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Assessment of COVID-19 Pandemic using Multivariate Data Analysis: A Case for Nigeria

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Authors' contributions

This work was carried out in collaboration among all authors. All authors took part in the visualization, data gathering, data analysis, and Statistical methodology. Authors AN and UN wrote the initial draft, while authors CA and MO wrote the literature review. All authors read and approved the final manuscript.

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Short Research Article

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ABSTRACT

Background: The reduction of dataset dimensions for better presentation, visualization, postulation testing, and clarification has not been reported by researchers in Nigeria COVID-19 cases. To realize the impact and magnitude of coronavirus (COVID-19) pandemic, univariate statistical analysis is monotonous in describing daily reported datasets. However, to truly understand the events and contrasting outcomes for different states in developing nations like Nigeria, multivariate analytical tools were applied to envisage and differentiate states more specifically and precisely. We made use of data analysis tools that can display the arrangement of data points in fewer proportions while keeping the dissimilarity of the original data to a feasible extent, and cluster states according to their results on the established proportions.
Methods: Pearson's correlation coefficient, principal component analysis, and hierarchical cluster analysis analyzed the data from 36 states of Nigeria and the FCT-Abuja; with COVID-19 cases for 6 months, eligible states included in the analysis are those with total cases of 20 or more with no irregular data.
Results: After performing Pearson's correlation coefficient, it reveals that the month of July, August, and October correlated with the discharged cases and active cases among the states but increased

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in the last quarter of 2020. The principal component analysis identified that total death emerged as the principal component for Lagos state was from October through December while Delta, Edo, Rivers, and Kano state were behind. Hierarchical cluster analysis associated the EndSars protest to have equally contributed to the striking clusters in some other states like Rivers, Enugu and Delta.
Conclusions: In summary, accurate multivariate analyses have shown to be of great value and can simplify concepts, impacts, communicate research findings, and reinforce decision-taking and public-policy drivers.

Keywords: Clustering; public health; applied mathematics; virology.

1. INTRODUCTION

It is very necessary to constantly record and report public health information for a better apprehension of disease, viral transmission, geographic area, endangerment, and possible routes of disease transmission. Secondly, it is also very pertinent to provide a baseline for ideal planning by authorities concerning epidemiological modeling to reduce disease transmission. This detailed and comprehensive information is very crucial in determining where monitoring and action should be prioritized and is the prime driver for this study [1].

This will be Addressing the public health consequeces of COVID-19 using the multivariate approach so that healthcare system in Nigeria can better understand this novel virus and a reflection of the information alreadily available to them and its statistical implications.To acquire more information and data accurately, statistical analyses with data representation are required to serve as instruments of the competent models of data science. The task of data scientists at this moment in time is more needful than before in identifying different trends, classifying different patterns, and making sense of outliers to help scientists and policymakers act more productively towards medical investigations, and precautionary public health practices and policy [2,3]. Healthcare practitioners have recognized and appreciated the value of conventional disease interpretation and prediction using several mathematical and statistical tools against the Coronavirus disease 2019 (COVID-19) outbreak, and other infectious diseases. These data visualizing and interpreting tools are of great value and have been in use before now with greater potential to remain potent, and more accurate in data analysis in the future like in the COVID-19 outbreak, hepatitis disease, and Ebola diseases [4–6].

During this COVID-19 outbreak, there have been many reported clinical outcomes from different states in many nations of the world affected by COVID-19 like the USA and the U.K. These outcomes are anticipated to have possible correlations with each other [7,8]. Multivariate analysis is applied to elucidate interactions amid the existing variables in the data set. This allows the reduction of dataset dimensions for better presentation, visualization, postulation testing, and clarification between the datasets. Thus scientists have improved perception towards the reported data from different states like the research findings in Wuhan, China, and Milan, Italy [9,10].

The current study, therefore, aims to apply the conventional multivariate statistical procedures, (Pearson's correlation coefficient PCC, principal component analysis PCA and hierarchical cluster analysis HCA) for structured representation and relative inference of COVID-19 status in different states of Nigeria. We performed PCC to study many factors at once and explain the variation; PCA is to maximize the variance of a linear combination while HCA is achieved under certain conditions, but a choice for pattern recognition. The multivariate tools analyzed four originally reported variables (confirmed cases, discharged cases, total deaths, and active cases) by the Nigerian Center for Disease Control (NCDC). The paper methodology is presented as a brief theoretical explanation of PCA, PCC, and HCA and the fundamentals of factor analysis in section 2. Section 3 describes the tabulated data, numerical and graphical results with discussions, and conclusions are presented in section 4. Hence, the study will be able to categorically group the datasets and better explain the different status of the states in Nigeria affected by the COVID-19 pandemic [11,12]

2. MATERIALS AND METHODS

In this study, the team got the appropriate and regularly updated COVID-19 data from the Nigerian center for disease control (NCDC) website [13] for 31 July, 31 August, 30

September, October 31, November 28, December 31, of 2020. Data were captured on the last three days of selected months to these specified dates. States with active COVID-19 cases less than 20 were omitted from the study to obtain a representative sampling of the variable.

The number of states included in the study was 36 states and capital. Data for handling and study were carried out using Microsoft Excel and Origin 9.0 Software. The cumulative cases of COVID-19 from all the states were also obtained from NCDC 2021 data [13,14].

Pearson's Correlation coefficient (PCC) was achieved using Microsoft Excel.15 From the excel sheet, the correlation coefficient (r) was determined using the Pearson's function, followed by the number of pairs in the data which is (N), and degrees of freedom as (DF). T-statistics was calculated to create the p-value by using the formula shown in equation 1 below:

$$t = \frac{((r \times SQRT\ (n-2))}{(SQRT\ 1-r^2)} \qquad \text{Eqn 1}$$

While The P-value was calculated using the TDist function of excel. Principle component analysis (PCA) was carried out using Origin 9.0 64bit [15,16].

The researchers used the representative designation for each of the studied variables which include; in any given state, Confirmed cases (CC) refers to total cases confirmed with COVID-19; Active cases (AC) refers to the total number of open cases including mild, serious, and critical; Total death (TD) refers to the total number of deaths with COVID-19 in the states and Discharge cases (DC) refers to the total number of discharged cases in each state. The contribution from each variable was divided by the datasets into subsets and application of verimax rotation to form new variables which are reduced to principal components after rotation. The calculated Eigenvalues will provide information on the total number of PCA to be considered and account for a significant part of the variance in the variable. Moreover, the contributions can be visualized in the plotted scatter plots of the principal components. The PCA will identify linear combinations of perceived variables being a factor that underlines the pattern of interdependences in the plotted correlation matrix [17,18].

In this study, the team also carried out hierarchical cluster analysis (HCA) [19,20]. The cluster analysis will split the given data set into a number with unique observations and characteristics concerning common attributes of the group. The HCA is expected to increase between-group variance and reduce within variance in the same group. A singular convenience is that any number of variables in consideration can be applied in the grouping of members of the same sample [21,22]. The HCA was plotted using column and bar dendrogram plot type instead of the regular line/scatter dendrogram to identify the variance that relates with each other across the states. Furthermore, we took datasets from the 3rd quarter of the year 2020 and compared them with the 4th quarter of the same year 2020 for all states owing to the availability of their data, and highlights of the data are given below in Table 1.

Table 1. Cumulative summary of monthly Covid-19 data from Nigeria center for disease control

	July	August	September	October	November	December
Sample tested	283, 916	405, 916	519, 140	659663	776,768	975,786
Confirmed cases	43, 151	54,008	58,848	62,964	67,412	90147
Affected states	37	37	37	21	17	27
Discharged cases	19,565	41,638	50,358	58790	63,055	75,044
Confirmed fatalities	879	1013	1112	1146	1173	1311
Demography	65 % male 35 % Female	64 % male 36 % Female	64 %male 36 % Female	UR	UR	UR
Persons of interest	11, 197	11, 622	27, 594	UR	UR	UR
Most affected age groups	31-40 (25%)	31-40 (25%)	31-40 (25%)	UR	UR	UR
Travel history	804 (2%)	850 (1%)	1,001 (1.7%)	< 10	<60	<65
Contacts	10, 621 (25%)	12, 778 (24%)	15, 527 (26.7%)	UR	UR	UR
Unknown exposure	31, 726 (73%)	40, 380 (75%)	42, 320 (71.6%)	UR	UR	UR

3. RESULTS AND DISCUSSION

Based on the official reports, the first COVID-19 reported case in Nigeria was an Italian who flew into Nigeria from Italy on the 25th of February 2020. Consequently, the virus began to spread and the number of cases continued to rise from February to December of the same year. Accordingly, table 1 described the highlights of COVID-19 data obtained from published facts and figures of NCDC. Most of the variables gradually increased from July to December due to previous under-reporting and insufficient testing facilities. As of December 31 of 2020, Nigeria had 975,786 COVID-19 samples tested across the states which returned 90,147 confirmed cases as CoVID-19 careers and typically described as "imported COVID-19" [23,24].

The month with the lowest Coronavirus cases across the six months was in November but invariably had the highest level of confirmed fatalities. By October through December, the partial lockdown in Nigeria had begun paying off as the travel history significantly decreased to less than ¼ of 1 % of total cases. Demography report also showed that more males were COVID-19 careers than females owing to the significant roles of males during the pandemic who were at higher risk on daily COVID-19 incidence in Nigeria [25].

On the contrary, a study revealed that among 300 COVID-19 cases studied in Japan, the median age for high infection rate in Japan was 68 years, and 59 % more females had COVID-19 infectious disease while only 41 % of males were infected [26]. Hence, gender is not a significant factor in COVID-19 transmission.

Table 2-3 describes the Pearson's correlation coefficient for the variables for the 3rd quarter and 4th quarter, of 2020. The number of distributions (N) decreased from 30 in July, to 29 in August and 17 in September. The converse was observed in the last quarter from October (18) to November (20) and December (33). It shows that the number of affected states decreased in the 3rd quarter of 2020 but increased in the 4th quarter of 2020. The reason is because of individuals traveling across the states for Christmas and end of the year celebrations potentially impact several activities relating to Christmas worldwide, including thanksgiving, shopping, parties, and anniversaries, lunar New Year, and church services [27,28].

Furthermore, the table reveals that during the month of July, August, and October the discharged cases (DC) and active cases (AC) had a moderate correlation, while the total death (TD) and active cases (AC) in August also had a moderate correlation. All other calculated PCC showed either a strong correlation (0.70-0.89) or a very strong correlation (0.90-0.10), hence indicating a strong link between the recorded variables. Similar research also observed a strong correlation link between the disease severity and some biochemical characteristics and concluded that to prevent or reduce strong correlations; for instance, between confirmed cases (CC) and total death (TD), the critical stage of the virus infection should be closely monitored and possibly prevented [29]. It is also commonly accepted that a p-value ≤ 0.05 shows a significant correlation and a p-value > 0.05 is not a significant correlation. Observation from tables 2 and 3 shows that all calculated p values were less than 0.05. Therefore it provided reliable information that the given data sets are normally distributed and are statistically significant correlations as similarly observed by a research paper that studied the predictability of COVID-19 in the USA [30].

We used the verimax rotation criteria to obtain new variable varifactors for the principal component analysis taking into consideration, two principal components. From Figure 1, it is observed that principal component 2 retained most of the variables. Also in July, Rivers, Delta, Kano, Ogun, and Oyo states had discharged cases as the main component for the month, while FCT had total death as a very significant principal component. By the month of August, Plateau and Oyo had the most significant active cases of COVID-19, while Rivers and Edo simultaneously had total death and active COVID-19 cases as the primary component in August. Oyo and Plateau states had more active cases in September, while Rivers and FCT showed the highest confirmed cases as their principal component.

Table 2. Pearson's correlation coefficient parameters for the 3rd quarter of the year 2020

		CC/DC	CC/TD	CC/AC	DC/TD	DC/AC	TD/AC
JULY	Coefficient	0.70	0.94	0.98	0.80	0.56	0.88
	N	30.00	30.00	30.00	30.00	30.00	30.00
	T statistic	5.20	14.15	28.44	7.10	3.56	9.91
	DF	28.00	28.00	28.00	28.00	28.00	28.00
	P value	1.62E-05	2.78E-14	3.35E-22	9.99E-08	1.34E-5	1.16E-10
AUGSUT	Coefficient	0.98	0.91	0.74	0.92	0.59	0.58
	N	29.00	29.00	29.00	29.00	29.00	29.00
	T statistic	25.57	11.65	5.70	12.37	3.80	3.67
	DF	27.00	27.00	27.00	27.00	27.00	27.00
	P value	1.84E-20	4.83E-12	4.6E-06	1.23E-12	7.4E-05	1.4E-04
SEPTEM ETR	Coefficient	1.00	0.92	0.98	0.94	0.96	0.85
	N	17.00	17.00	17.00	17.00	17.00	17.00
	T statistic	67.65	9.38	17.15	10.28	13.51	6.16
	DF	15.00	15.00	15.00	15.00	15.00	15.00
	P value	4.60E-20	1.15E-07	2.88E-11	3.46E-08	8.41E-10	1.81E-05

AC: active cases, CC: confirmed cases, DC: Discharged cases, TD: Total death,

Table 3. Pearson's correlation coefficient values for 4th Quarter of the year 2020 Covid-19 data

		CC/DC	CC/TD	CC/AC	DC/TD	DC/AC	TD/AC
October	Coefficient	1.00	0.93	0.64	0.93	0.61	0.56
	N	18.00	18.00	18.00	18.00	18.00	18.00
	T statistic	94.54	9.94	3.35	9.92	3.07	2.68
	DF	16.00	16.00	16.00	16.00	16.00	16.00
	P value	2.04E-23	2.99E-08	4.07E-04	3.05E-08	7.28E-04	1.63E-03
Novemb er	Coefficient	1.00	0.97	0.88	0.97	0.87	0.85
	N	20.00	20.00	20.00	20.00	20.00	20.00
	T statistic	189.38	18.50	7.73	18.22	7.33	6.99
	DF	1.00	0.97	0.88	0.97	0.87	0.85
	P value	3.73E-31	3.69-13	4.00E-07	4.79E-13	8.25E-07	1.57E-06
Decembe r	Coefficient	0.99	0.92	0.88	0.92	0.83	0.79
	N	33.00	33.00	33.00	33.00	33.00	33.00
	T statistic	54.48	13.33	10.48	13.30	8.31	7.12
	DF	31.00	31.00	31.00	31.00	31.00	31.00
	P value	2.38E-32	2.24E-14	1.03E-11	2.39E-14	2.16E-09	5.32E-08

By the last quarter of the year 2020, FCT and Oyo had active cases from October to December as the principal component despite having targeted lockdown and other preventive measures. Hence regardless of lockdown or festive activities, a similar work identified that at this point, the government had failed to implement an all-inclusive palliative scheme to make people remain indoors and reduce the spread of COVID-19 [31]. Additionally, there was the need for effective engagement of community health workers and enabling a workplace environment for essential workers to reduce the chances of occupational exposure at this stage [32]. Interestingly, Lagos stood out as having total death (TD) as the principal component from October through December, though havingDelta, Edo and Rivers, and Kano trailing behind. The reason might not be far-fetched. According to a recent work that studied empirical links between Covid-19 situation report and available data in Nigeria, Lagos and Abuja have the highest infectious rate in Nigeria, of 11 per 10,000 population and an operational international airport, while Kano and Rivers trailing behind had correspondingly, higher population than Northwest and South-south regions of Nigeria, with operational local flights. Therefore community engagement, population, and migration play an important role in reducing infectious transmission of COVID-19 [33].

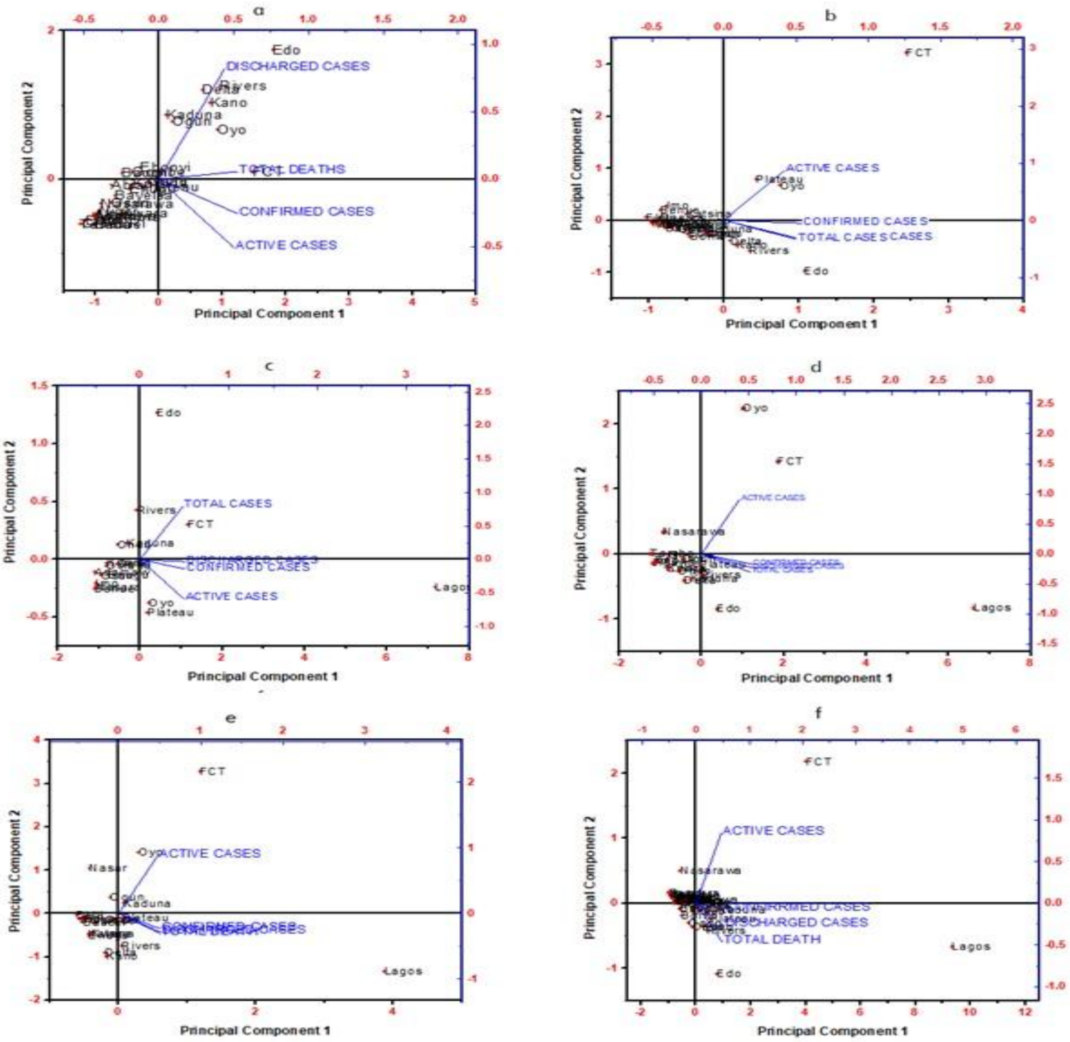

Fig. 1. Principal component analyses plot for COVID-19 data from NCDC; (a) July; (b) August, (c) September; (d) October; (e) November; (f) December

From the extracted Eigenvalues, the coefficient of principal component 1 shows the presence of 60 to 80 % of states in the 3rd quarter and about 40 to 65 % in the 4th quarter. Hence, the primary concern within these clusters will be population behavior, population density, host susceptibility, and social distancing. However the forecast from the behavior of principal component 1, and principal component 2, in the 3rd and 4th quarter of the year 2020 shows that the pandemic has been reached its peak and will start decreasing slowly over the forthcoming months if the proper management scenario is put in place [34].

Hierarchical Cluster analysis (HCA) was applied as a multivariate tool towards finding' patterns and groupings that exist among the states over COVID-19 cases. The groupings and patterns within the dataset represent the distance (variables) while the states represent the directions, and create several unique observations of certain common attributes or values of the group. We adopted the bar and column cluster plot from Origin 9.0 to maximize the variance between groups and to reduce variance in the same group as can be seen in Figure 2. Each of the sub-figures represents the different months of the year from July through December. The initial remark shows that the figures divided the studied variables into two main groups.

The first-three figures of 2(a), (b), and (c) had the biggest clusters around the initial observations towards the left-hand side, while the last three cluster figures of 2 (d), (e), and (f) had largest clusters towards the right-hand side. Thus it was possible to classify Nigerian states using HCA into possible cluster groups [35]. During July, It was observed that Lagos and Ogun formed the 1st cluster 1 in July, while Lagos and Rivers continued as the Cluster 1 (C1) in August, September, and November. Another Significant state was Kaduna which formed cluster 1 in October and December. These show that during the study period, Lagos, Rivers, Ogun, and Kaduna states had closely matched similarities among the variance; confirmed cases, discharged cases, total death, and active cases regardless of the projected/reported data. Cluster 2 (C2) had states like Oyo, Kaduna, FCT, Enugu, Ondo, Delta as the closely grouped variance. Interestingly, FCT and Ondo pair repeatedly appeared in September, November, and December. Then again, FCT paired with Kaduna in July, Enugu in September, and Delta in October. FCT is also the capital territory within Abuja the nation's capital and air travel had remained dominant more than other state airports. Accordingly, it is also noted that there seems to have been a hurried attempt to reopen the economy within the first 100 days [36]. They also observed that despite Lagos accounting for over 50 % of COVID-19 cases, and Abuja accounting for about 20%, they continued to run as the trade and administrative hubs of the nation [36,37].

On the other hand, Lagos and Abuja became the centers of protest activities against indiscriminate shootings and killings by Nigerian police tagged ENDSARS protest in Nigeria [38]. This also spiked up reported cases in some areas and cities where protests were held. Although, the role of digital technology in the ENDSARS protest fueled and coordinated the protest [39]. However, COVID-19 is a transmittable and pathogenic viral infection; hence the protest equally increased the transmission rate of COVID-19 that led to dramatic clusters in figure 2 together with some other high areas of protest like Rivers, Enugu, and Delta states [40]. Cluster 3 and cluster 4 had states like Edo, Osun, Gombe, Taraba, Oyo Yobe, and Jigawa states which occupied less than 20 % of the distance in the graph among the months, hence they were insignificant when compared to cluster 1 and cluster 2 that occupied over 75 % of the entire groupings. Therefore, this highlighted the importance of cluster analysis in identifying the factors that increase the risk of COVID-19 [41].

From the study above, It is now clear that COVID-19 pandemic will live with us for longer periods with unprecedented challenges. Likewise, the result of the data study showed that the Nigerian government did not perform badly. However, there are still opportunities for collective action to be initiated against coronavirus to reduce as much as possible any foreseeable and unforeseeable consequences on the economy, infrastructures, health and societal cost in terms of well-being.

This becomes imperative as Nigeria local-economy in Nigeria is yet to fully recover plus the accompanying steep rise and fall in oil prices driving unprecedented inflation. Hence, the current study has also identified the need for the oil and gas dependent economy to diversify its economy and advance its health care system. This as predicted by this study will cause any induced impacts to be sharp but short-lived, while economic and healthcare activities would return to normal thereafter with very minimal death cases.

4. CONCLUSIONS

In utilizing the multivariate analysis technique, the study simplified complex data using statistical tools (PCC, PCA, and HCA) that aided in the visualizing impact and magnitude of a given state or cluster of states. COVID-19 monthly published data for each state were summarized and reduced and efficiently interpreted. PCC showed that nearly all the calculated p-value were less than 0.05 and significant. HCA showed that Lagos, Rivers, Ogun and Kaduna had closely matched similarities among the variance, while the PCA identified that the pandemic has reached its peak, and that confirmed cases will decrease slowly if the proper management actions are put in place, hence, a relieve to healthcare systems and policy-makers. Moreover, reopening the economy within the first 100 days increased the COVID-19 infection rate in the administrative capital (Abuja) and commercial capital (Lagos) of Nigeria. Furthermore, the Eigenvalues captured the peak period and by prediction indicated that a decrease of infection will be observed over the forthcoming periods if effective preventive and control measures are implemented.

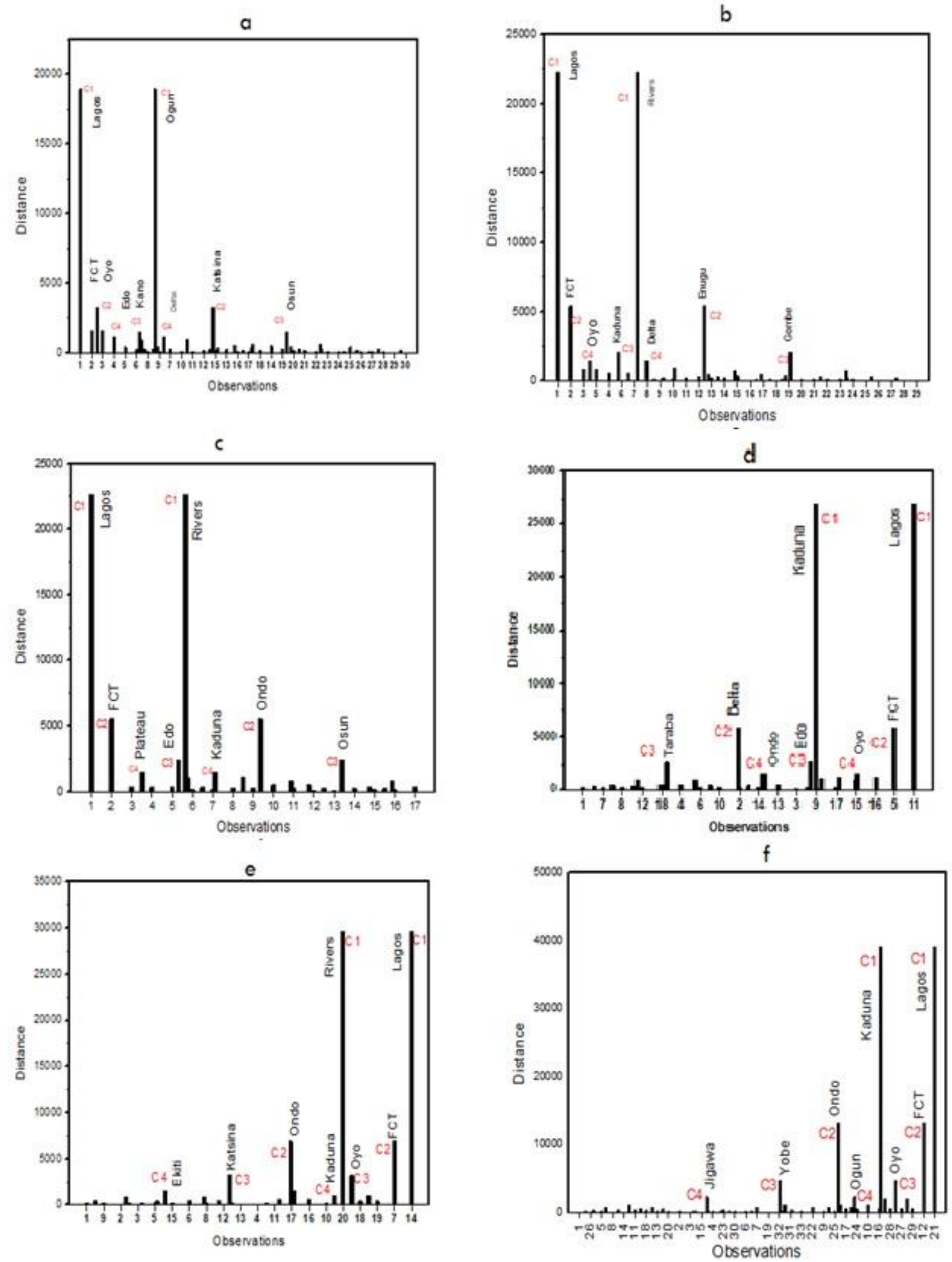

Fig. 2. Hierarchical cluster analysis plot for COVID-19 data from NCDC; (a) July; (b) August, (c) September; (d) October; (e) November; (f) December

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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