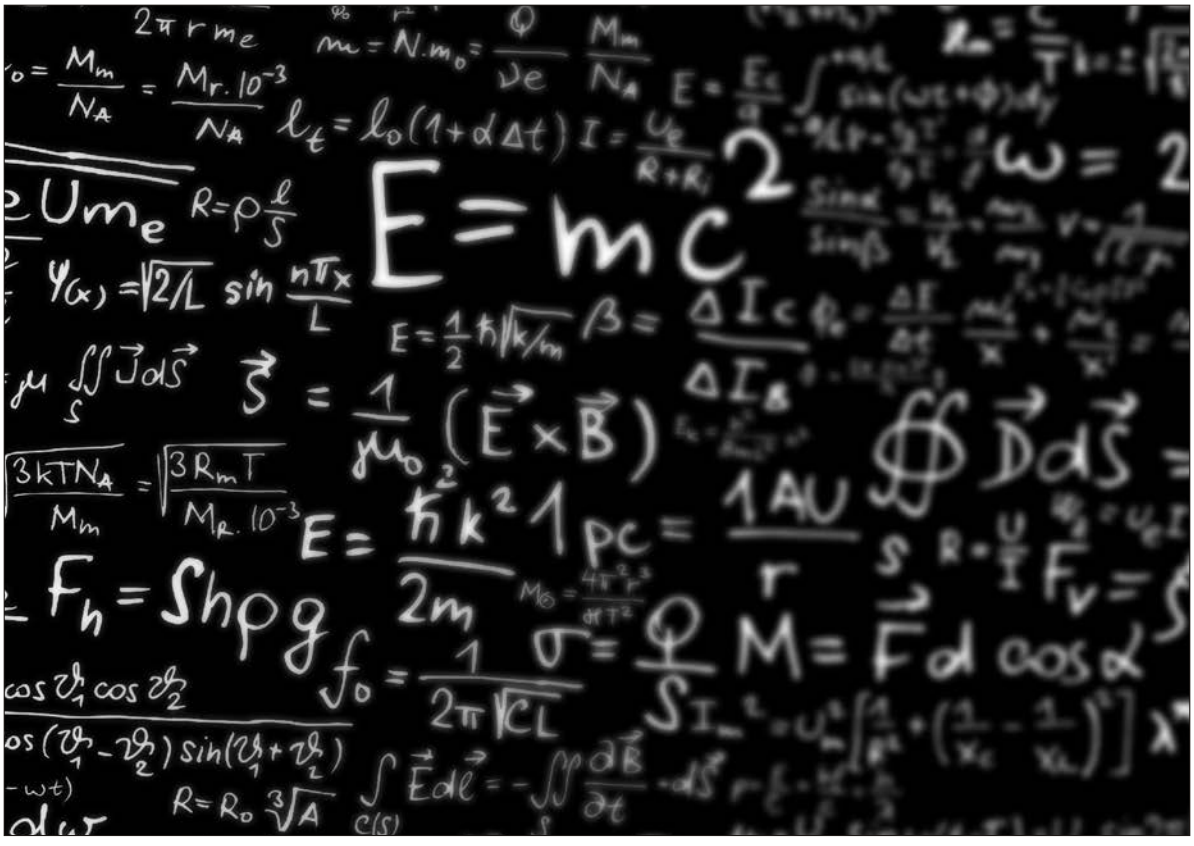

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Research Article
Estimation of Spatial Effects of COVID-19 in Africa: Spatial Panel Data Model (SPDM) Approach

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Abstract

Background and Objective: Data containing time-series observations of several spatial units are treated best using spatial panels this is because panel data offers extended modelling possibilities to researchers as compared to the single equation cross-sectional procedures, which was the primary focus of the spatial statistics as contained in the literature for a long time. This study estimated the spatial effect of COVID-19 in Africa by exploring the factors influencing the rate of confirmed cases and examining the spatial spillover effects of COVID-19 within the African continent and interpreting the most efficient and consistent model with direct and indirect spatial effects. **Materials and Methods:** The study considered the spatial effect of COVID-19 in Africa using the Spatial Panel Data Models (SPDM) approach. The COVID-19 data on 54 countries in Africa with confirmed cases of COVID-19 as of 12th May, 2020 were extracted from the COVID-19 dashboard of the Center for Systems Science and Engineering at the John Hopkins University (CSSE, JHU). **Results:** The study revealed a daily increase in the rate of confirmed cases and that an increase of 0.1527 per 100,000 people is expected in the coming weeks in Africa if the pattern of spread remains constant. **Conclusion:** Conclusively, we have been able to provide information about the effect of the spread of COVID-19 across the African continent. We also gathered from the results that the rate of death and recovery from COVID-19 in Africa has a significant positive effect on the spread of the virus within the continent.

Key words: COVID-19, spatial effects, spatial panel data models, public health, modeling, health infrastructures, panel data

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Coronavirus disease (COVID-19) caused by a newly discovered novel coronavirus is an infectious disease[1]. Mild to moderate symptoms and recovery without special treatment is what most people who fall sick with COVID-19 experience[1]. The COVID-19 is mainly transmitted through droplets generated when an infected person coughs, sneezes, or exhales. These droplets are too heavy to hang in the air and quickly fall on floors or surfaces[2]. It has been discussed at different levels how one can be infected, which is majorly by breathing in the virus if you are within proximity of someone who has COVID-19 or by touching a contaminated surface and then your eyes, nose or mouth. Various strategies have since been put in place by affected countries. These included the regular use of face masks, social distancing, washing of hands regularly and staying indoors among others. Most of these strategies are difficult to implement in Africa due to our limitations in terms of health infrastructures, the culture of buying and selling, modes of transportation and bad data management policies among others.

The spatial statistics literature has maintained a growing interest in the specification and estimation of relationships based on spatial panels in recent times. Spatial panels typically refer to data containing time-series observations of several spatial units[2]. This property explained why the study adopted the use of the Spatial Panel Data Model (SPDM) since it offered an extended modelling possibility as compared to the single equation cross-sectional setting, which was the primary focus of the spatial statistics as used in econometric literature for a long time. Panel data are generally more informative and they contain more variation and less collinearity among the variables. The use of panel data results in greater availability of degrees of freedom and hence increases efficiency in the estimation. Panel data also allow for the specification of more complicated behavioural hypotheses, including effects that cannot be addressed using pure cross-sectional data[3]. With these in mind, this paper applied the spatial panel data models to determine the rate of spread of COVID-19 across the continent of Africa.

MATERIALS AND METHODS

Study area: The study was carried out at the Biostatistics Unit, Department of Statistics, University of Ibadan, Nigeria. The COVID-19 data was extracted from the COVID-19 dashboard of the Center for Systems Science and Engineering at the John Hopkins University (CSSE, JHU), sampling from 29 February to 12 May, 2020 for the 54 countries of Africa with confirmed cases of the Novel Coronavirus (COVID-19).

Spatial panel models: Consider a simple pooled linear regression model with spatial specific effects but without spatial interaction effects[4]:

$$y_{it} = x_{it}\beta+\mu_i+\varepsilon_{it} \quad (1)$$

where, i is an index for the cross-sectional dimension (spatial units), with i = 1,..., N and t is an index for the time dimension (periods), with t = 1,..., T. y_{it} is an observation on the dependent variable at i and t, x_{it} an (1, K) row vector of observations on the independent variables and β a matching (K, 1) vector of fixed but unknown parameters. The ε_{it} is an independently and identically distributed error term for i and t with zero mean and variance σ^2, while μ_i denotes a spatial specific effect. The standard reasoning behind spatial specific effects is that they control for all space-specific time-invariant variables whose omission could bias the estimates in a typical cross-sectional study. When specifying interaction between spatial units, the model may contain a spatially lagged dependent variable or a spatial autoregressive process in the error term, known as the spatial lag and the spatial error model, respectively. The spatial lag model posits that the dependent variable depends on the dependent variable observed in neighbouring units and on a set of observed local characteristics:

$$y_{it} = \delta\sum_{j=1}^{N} w_{ij}y_{jt} + x_{it}\beta + \mu_i + \varepsilon_{it} \quad (2)$$

where, δ is called the spatial autoregressive coefficient and w_{ij} is an element of a spatial weights matrix W describing the spatial arrangement of the units in the sample. It is assumed that W is a pre-specified non-negative matrix of order N2. Baltagi *et al.*[5] studied the spatial lag model which was typically considered the formal specification for the equilibrium outcome of a spatial or social interaction process, in which the value of the dependent variable for one agent is jointly determined with that of the neighbouring agents.

The spatial error model, on the other hand, posits that the dependent variable depends on a set of observed local characteristics and that the error terms are correlated across space:

$$y_{it} = x_{it}\beta+\mu_i+\varphi_{it} \quad (3)$$

$$\varphi_{it} = \rho\sum_{j=1}^{N} w_{ij}\varphi_{it} + \varepsilon_{it} \quad (4)$$

where, φ_{it} reflects the spatially autocorrelated error term and ρ is called the spatial autocorrelation coefficient. Baltagi *et al.*[5] also noted that a spatial error specification does not require a theoretical model for a spatial or social interaction process, but, instead, it's a special case of a non-spherical error covariance matrix. In the empirical literature on strategic interaction among the outcome variables such as confirmed cases, reported deaths and discharged/recovered persons, the spatial error model is consistent with a situation where independent variables omitted from the model are spatially autocorrelated and with a situation where unobserved shocks follow a spatial pattern.

In both the spatial lag and the spatial error model, stationarity requires that $1/\omega_{min}<\delta<1/\omega_{max}$ and $1/\omega_{min}<\rho<1/\omega_{max}$, where, ω_{min} and ω_{max} denote the smallest (i.e., most negative) and largest characteristic roots of the matrix W. While it is often suggested in the literature to constrain δ or ρ to the interval (-1, +1), this may be unnecessarily restrictive. For row-normalized spatial weights, the largest characteristic root is indeed +1, but no general result holds for the smallest characteristic root and the lower bound is typically less than -1.

As an alternative to row-normalization, W might be normalized such that the elements of each column sum to one. This type of normalization is sometimes used in social economics literature[5]. Note that the row elements of a spatial weights matrix display the impact on a particular unit by all other units, while the column elements of a spatial weights matrix display the impact of a particular unit on all other units. Consequently, row normalization affects that the impact on each unit by all other units is equalized, while column normalization effects that the impact of each unit on all other units are equalized.

If W_0 denotes the spatial weights matrix before normalization, one may also divide the elements of W_0 by its largest characteristic root, $\omega_{0,max}$ to get $W = (1/\omega_{0,max})\ W_0$ or normalize W_0 by:

$$W = D^{-1/2}W_0D^{-1/2}$$

where, D is a diagonal matrix containing the row sums of the matrix W_0. The first operation may be labelled matrix normalization since it affects that the characteristic roots of W_0 are also divided by $\omega_{0,max}$, as a result of which $\omega_{max} = 1$, just like the largest characteristic root of a row- or column- normalized matrix. Croissant and Millo[6]. proposed the second operation which affects the characteristic roots of W, which are also identical to the characteristic roots of a row-normalized W_0.

Two main approaches have been suggested in the literature to estimate models that include spatial interaction effects. One is based on the maximum likelihood (ML) principle and the other on instrumental variables or generalized method of moments (IV/GMM) techniques[7]. Although IV/GMM estimators are different from ML estimators in that they do not rely on the assumption of normality of the errors, both estimators assume ω_{max} denotes the smallest (i.e., most negative) and largest characteristic roots of the matrix W. While it is often suggested in the literature to constrain δ or ρ to the interval (-1, +1), this may be unnecessarily restrictive. For row-normalized spatial weights, the largest characteristic root is indeed +1, but no general result holds for the smallest characteristic root and the lower bound is typically less than -1. Importantly, the mutual proportions between the elements of W remain unchanged as a result of these two alternative normalizations. This is an important property when W represents an inverse distance matrix, since scaling the rows or columns of an inverse distance matrix so that the sum of the weights to one would cause this matrix to lose its interpretation for this decay[8].

RESULTS AND DISCUSSION

To achieve the stated objective of this study, Novel Coronavirus (COVID-19) cases data was extracted from the COVID-19 dashboard of the Center for Systems Science and Engineering at the John Hopkins University (CSSE, JHU)[9,10]. This covered between 29 February to 12 May, 2020 for the 54 countries of Africa with confirmed cases of the Novel Coronavirus (COVID-19). This study analyzed the relationship between the rate of confirmed cases (Reconfirmed), the death rate (R-death) and the recovery rate (R-recovery) of COVID-19 in Africa with the spatial and temporal effects of the disease. The study calculated the rates by creating categories for each variable of the population by country. The population statistics for each country were extracted from the website of World meter as projected by the Elaboration of data by the United Nations, Department of Economic and Social Affairs, Population Division. These statistics are presented in Table 1.

Table 1 revealed that Djibouti has the highest concentration rate of confirmed cases in Africa (127.126 cases per 100,000 populations). This is followed by Sao Tome (94.908 cases per 100,000 population) and then Cabo Verde (48.023 cases per 100,000 population). The least rate of confirmed cases was observed in Mauritania, Angola and Burundi. These figures are as observed by the 12th of May, 2020.

Table 1: COVID-19 descriptive statistics in Africa as at 12th of May, 2020

Country/Region	Population	Total confirmed cases	Deaths	Recovered	$R_{confirmed}$	R_{death}	$R_{recovery}$
Algeria	43851044	6067	515	2998	13.83547	8488.545	49414.87
Angola	32866272	45	2	13	0.136918	4444.444	28888.89
Benin	12123200	327	2	76	2.697308	611.6208	23241.59
Burkina Faso	20903273	766	51	588	3.664498	6657.963	76762.4
Cabo Verde	555987	267	2	58	48.02271	749.0637	21722.85
Cameroon	26545863	2689	125	1524	10.12964	4648.568	56675.34
Central African Republic	4829767	143	0	10	2.960805	0	6993.007
Chad	16425864	357	40	76	2.173402	11204.48	21288.52
Congo (Brazzaville)	89561403	333	11	53	0.371812	3303.303	15915.92
Congo (Kinshasa)	5518087	1102	44	146	19.97069	3992.74	13248.64
Cote d'Ivoire	26378274	1857	21	820	7.039884	1130.856	44157.24
Djibouti	988000	1256	3	886	127.1255	238.8535	70541.4
Egypt	102334404	10093	544	2326	9.862763	5389.874	23045.68
Equatorial Guinea	1402985	439	4	13	31.29043	911.1617	2961.276
Eritrea	3546421	39	0	38	1.0997	0	97435.9
Eswatini	1160164	184	2	28	15.85983	1086.957	15217.39
Ethiopia	114963588	261	5	106	0.227028	1915.709	40613.03
Gabon	2225734	863	9	137	38.77373	1042.874	15874.86
Gambia	2416668	22	1	10	0.910344	4545.455	45454.55
Ghana	31072940	5127	22	494	16.49989	429.1008	9635.264
Guinea	13132795	2298	11	816	17.49818	478.6771	35509.14
Kenya	53771296	715	36	26	1.329706	5034.965	3636.364
Liberia	5057681	211	20	259	4.171872	9478.673	122748.8
Madagascar	27691018	186	0	85	0.671698	0	45698.92
Mauritania	4649658	9	1	28	0.193563	11111.11	311111.1
Mauritius	1271768	332	10	101	26.10539	3012.048	30421.69
Morocco	36910560	6418	188	398	17.38798	2929.261	6201.309
Namibia	2540905	16	0	6	0.629697	0	37500
Niger	24206644	854	47	322	3.527957	5503.513	37704.92
Nigeria	206139589	4787	158	2991	2.322213	3300.606	62481.72
Rwanda	12952218	286	0	34	2.208116	0	11888.11
Senegal	16743927	1995	19	11	11.91477	952.381	551.3784
Seychelles	98347	11	0	648	11.18489	0	5890909
Somalia	15893222	1170	52	959	7.361629	4444.444	81965.81
South Africa	59308690	11350	206	153	19.13716	1814.978	1348.018
Sudan	43849260	1661	80	742	3.787977	4816.376	44671.88
Tanzania	59734218	509	21	10	0.852108	4125.737	1964.637
Togo	8278724	199	11	126	2.403752	5527.638	63316.58
Tunisia	11818619	1032	45	4357	8.731985	4360.465	422189.9
Uganda	45714007	129	0	173	0.282189	0	134108.5
Zambia	18383955	441	7	183	2.398831	1587.302	41496.6
Zimbabwe	14862924	36	4	92	0.242213	11111.11	255555.6
Mozambique	31255435	104	0	740	0.332742	0	711538.5
Libya	6871292	64	3	55	0.931411	4687.5	85937.5
Guinea-Bissau	1968001	820	3	117	41.66665	365.8537	14268.29
Mali	20250833	730	40	9	3.60479	5479.452	1232.877
Botswana	2351627	24	1	17	1.02057	4166.667	70833.33
Burundi	11890784	15	1	7	0.126148	6666.667	46666.67
Sierra Leone	7976983	338	19	72	4.237191	5621.302	21301.78
Malawi	19129952	57	3	24	0.297962	5263.158	42105.26
South Sudan	11193725	194	0	2	1.733114	0	1030.928
Western Sahara	597339	6	0	6	1.004455	0	100000
Sao Tome and Principe	219159	208	5	4	94.90826	2403.846	1923.077
Comoros	869601	11	1	0	1.264948	9090.909	0

The rates are multiplied by 100,000

Estimation of spatial panel models: The standard weight matrix (W) was used to characterize the spatial relationship among the variables. The dimension of the W matrix in this study is 5454 which is the number of African countries under consideration. This study also standardized the rows of the W matrix with zero diagonal factors which were conceptualized with the spatial relationships within the polygon rook contiguity.

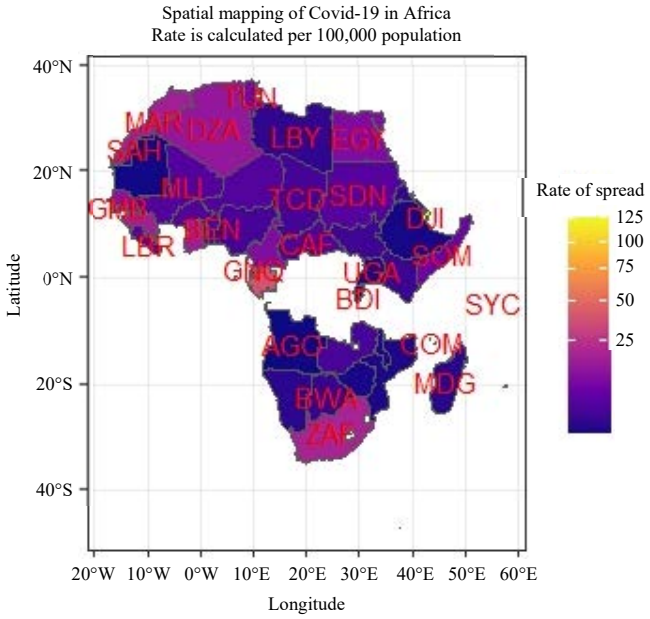

Fig. 1: Spread of COVID-19 in Africa as of May 12th, 2020

This is presented formally using the equation:

$$\omega_{ij}^{'} = \begin{cases} 1 \text{ if country shares a common boundry with region i} \\ 0; \text{ otherwise} \end{cases} \quad (5)$$

$$\omega_{ij}^{'} = \frac{\omega_{ij}^{'}}{\sum_{j=1}^{n} \omega_{ij}^{'}} \quad (6)$$

$$\sum_{j=1}^{n} w_{ij} = 1,\ i = 1,\ldots,n$$

The standard weight matrix was converted into an appropriate format for processing in Stata 15 that uses the command "xsmle" for the spatial panel regression model. The spatial panel data model was used to monitor the influence of the dependent variable on spatial autocorrelation and to analyze specifically the controlling variables and their temporal spillover impacts. The traditional linear panel data model was contrasted to the spatial panel data model since the spatial panel data model takes spatial factors such as spillover effects and spatial dependency into account.

Before the estimation of the spatial panel data models, there is the need to test for cross-sectional dependence which is the primary issue when confronted with spatially referenced data and to determine the existence of the spatial dependence. This means finding out whether nearby cases exhibit a stronger correlation than distant cases.

Figure 1 presents the visual representation of the spatial dependence observed in the spread of COVID-19 in Africa as of May 12th, 2020. This might be an indication of a degree of spatial autocorrelation between the rate of spread of the virus within the African geographical space.

Estimation of spatial models for COVID-19 in Africa: The application of the Pesaran[11] test for general cross-sectional dependence, Croissant and Millo[6] is a versatile way of determining how dependence is linked spatially in the cross-section of a panel dataset.

The results from the analysis considering the standard linear model and the other six-panel data models considered is as summarized in Table 2. The parameters of the spatial panel data models were estimated with the quasi-maximum likelihood estimator according to Lee and Yu[12] and the p-values were calculated with the robust standard error. The models were estimated to include both the temporal time effects and the individual cross-sectional effects.

Table 3 summarizes the temporal time effects for each of the estimated spatial panel data models. The initial step of the analysis was to remove the spatial Durbin model SDM (1), spatial durbin error model SDEM (2), Spatial lagged model SLX (3) and spatial error model SEM (5) because these models are observed to lack spatial effect and tested to be statistically insignificant. Therefore, the study selected the most parsimonious model from spatial autoregressive model SAR (4) and spatial autocorrelation model SAC (6). The coefficients estimated for the spatially lagged variables ($LM_{recovery}$ and LM_{death}) in the spatial autocorrelation model are observed to be statistically significant at a 0.05 significance level. Besides, the R^2 (0.9834), Likelihood Ratio Statistic (76.881), as well as the L-M test of common spatial terms statistic (9.394), are higher for the spatial autocorrelation model than for spatial autoregressive model SAR, also, the corrected Akaike information criterion (30.542) and the bayesian information criterion (29.052) computed for the spatial autocorrelation model is observed to be lowest among every other candidate models. Note that these statistics are computed for small samples. The test of significance on $LM_{recovery}$ and LM_{death} for the selected model are statistically significant at a 0.05 level of significance. Therefore, the spatial effects of the explanatory variables $LM_{recovery}$ and LM_{death} are significantly different from zero. The Hausman test statistic (17.279) computed for the spatial autocorrelation model is observed to be more consistent for the fixed effect model than for the random effect model as $p<0.01$. Hence, the spatial autocorrelation model can be considered to be the most parsimonious spatial panel regression model for the spread of COVID-19 in Africa. Therefore, this study will interpret the influencing factors using the results obtained from the estimation of the spatial autocorrelation model in subsequent analysis.

Table 2: Spatial Panel Models for COVID-19 in Africa

	Spatial panel models						
Variables	SLM	SDM (1)	SDEM (2)	SLX (3)	SAR (4)	SEM (5)	SAC (6)
$R_{recovery}$	-0.7802	-0.7935***	-0.7935***	-0.7935***	-0.7928***	-0.7832***	-0.7935***
R_{death}	28.9284	28.6132***	28.6080***	28.6618***	28.6223***	28.6241***	28.6301***
Cons	0.0001	0.034**	0.044**	0.044**	0.041**	0.037**	0.044**
ρ		-0.036			0.006***		0.006***
π						-0.051	-0.158**
lag.recovery		-0.143	-0.011	-0.361	-0.239**		-0.0935
Lag.deaths			1.1341	1.2741*	2.8341**		1.3046*

SLM: Standard linear regression model, SDM: Spatial durbin model, SDEM: Spatial durbin error model, SLX: Spatial lagged x model, SAR: Spatial autoregressive model, SEM: Spatial error model, SAC: Spatial autocorrelation model, *p<0.10, **p<0.05 and ***p<0.01

Table 3: Model statistics

Temporal effects	SLM	SDM (1)	SDEM (2)	SLX (3)	SAR (4)	SEM (5)	SAC (6)
F-stat/LR stat	71.179**	63.445**	75.117**	69.362**	73.693**	71.514**	76.851**
R^2/Pseudo R^2	0.9663	0.9347	0.9182	0.9505	0.9786	0.9744	0.9834
LM test of common spatial terms	9.339	0.446	9.381	9.390	9.380	9.382	9.394
AIC_c	32.571	27.652	28.553	29.656	31.351	32.459	30.542
BIC_c	30.865	30.879	31.549	30.157	29.951	30.755	29.052

Pesaran-CD test stat: 17.279 prob<0.01, SAC model Hausman Test chi (23): 24.795 (prob<0.001), SAC Model LMr test chi (1): 7.512 (prob<0.050), SAC Model LMd chi (1): 9.045 (prob<0.001) and **p<0.05

This implies that the rate of confirmed COVID-19 cases for countries in Africa is spatially autocorrelated which is an indication that the spatial autocorrelation model provides an appropriate representation of COVID-19 spread in Africa and it will be employed to estimate the spatial effect of COVID-19 in Africa. Since the objective of this study is to explore the factors influencing the rate of confirmed cases and examine their spatial spillover effects.

Based on the spatial panel data model estimated for the 54 countries in Africa with confirmed cases of COVID-19 as of 12th May, 2020, this study estimated the spatial effect of COVID-19 in Africa by exploring the factors influencing the rate of confirmed cases and examining the spatial spillover effects of COVID 19 in within the African continent. Before the estimation of the model, the cross-sectional dependence of the data was examined using the Pesaran test which revealed that there exists cross-sectional dependence within the units. The maximum pseudo-R^2, LR-test, LM-test statistics and minimum AICc and BICc values were used to determine the most parsimonious spatial panel data regression models and to select the most efficient and consistent model which spatial effects of COVID-19 in Africa and it was observed that the spatial autocorrelation model presents an appropriate representation of the data based on the criteria. The selected model was therefore, considered using the dependent and independent variables separately. From the Spatial Autocorrelation model, this study examined the variables separately by splitting the effects of the independent variables into the total, indirect (spatial spillover effects) and direct effects to enhance the identification of the actual impacts and spatial interactions of the factor components on COVID-19 in Africa. We can, therefore, conclude from the total effect that the death rate from COVID-19 in Africa has a significant positive effect on the spread of the virus within the continent and the recovery rate harms the spread of the virus.

As observed from the results, the average direct effect when compared with the average indirect effect can be said to have reflected the actual effects of the influencing factors more comprehensively. The indirect effect for the recovery rate was computed to be equal to 1.073 ($p<0.001$) which implies that every 1% increase in the death rate in any of the African countries with reported cases will bring about a 1.073% increase in the rate of confirmed cases in other neighbouring African countries. Also, the indirect effect of the rate of recovery was computed to be equal to -2.398 ($p<0.001$) which is significant at a 5% level of significance.

Table 4 summarizes the temporal effects of the spatial autocorrelation model and these depict that the rate of spread of COVID-19 in the early period of the pandemic (January) experienced a slight increase across Africa which is not statistically significant. However, the forecast from the Spatial Autocorrelation model depicts a surg from the last week in February from where significant increases were observed in the rate of confirmed cases. Therefore, we can conclude that an increase of 0.1527 per 100,000 people is expected in the coming weeks if the pattern of spread remains constant. Also, considering the direct effect, the rate of death and recovery from COVID-19 in Africa has a significant positive effect on the spread of the virus within the continent. This implies that a 1% increase in the death rate in any of the African countries with

Table 4: Spatial effect of the independent variables on the spatial autocorrelation model

Variables	dy/dx	Delta-method Std. Err	Probability	Confidence interval Lower	Upper
Direct spatial effect					
$R_{recovery}$	-14.017	0.281	<0.001	-13.736	-14.298
R_{death}	3.375	0.093	<0.001	3.282	3.468
Indirect spatial effects					
$R_{recovery}$	-2.398	0.437	<0.001	-1.961	-2.835
R_{death}	1.073	0.084	<0.001	0.989	1.157
Total spatial effects					
$R_{recovery}$	-16.415	0.718	<0.001	-15.697	-17.133
R_{death}	4.448	0.177	<0.001	4.271	4.625

reported cases will bring about a 3.3% increase in the rate of confirmed cases in other neighbouring African countries while the recovered cases have a significant negative effect on the spread of the virus within the continent. This implies that a 1% increase in the death rate in any of the African countries with reported cases will bring about a 14% decrease in the rate of confirmed cases. Lastly, from the indirect effects, the rate of death was observed to maintain significant positive effects on COVID-19 spread in the neighbouring African countries and the rate of recovery has significant negative effects.

As a result of the temporal effects as observed from the analysis, we observed a daily increase in the rate of confirmed cases, Examining the number of confirmed cases on the 29th of February, 2020 (Study start period) and the 12th of May, 2020 (Study end period), This study observed that the rate of confirmed cases has increased from 0.09 cases per 100,000 population to 94 cases per 100,000 population. There is a need to address some limitations while discussing the results of this study. It is impossible to generalize the model for the death rate from COVID-19 in Africa due to the presence of a large difference in the number of deaths across the countries. Also, the time frame under consideration appears to be short considering the pattern of the period it takes a patient to recover from the virus, therefore, future studies can consider using data with a longer period.

CONCLUSION

This study considered the spatial effect of COVID-19 in Africa using the spatial panel data model approach and it has been able to provide information about the effect of the spread of COVID-19 across the African continent. It can be observed from the results that an increase of 0.1527 per 100,000 people is expected in the coming weeks if the pattern of spread remains constant. And also, the rate of death and recovery from COVID-19 in Africa has a significant positive effect on the spread of the virus within the continent.

SIGNIFICANCE STATEMENT

This study addressed the temporal and spatial effects of the spread of COVID-19 in Africa and discovered that the rate of death and recovery from COVID-19 in Africa has a significant positive effect on the spread of the virus within the continent. These findings will help future researchers to uncover critical areas of spatial panel data models and their application to published data that many researchers were not able to explore. Thus, a new theory on the rate of spread and effect of COVID-19 in Africa can be established.

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