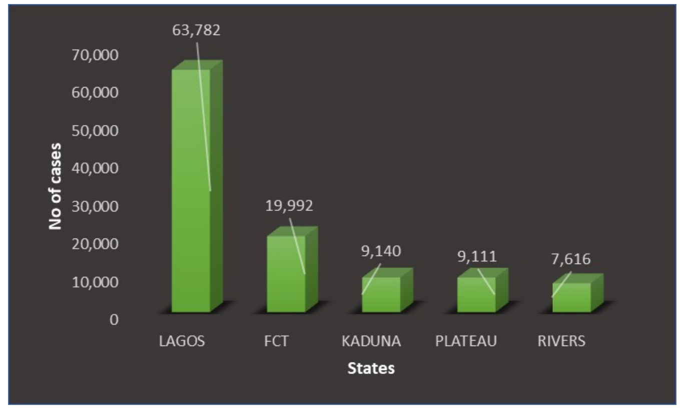

Figure 2a: Graph of Nigeria's top-five states with leading COVID-19 confirmed cases

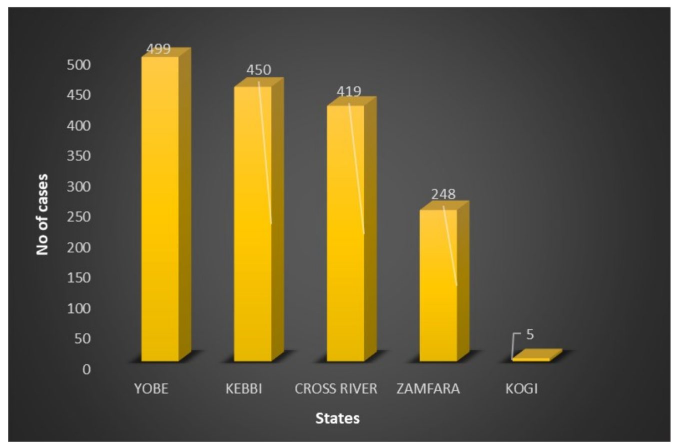

Figure 2b: Graph of Nigeria's bottom-five states with the least COVID-19 confirmed cases.

the independent variables. A test for autocorrelation was also carried out to evaluate the relationship between successive values of the same variable using the Durbin-Watson test. It is estimated to be 2.113 (approximately 2), which affirms that the assumption of no-autocorrelation was satisfied. However, inconsistency of some observations with other observations summed up to a violation of the Normal-distribution of residuals generated for all the combined variables.

Figures 2a and 2b show that the top-five states with leading COVID-19 confirmed cases are Lagos, F.C.T., Kaduna, Plateau, and Rivers States. The bottom five states with the least COVID-19 confirmed cases starting from the least are Kogi, Zamfara, Cross River, Kebbi, and Yobe States, respectively.

Consequently, this imbalance in the model suggests that the Ordinary Least Square (O.L.S.) estimator is not efficient. The method of O.L.S., as seen in Table 3, shows that the cumulative confirmed cases for each State are

Table 2: Rank of Nigeria states in Cases, Population, Temperature and Cases (% of Total)

STATES	CASES (RANK)	POPULATION (RANK)	TEMPERATURE (RANK)	CASES (% OF TOTAL)
LAGOS	1	2	14	36.676
FCT	2	29	29	11.496
KADUNA	3	3	24	5.256
PLATEAU	4	26	37	5.239
RIVERS	5	6	23	4.379
OYO	6	4	18	4.091
EDO	7	25	25	2.845
OGUN	8	16	19	2.749
KANO	9	1	8	2.317
ONDO	10	19	32	2.032
KWARA	11	33	17	1.860
DELTA	12	11	22	1.542
OSUN	13	18	20	1.505
AKWA IBOM	14	14	31	1.466
ENUGU	15	23	35	1.432
NASARAWA	16	36	15	1.381
KATSINA	17	5	7	1.239
GOMBE	18	32	12	1.235
EBONYI	19	35	26	1.175
ANAMBRA	20	13	27	1.103
ABIA	21	28	33	0.978
IMO	22	15	30	0.971
BAUCHI	23	7	10	0.893
BENUE	24	10	16	0.785
BORNO	25	8	1	0.773
ADAMAWA	26	24	3	0.652
TARABA	27	34	11	0.576
EKITI	28	31	36	0.558
NIGER	29	12	21	0.551
BAYELSA	30	37	28	0.542
SOKOTO	31	17	2	0.452
JIGAWA	32	9	5	0.323
YOBE	33	30	4	0.287
KEBBI	34	22	3	0.259
C/RIVER	35	27	34	0.241
ZAMFARA	36	20	9	0.143
KOGI	37	21	13	0.003

Table 3: Spearman's correlation test between confirmed cases and other meteorological and demographic factors

Variables	Confirmed Cases	Population	Temperature
Confirmed Cases	1	0.281	-0.341
Population	0.281	1	0.257
Temperature	-0.341	0.257	1

only significantly associated with the population of the corresponding states, with an adjusted R2 value (21.9%).

This is, however, contrary to what the M-estimator in Table 4 reveals. This may be due to irregularities brought about by the presence of observations inconsistent with others, as Fig. 1 suggests. Observations from Lagos (1), F.C.T. (3), Plateau (13), Rivers (16), and Kaduna (5) in the y-direction are outliers. The O.L.S. estimator is extremely sensitive to multiple outliers in linear regression analysis. A single outlier can easily be biased because of its low breakdown point [46]. The breakdown point is the percentage of outliers allowed in a dataset for an estimator to remain unaffected [47]. Depending on the estimates of the least square technique reported with data consisting of outlying observations can therefore be misleading [48]. Data transformation is one of the ways to handle the influence of outliers, but straightforward interpretation may be difficult using transformed data [49]. Removing outli-

Table 4: Regression estimates with Ordinary Least Square (OLS) method

Model	β	Std Error	p-values	VIF	Durbin Wat-	Adjusted R^2
Constant	29,248	25144.761	0.253			
Population	0.002	0.001	0.002^{***}	1.041	2.113	21.9%
Temperature	-1,252	890.394	0.169			

** Significant at 1%

ers from the database directly is another simple practice to avoid the problem. This can lead to a specification error in linear regression and potential threats to internal validity [50, 51]. In this study, since there is no compelling reason to exclude those outliers from the analysis as suggested by some authors, robust regression as an alternative to O.L.S. was used to accommodate those outliers.

Table 2 shows the hierarchy by the rank of all the Nigerian states regarding the population size and atmospheric temperature. Table 3 presents the spearman's rank correlation test used for investigating the agreement on the results ranking between cumulative confirmed cases and individual state populations and their respective atmospheric temperature. This test is an alternative to the Pearson correlation coefficient since the Spearman rank is less sensitive to outliers due to the utilisation of ranks rather than actual observations of variables in concern. It goes beyond linear associations and always captures the strength of monotonic relationships [52]. It appears from Table 3 that a weak positive correlation exists between COVID-19 cumulative confirmed cases and Nigeria's population by State ($r = 0.281$). However, a weak negative correlation exists between COVID-19 cumulative confirmed cases and atmospheric temperature ($r = -0.341$).

Table 5 shows the result of the robust regression estimation with the M-method for the relationship between COVID-19 cumulative confirmed cases and population by states and average atmospheric temperature for states in Nigeria. A significant relationship exists between cumulative confirmed cases and Nigeria's population by State ($\beta_1 = 0.0006$, $p < 0.05$), implying that for every unit increase in a state's population, the cumulative confirmed cases will increase by 0.06%. Similarly, a significant relationship exists between cumulative confirmed cases and atmospheric temperature ($\beta_2 = -683$, $p < 0.05$), implying that for every unit increase in atmospheric temperature of a state, the cumulative confirmed cases will reduce by 683 persons. In contrast, the influences of other factors on

Table 5: Robust regression estimates with the M-estimation method

Model	β	P-values
Constant	19,222	0.0027^{***}
Population	0.0006	0.0004^{***}
Temperature	-683	0.0027^{***}

** Significant at 1%

cumulative confirmed cases of Nigerian states are enclosed in the estimate of the constant ($\beta_0 = 19{,}222$).

Table 4 presents the Ordinary Least Square (O.L.S.) estimation method. From the result, only population size is significantly contrary to the M-estimation method, where the constant, the population size, and the temperature are all significant. It is imperative to discuss the implication of reliance on the results of the ordinary least square, which suggests a significant relationship between cumulative confirmed cases and population only. The estimator in this sense might be misleading as it discards truly existing significant influence of atmospheric temperature and some other factors on COVID-19 cumulative confirmed cases ($\beta_2 = -1{,}252$, $p > 0.05$; $\beta_0 = 29{,}248$, $p > 0.05$).

The findings in this study are in line with those from [53], who measured a negative correlation between the COVID -19 transmission and atmospheric temperature in Lagos, Nigeria. It is also considered close to what Hassan et al. [54] found: about 70% of COVID-19 confirmed cases are concentrated in Lagos, F.C.T., Edo, Oyo, Delta, and Kano (Table 2). Some other studies reported a significant association between the spread of covid-19 and temperature [28, 55, 56, 57]. Another study also concluded that atmospheric temperature lowered the early spread of the novel disease [58].

In theory, it is believed that densely populated areas are potential hotspots for the rapid spread of emerging infectious diseases due to closer contact and more interaction among residents [59]. The findings in this work concerning the population and spread of Covid-19 are consistent with some researchers in Iran, where population density and movement variables significantly influenced the infection rate [60]. Another Brazil study suggests that the number of Covid-19 confirmed cases were mainly related to the number of arriving flights and population density, and cases kept increasing with both factors [61].

This study has taken considerable time to cover Nigeria's two seasons. This is an edge and an additional contribution to the body of knowledge that is already in existence on the impact of atmospheric temperature and population on the covid-19 spread. However, this study did not consider preventive practices within the State and the population of the State and how committed each state is to enforcing these measures. This is another factor affecting the number of cases associated with each State.

In conclusion, COVID-19 is no longer a new infection, as many studies have scrutinized its understanding of transmissibility and susceptibility. The findings in this research affirm the long-time existing relationship between the cumulative confirmed cases and population size. This implies that the rapid spread of Covid-19 might be experienced in states with high population sizes. The weak positive correlation between cumulative confirmed cases of covid-19 and population size helps us understand how some states with a comparable population size may suffer differently in the transmission rates of COVID-19. States and Cities that are densely populated need to take note, especially as the third world wave of Covid-19 beacons with some indications.

The findings in this study also establish a degree of relationship between the cumulative confirmed cases of covid-19 and atmospheric temperature. The weak negative correlation suggests high temperature might reduce the spread of the disease but ascertains the possibility of the variation of COVID-19 rate of transmission within the circle of states with a similar degree of hotness and coldness in the atmosphere. This study further reveals how misleading it can be when the Ordinary Least Square estimation method is used to estimate parameters in a linear regression model, especially when there are obvious outliers in the datasets.

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Conflicts of Interest

The authors declare no competing interests.

Authors' Contributions

ATO, OJO and **WAK** conceived and designed the study, contributed analysis tools and performed analysis. **JII** and **WAK** collected the data wrote the paper, proof read the text, provided input and recommendations for improving the article. All authors read and approved the final manuscript.

REFERENCES

1. Ksiazek TG, Erdman D, Goldsmith CS, Zaki SR, Peret T, Emery S, et al. A Novel Coronavirus Associated with Severe Acute Respiratory Syndrome. N Engl J Med. 2003:1953.
2. Zaki AM, Van-Boheemen S, Bestebroer TM, Osterhaus ADME, Fouchier RAM. Isolation of a novel coronavirus from a man with pneumonia in Saudi Arabia. PubMed. 2012; 367(19): 1814-1820.
3. Zhou P, Yang X, Wang X, Hu B, Zhang L, Zhang W et al. A pneumonia outbreak associated with a new coronavirus of probable bat origin. Nature. 2020; 579(7798): 270-273
4. Giordano G, Blanchini F, Bruno R, Colaner P, Filippo AD, Matteo AD et al. Modelling the Covid-19 epidemic and implementation of population-wide intervention in italy. Nature Medicine. 2020; 26: 855-860.
5. Guo Y, Cao Q, Hong Z, Yan Y, Chen S, Jin H et al. The origin, transmission and clinical therapies on coronavirus disease 2019 (COVID-19) outbreak –an update on the status. Military Medical Research. 2019; 7(1): 1-10.
6. Ayinde K, Lukman AF, Rauf RI, Alabi OO, Okon CE, Ayinde OE. Modelling Nigerian Covid-19 cases: A comparative analysis of models and estimators. Chaos, Solitons and Fractals. 2020; 138: 109911.
7. Ayanshina OA, Adeshakin AO, Afolabi LO, Adeshakin FO, Alli-Balogun GO, Yan D et al. Seasonal variations in Nigeria: understanding COVID-19 transmission dynamics and immune responses. Journal of Global Health Reports. 2020; 4, e2020084.
8. World Health Organization. Coronavirus (COVID-19) events as they happen. 2020; https://www.who.int/emergencies/diseases/novelcoronavirus-2019/events-as-they-happen
9. Xiang Y, Li W, Zhang Q, Jin Y, Rao W, Zeng L et al. Timely research papers about COVID-19 in China. The Lancet. 2020; 395(10225): 684-685.
10. Miller IF, Becker AD, Grenfell BT, Metcalf CJE. Disease and healthcare burden of COVID-19 in the United States. Nat Med. 2020; 1-6.

11. Boccia S, Ricciardi W, Ioannidis JPA. What Other Countries Can Learn From Italy During the COVID-19 Pandemic. JAMA Intern Med. 2020: 180(7); 927-928.
12. Tang X, Wu C, Li X, Song Y, Yao X, Wu X et al. On the origin and continuing evolution of SARS-CoV-2. Natl Sci Rev. 2020; 7(6): 1012-1023.
13. Agusi ER, Ijoma SI, Nnochin CS, Njoku-Achu NO, Nwosuh CI, Meseko CA. The COVID-19 pandemic and social distancing in Nigeria: ignorance or defiance. The Pan African Medical Journal. 2020; 35(2): 52.
14. Raut MK. Global age-specific denominator estimation for monitoring of health and nutrition SDGs and indicators based on population projections of the UN world population prospects, 2017 revision, for the year 2018. Int J Community Med Public Health. 2019; 6(1): 177-189.
15. Lina B, Baba-Hamed K, Bouanani A. Characterization of the climatic drought indices application to the Mellah catchment, north-east of Algeria. J Water Land Dev. 2019; 43: 28–40.
16. Ihekweazu C and Agogo E. Africa's response to COVID-19. BMC Medicine. 2020; 18(1): 1-3.
17. Moriyama M, Hugentobler WJ, Iwasaki A. Seasonality of respiratory viral infections. Annual Review of Virology. 2020; 7: 83-101.
18. Wu X, Lu Y, Zhou S, Chen L, Xu B. Impact of climate change on human infectious diseases: Empirical evidence and human adaptation. Environ Int. 2016; 14-23.
19. Tan J, Mu L, Huang J, Yu S, Chen B, Yin J. An initial investigation of the association between the SARS outbreak and weather: with the view of the environmental temperature and its variation. Journal of Epidemiology & Community Health. 2005; 59(3):186–192.
20. Dowell S. Seasonal variation in host susceptibility and cycles of certain infectious diseases. Emerg Infect Dis. 2001; 7(3): 369-374.
21. Chan KH, Peiris JS, Lam SY, Poon LL, Yuen KY, Seto WH. The effects of temperature and relative humidity on the viability of the SARS coronavirus. Adv Virol. 2011; 734690,.
22. Araújo MB, Naimi B. Spread of SARS-CoV-2 Coronavirus likely to be constrained by climate. medRxiv. 2020; https://doi.org/10.1101/2020.03.12.20034728
23. Dowell SF, Ho MS. Seasonality of infectious diseases and severe acute respiratory syndrome-what we don't know can hurt us. Lancet Infect Dis. 2004; 4(11): 704–708.
24. Fouque F, Reeder JC. Impact of p ast and on-going changes on climate and weather on vector-borne diseases transmission: A look at the evidence. Infect Dis Poverty. 2019; 8(1): 1-9
25. Lowen AC, Mubareka S, Steel J, Palese P. Influenza virus transmission is dependent on relative humidity and temperature.PLos pathogens. 2007; 3(10): e151.
26. Yao Y, Pan J, Liu Z, Meng X, Wang W, Kan H et al. No association of COVID-19 transmission with temperature or U.V. radiation in Chinese cities. European Respiratory Journal. 2020; 55(5), 2000517.
27. Caspi G, Shalit U, Kristensen SL, Aronson D, Caspi L, Rossenberg O et al. Climate effect on COVID-19 spread rate: an online surveillance tool.medRxiv preprint. 2020; https://doi.org/10.1101/2020.03.26.20044727
28. Ma Y, Zhao Y, Liu J, He X, Wang B, Fu S, Yan J, Niu J, Zhou J, Luo B. Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. Science of the Total Environment. 2020; 724:138226.
29. Glew RH, Crossey MJ, Polanams J, Okolie HI, Vander J. Vitamin D Status of Seminomadic Fulani Men and Women. J Natl Med Assoc. 2010; 106(2): 485-490.
30. Owie E, Afolabi BB. Vitamin D deficiency in pregnant women and newborns in Lagos, Nigeria. Journal of Obstetrics and Gynaecology. 2018; 38(5): 616-621.
31. National Centre for Disease Control. COVID-19 case update. 2020; https://covid19.ncdc.gov.ng
32. Chan JF-W, Yuan S, Kok K, To K, Chu H, Yang J et al. A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: A study of a family cluster. The Lancet. 2020; 395 (10223): 514-523.
33. Ogaugwu C, Hammed MH, Ogaugwu E, Uchechukwu NU, Okoh H, Agbo S et al. Effect of Weather on COVID-19 Transmission and Mortality in Lagos, Nigeria. Hindawi, Scientifica. 2020; https://doi.org/10.1155/2020/2562641
34. Fang W, Wahba S. Urban density is not an enemy in the coronavirus fight: evidence from China.World Bank Blogs. 2020; https://blogs.worldbank.org/sustainablecities/urban-density-not-enemy-coronavirus-fight-evidence-china.
35. Babbit D, Garlant P, Jonhson O. Lived population density and the spread of COVID-19. arXiv preprint. 2020; arXiv:2005.01167
36. Bouda-Olga O. La densité favorise-t-elle l'épidémie. 2020. https://blogs.univ-poitiers.fr/o-bouba-olga/2020/04/29/la-densite-favorise-t-elle-lepidemie-episode-26/
37. Coşkun H, Yıldırım N, Gündüz S, The spread of COVID-19 virus through population density and wind in Turkey cities. Science of the Total Environment. 2021; 751: 141663.
38. Reuben RC, Danladi MMA, Saleh DA, Ejembi PE. Knowledge, Attitudes, and Practices Towards COVID-19:

An Epidemiological Survey in North-Central Nigeria. J Community Health. 2020; 46(3): 457-470.

39. Rosenthal B. Density is New York City's big "enemy" in the coronavirus fight. The New York Times. 2020; https://www.nytimes.com/2020/03/23nyregion/coronavirus-nyc-croowds-density.html
40. Olsen H. The United States might have a secret weapon against coronavirus. The Washington Post. 2020; https://www.washingtonpost.com/opinions/2020/03/19/united-states-might-have-secret-weapon-against-coronavirus/
41. Weather Spark. The Weather Year Round Anywhere on Earth. https://weatherspark.com
42. National Bureau of Statistics. Population by State and Sex. Demographic Statistics Bulletin. 2017; https://nigeriastat.gov.ng
43. Lukman AF, Ayinde K. Review and classifications of the ridge parameter estimation techniques. Hacet J Math Stat. 2017; 46(5): 953–967.
44. Dawoud I, Abonazel MR. Robust Dawoud–Kibria estimator for handling multicollinearity and outliers in the linear regression model. Journal of Statistical Computation And Simulation. 2021; 91(17): 3678-3692
45. Huber P. Robust estimation of a location parameter. Annals of Mathematical Statistics. 1964; 35: 73–101.
46. Rousseeuw PJ, Leroy AM. Robust Regression and Outlier Detection, New York. Wiley-Interscience. 1989; 31(2): 260
47. Peter JB, Doksum K, Hodges JL. A Festschrift for Erich L Lehmann. 1983; https://www.routledge.com/A-Festschrift-For-Erich-L-Lehmann/Bickel-Doksum-Hodges/p/book/9780534980443
48. Alma OG. Comparison of robust regression methods in linear regression. Int. J. Contemp. Math. Sciences. 2011;6 (9): 409-421.
49. Osborne JW, Overbay A. The power of outliers (and why researchers should always check for them) Practical Assessment. Research & Evaluation. 2004; 9(6): https://doi.org/10.7275/qf69-7k43
50. Heckman J. Sample selection bias as a specification error. Econometrica. 1979; 47: 153–161.
51. Maronna RA, Martin RD, Yohai VJ. Robust statistics: Theory and methods (with R), 2nd Edition. Chichester: John Wiley & Sons. 2006.
52. Conover W. Practical Nonparametric Statistical, New York. John Wiley & Sons Inc. 1999. 428-433.
53. Ogaugwu C, Mogaji H, Ogaugwu E, Nebo U, Okoh H, Agbo S et al. Effect of Weather on COVID-19 Transmission and Mortality in Lagos, Nigeria. Scientifica (Cairo). 2020; doi: 10.1155/2020/2562641.
54. Hassan Z, Hashim M.J, Khan G. Population risk factors for COVID-19 deaths in Nigeria at sub-national level. Pan African Medical Journal. 2020; 35(Suppl 2): 131: doi: 10.11604/pamj.supp.2020.35.131.25258
55. Tosepu R, Gunawan J, Effendy DS, Ahmad LOAI, Lestari H, Bahar H et al. Correlation between weather and Covid-19 pandemic in Jakarta, Indonesia. Science of the Total Environment. 2020; doi.org/10.1016/j.scitotenv.2020.138436
56. Qi H, Xiao S, Shi R, Ward MP, Chen Y, Tu W et al. COVID- 19 transmission in Mainland China is associated with temperature and humidity: a time-series analysis. Sci Total Environ. 2020; doi.org/10.1016/j.scitotenv.2020.138778
57. Wu Y, Jing W, Liu J, Ma Q, Yuan J, Wang Y et al. Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. Sci Total Environ. 2020; doi.org/10.1016/j.scitotenv.2020.139051
58. Hamidi S, Sabouri S, Ewing R. Does Density Aggravate the COVID-19 Pandemic?. Journal of the American Planning Association. 2020; 86(4):495-509.
59. Demongeot J, Flet-Berliac Y, Seligmann H. Temperature decreases spread parameters of the new COVID-19 case dynamics. 2020; 9:94.
60. Ahmadi M, Sharifi A, Dorosti S, Ghoushchi SJ, Ghanbari N. Investigation of effective climatology parameters on COVID-19 outbreak in Iran. Science of the Total Environment. 2020; doi: 10.1016/j.scitotenv.2020.138705
61. Pequeno P, Mendel B, Rosa C, Bosholn M, Souza JL, Baccaro F, Barbosa R, Magnusson W. Air transportation, population density, and temperature predict the spread of COVID-19 in Brazil. PeerJ. 2020; 8: e9322